SKIN DISEASE DETECTION DEVICE

BY

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Certificate

This is to certify that the project report entitled:

"SKIN DISEASE DETECTION DEVICE"

Submitted by:

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Is a record of original research work carried out under my supervision and guidance in the **Department of** [**ENGINEERING AND COMPUTER SCIENCE**] at [**21 SEPTEMBER UNIVERSITY FOR MEDICAL APPLIED SCIENCES**]. To the best of my knowledge, the work embodied in this report has not been submitted to any other University or Institute for the award of any degree.

Internal Supervisor	**Head of Department**
AMMAR SHARF- ALDIN	AMMAR SHARF- ALDIN

Date: ____________________

Dedicated to

Our family And Friends

Acknowledgments

First and foremost, we would like to express our deepest gratitude to our supervisor, **Dr.** AMMAR SHARF- ALDIN, for his invaluable guidance, constant encouragement, and immense knowledge throughout the duration of this research. His insightful comments and constructive criticisms have been instrumental in the completion of this work.

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Abstract

Skin diseases affect a significant portion of the global population, requiring accurate and timely diagnosis to ensure effective treatment. This project presents the design and development of a medical device aimed at assisting in the diagnosis of various dermatological conditions. The device integrates imaging sensors with advanced machine learning algorithms to analyze skin lesions and classify them into specific disease categories. A comprehensive dataset of skin images was utilized to train and validate the system, ensuring high accuracy and reliability. The proposed device offers a user-friendly interface, rapid diagnostic capabilities, and potential integration with clinical workflows, providing healthcare professionals with an efficient tool to support decision-making. The results demonstrate that the device can significantly enhance early detection and monitoring of skin conditions, ultimately improving patient outcomes.

List of Figures

List of Tables

List of Abbreviations

CNNs	Convolutional Neural Networks
df	*Dermatofibroma*
bkl	Benign keratosis
vasc	Vascular Lesions
nv	Melanocytic Nevi
bcc	Basal Cell Carcinoma
AI	Artificial Intelligence
AUCs	C Accuracy
ISIC	International Skin Imaging Collaboration
CAM	Class Activation Map
RAM	Random Access Memory
GPU	Graphics Processing Unit
UI	User Interface
GUIs	Graphical User Interfaces
HDR	High Dynamic Range
ADC	Analog-to-Digital Converter
DSP	Digital Signal Processor
I/O	input/outpu
I2C	KIntegrated Circuit
UART	Universal Asynchronous Receiver-Transmitter
SCL	Serial Clock
UV	L ultraviolet

SCC $\quad$ *L*Squamous Cell Carcinoma

Contents

CHAPTER 1

Introduction

Skin diseases represent a major public health concern due to their high prevalence and diverse clinical manifestations. They affect individuals of different ages, skin types, and backgrounds, and range from mild conditions to severe diseases that may require long-term treatment. Early and accurate diagnosis plays a crucial role in reducing complications, improving treatment outcomes, and enhancing patients' quality of life. However, accurate diagnosis often depends on the availability of experienced dermatologists and specialized medical facilities, which may not always be accessible. Traditional methods for diagnosing skin diseases rely primarily on visual inspection, clinical experience, and sometimes laboratory tests. While these methods can be effective, they are often subjective and may vary depending on the expertise of the clinician. Additionally, many skin diseases share similar visual characteristics, making differentiation difficult, especially in early stages. These challenges highlight the need for supportive diagnostic tools that can assist in the evaluation process and provide consistent, objective analysis. In recent years, advances in artificial intelligence and deep learning have enabled significant progress in medical image analysis. Convolutional Neural Networks (CNNs), in particular, have demonstrated strong performance in extracting complex visual features from images and performing accurate classification tasks. The application of these techniques in dermatology has gained increasing attention due to the image-based nature of skin disease diagnosis.

By learning from large datasets of labeled skin images, deep learning models can identify patterns that may not be easily distinguishable by the human eye. This project proposes an intelligent system for skin disease detection based on image analysis using deep learning models. The system captures skin images through a camera and processes them locally to classify multiple skin disease categories. To enhance the diagnostic context, skin temperature is measured using a non-contact infrared temperature sensor and presented as supplementary information alongside the classification result. Although temperature measurements alone are not sufficient for diagnosis, they may provide additional insight that supports clinical interpretation in certain cases.

The proposed system is designed as an experimental prototype intended for academic and research purposes. It operates entirely in a local environment without reliance on cloud-based services and does not store patient data, ensuring simplicity and privacy during testing. The system focuses on demonstrating the feasibility of integrating image-based deep learning techniques with sensor data within a unified framework. The main objective of this project is to explore the potential of intelligent systems to support skin disease detection and analysis. Rather than replacing medical professionals, the system aims to assist in preliminary assessment and decision support. Through system implementation, testing, and evaluation, this project investigates both the strengths and limitations of such an approach and provides insights for future improvements and research directions in intelligent medical diagnostic systems.

1.1 Overview

In recent years, the increasing availability of medical image datasets and the rapid advancement in computational capabilities have played a significant role in the development of intelligent diagnostic systems. These systems aim to minimize reliance on subjective human judgment and provide consistent, repeatable, and data-driven diagnostic support. In the field of dermatology, image-based analysis has gained particular importance due to the visual nature of skin diseases. Despite the notable progress in this domain, automated skin disease detection still faces several practical challenges. Variations in lighting conditions, image resolution, camera positioning, and differences in skin tone can significantly influence classification accuracy. In addition, many intelligent diagnostic systems rely solely on visual information, which may not always be sufficient to provide a comprehensive diagnostic context, particularly in ambiguous or borderline cases. This project aims to develop a portable intelligent device capable of quickly and accurately examining and diagnosing skin diseases. The device uses multiple imaging and sensing technologies to capture comprehensive skin data, which is then analyzed by artificial intelligence to provide preliminary diagnostic results that can assist doctors or users in early detection of skin conditions .

How the Device Works : The user places the area of skin to be examined in front of the device . The device captures multiple images using a set of different sensors and cameras, covering various aspects such as: natural skin appearance,skin temperature measurement, ambient temperature measurement of the device. All data is sent to a processing unit, where the software analyzes and processes the images .

A pre-trained AI model classifies the

condition and provides probable diagnosis along with confidence scores . Results are displayed on a simple, user-friendly interface.

1.2 Problem Statement

The primary problem is that the manual diagnosis of skin diseases by human doctors faces several challenges, leading to delays in diagnosis, increased costs, and a higher probability of error.

1.2.1 Challenges with Human Diagnosis

- The diagnosis of skin diseases is heavily based on the visual expertise of the physician.

- The similarity in symptoms between many skin conditions (such as benign moles and early-stage skin cancer) makes it difficult to differentiate between them. This can lead to misdiagnosis or the need for additional expensive examinations.

1.2.2 Shortage of Specialists

- Dermatologists are not available in all areas, especially in rural and remote regions.

- This shortage leads to long waiting times for appointments, which can delay the detection of serious diseases like skin cancer.

1.2.3 Delayed Diagnosis and Early Detection

- Many skin diseases, particularly cancers, are more treatable when detected in their early stages.
- Delays in reaching a doctor or getting an accurate diagnosis reduce the chances of a full recovery.

1.3 project objectives

The primary goal of this project is to design and implement a portable skin disease detection device that combines advanced imaging technologies with artificial intelligence to provide fast, accurate, and user-friendly diagnostic support. The objectives are comprehensive and can be divided into several key areas:

1.3.1 Early Detection of Skin Diseases

- Enable rapid identification of various skin conditions, including acne, psoriasis, eczema, and potential skin cancers .

- Reduce the reliance on manual examinations, which can be subjective and time-consuming .
- Allow early intervention, improving treatment outcomes and reducing complications.

1.3.2 Accessibility and Portability

- device that can be easily transported and used in remote or underserved regions where dermatologists may not be available .
- Provision a tool that can assist both healthcare professionals and individuals for on-the-spot skin assessments .
- Minimize the need for large, expensive diagnostic equipment,making skin health monitoring more widespread and affordable .

1.3.3 Multi-Sensor Integration

- Utilize a combination of camera , infrared thermal sensor to capture detailed and complementary information about the skin .
- Artificial Intelligence Assistance Implement a pre-trained AI model capable of analyzing skin images and providing probable diagnoses with confidence scores .
- Reduce human error and improve diagnostic consistency .
- Offer decision support to dermatologists while providing actionable insights to users .

1.3.4 Simple User interface

- Design an intuitive interface that allows users to capture skin images easily and view results clearly .

1.4 project scope and Limitations

1.4.1 Project Scope

The scope of this project defines the boundaries and extent of the portable skin disease detection system

- Targeted Skin Conditions: The device focuses on detecting common skin diseases and conditions, **such as :**

  1 . Psoriasis / Lichen Planus

  2 . Dermatofibroma (df)

  3 . Benign keratosis (bkl)

  4 . Eczema

  5 . Acne Rosacea

  6 . Melanoma

  7 . Vascular Lesions (vasc)

  8 . Melanocytic Nevi (nv)

  9 . Vascular tumors

  10 . Actinic keratoses

  11 . Basal Cell Carcinoma (bcc)

- Multi-Sensor Data Acquisition: The system utilizes camera, infrared thermal sensor to capture comprehensive skin data.

- Each sensor provides complementary information to improve diagnostic accuracy.

- Artificial Intelligence Integration: A VGG19 RES net 50 AI models is employed to analyze skin images and classify possible conditions.

- User Interaction: Users can capture images, view diagnostic results.

- The interface is designed to be user-friendly and intuitive for non-specialists.
- Portability and Accessibility: The device is designed to be compact and portable, suitable for use in clinics, hospitals, or remote areas.
- Software Components: The system includes data acquisition software, image processing modules, AI inference engine, and user interface

1.4.2 Project Limitations

its capabilities, the project has certain limitations:

- Medical Accuracy Constraints: The device provides preliminary diagnostic suggestions only; it is not a substitute for professional medical evaluation.
- Accuracy depends on the quality of the captured images and the training dataset used for AI.
- Limited Dataset Coverage: The AI model may not recognize rare skin conditions or diseases not included in the training dataset.
- Environmental Factors: External lighting, skin tone variations, and camera angles may affect the accuracy of detection.
- Infrared Thermal Sensors may require specific conditions for optimal performance.
- User Skill Requirement: Users need basic understanding of how to position the skin area and operate the device properly to obtain reliable results.

1.5 Project Methodology

In this project, we followed a structured methodology that aimed to ensure accurate results and a smooth workflow. The methodology was divided into several stages, where each stage built upon the previous one to gradually transform the idea into a practical system.

- Stage One: Problem Identification and Analysis

At the beginning, we studied the challenges related to diagnosing skin diseases using traditional methods. We noticed that diagnosis often requires long medical experience, and sometimes patients face delays in identifying their condition due to the lack of accessible and quick tools. Therefore, the first step was to define our objective clearly: to develop a smart tool that can assist in the early detection of skin diseases with reasonable accuracy.

- Stage Two: Data Collection

After identifying the problem, we moved on to collecting data. We gathered medically approved and well-labeled images of different skin diseases such as acne, psoriasis, eczema, and more. This dataset formed the foundation for training and testing the system later on.

- Stage Three: System Design and Planning

At this stage, we created the initial design of the system. We mapped out how images would be captured from the camera or sensor, how they would be processed, and how the artificial intelligence model would analyze them. This step helped us build a clear roadmap before diving into the technical details.

- Stage Four: Development of the AI Model

This was one of the most critical phases. We used deep learning techniques to train a model capable of distinguishing between different skin conditions. The process required multiple iterations of training, tuning parameters, and evaluating performance until we achieved an acceptable level of accuracy.

- Stage Five: Integration with the User Interface

Once the model was ready, we worked on connecting it with a user-friendly interface. The focus here was to make the system easy to use, where a user (either a doctor or a patient) could simply upload or capture an image and instantly receive the analysis results.

- Stage Six: Testing and Evaluation

We tested the system using images that were not included in the training dataset, to evaluate its reliability and accuracy. Feedback from these tests was very important, as it allowed us to detect errors and make improvements. The goal was to ensure that the system is not just theoretical but practical and dependable.

- Stage Seven: Documentation and Improvement

  Finally, we documented all the steps of the project in detail. Documentation is important not only for presenting the project but also for any future development or improvements that might be required.

1.6 Project Organization

- The organization of the project played a very important role in keeping everything on track and ensuring that we were able to move step by step without losing focus. From the beginning, we decided to divide the work in a way that each member of the team had a clear responsibility, but at the same time, we worked closely together and supported one another whenever it was needed.

- At the start, we agreed on setting a timeline that outlined the major stages of the project, such as research, data collection, model development, testing, and final reporting. This timeline served as a guide that reminded us of deadlines and prevented us from delaying tasks until the last moment. Even though unexpected challenges appeared, having this schedule helped us remain organized and make adjustments without losing the overall balance of the work.

- In terms of roles, we distributed the tasks according to each member's strengths and interests. For example, one member was mainly responsible for data collection and organizing the dataset, another focused on coding and training the AI model, while others worked on system design, user interface, and documentation. However, the organization was not rigid—there were many times when tasks overlapped, and we helped each other to make sure everything was completed on time.

- Communication was another key part of our organization. We arranged regular meetings to review progress, discuss challenges, and suggest solutions. These meetings were very useful because they kept everyone updated and allowed us to quickly identify any problems before they grew bigger. We also used digital tools like shared folders and messaging groups to exchange files, datasets, and code, which made the workflow smoother.

- Another important aspect of the organization was keeping records of what we did in every phase. We wrote down the methods we used, the difficulties we faced, and the solutions we applied. This was not only helpful for preparing the final report, but it also ensured that if we needed to revisit a step or explain a decision, we had a clear reference.

- Towards the end of the project, we organized our work by focusing on final testing, presentation preparation, and report writing. Each member contributed to the documentation, but we also assigned one person to review and edit the final draft so that the report would be consistent and well-structured. Similarly, for the presentation, we practiced together and divided the speaking parts equally so that every team member was actively involved.

- In summary, the organization of the project was based on teamwork, clear division of tasks, regular communication, and proper time management. This structure helped us reduce stress, maintain discipline, and achieve a final outcome that reflected the combined effort of all team members. Without this level of organization, it would have been much harder to complete the project within the limited time and resources we had.

CHAPTER 2

Background and Review

2.1 Background

skin disease detection device is an advanced medical tool used to diagnose and monitor skin diseases. It relies on multiple technologies such as:

1. Digital imaging: to capture high-resolution images of the skin.
2. Synergistic Visual-Thermal Sensing :

   This section discusses the integration of optical imaging and thermal sensing to provide a multi-dimensional diagnostic approach for skin lesion analysis.

3. Artificial intelligence: to analyze images and provide accurate diagnoses. devices help doctors in:

- Early detection: of skin diseases like cancer.
- Accurate diagnosis: to determine the type and severity of the disease.
- Treatment monitoring: to evaluate the effectiveness of treatment and adjust it as needed.

The development of these devices aims to improve diagnostic accuracy and increase the chances of successful treatment for skin diseases.

2.1.1 Digital Imaging

Digital imaging in portable skin disease detection devices uses high-resolution cameras to capture clear and detailed images of the skin. These images help doctors in:

- Seeing fine details : such as changes in skin color, shape, and size.
- Documenting the condition: to track changes over time and evaluate the effectiveness of treatment.
- Diagnosis: doctors can use these images to diagnose various skin diseases.

2.1.2 Synergistic Visual-Thermal Sensing

The integration of visual imaging and infrared thermography represents a dual-modality approach to dermatological assessment. While camera data provides high-resolution information regarding the morphology, color, and texture of skin lesions, the infrared thermal sensor (MLX90614) captures the underlying physiological heat patterns.

By correlating visual features with thermal signatures, the system can detect subcutaneous inflammatory activities that may not be apparent to the naked eye. This synergistic sensing mechanism enhances the feature extraction process, allowing the AI model to cross-reference visual abnormalities with localized temperature spikes, thereby increasing the overall diagnostic reliability and reducing false positives in various skin conditions.

2.1.3 Artificial Intelligence

Artificial Intelligence (AI) plays a significant role in analyzing medical images and providing accurate diagnoses. AI can:

- Analyze images: AI algorithms can analyze digital images of the skin and identify pathological features.
- Learn from data: AI can learn from large medical image data sets to improve diagnostic accuracy.

- Provide recommendations: AI can provide treatment recommendations based on diagnosis and clinical data.

General Benefits:

- Early detection: portable skin disease detection devices can detect diseases in their early stages, increasing the chances of successful treatment.
- Accurate diagnosis: these devices can provide accurate and reliable diagnoses, reducing the need for invasive procedures or additional tests.
- Treatment monitoring: these devices can be used to monitor the effectiveness of treatment and adjust it as needed.

2.2 Review

Portable Skin Lesion Segmentation System The Portable Skin Lesion Segmentation System is an advanced system that uses weakly supervised learning techniques to accurately detect and segment skin lesions. The system consists of three main units:

- Primary Segmentation Network Unit: generates an approximate mask for the skin lesion.
- Dual CAM-Guided Classification Unit: uses the approximate mask and classification of the skin lesion to generate a precise mask for lesion detection.
- Secondary Segmentation Network Unit: leverages information gained from previous units to improve the accuracy of skin lesion segmentation.

Features of the System:

- High Accuracy : the system achieved excellent results in evaluations on HAM10000 and ISIC datasets, with average AUCs of 80
- Practical Use: the system is designed to be portable and user-friendly, allowing its application in various clinical settings.

- Integration of Classification and Segmentation: the system relies on the integration of neural networks for classification and segmentation, enabling it to extract common features and improve performance in both tasks.

Technologies Used:

- Weakly Supervised Learning: the system uses weakly supervised learning to generate accurate masks for skin lesions without requiring densely labeled data.
- Convolutional Neural Networks: the neural networks in the system rely on a dual CAM CNN architecture to improve the accuracy of skin lesion detection.
- Softmax Cross-Entropy Loss and Binary Cross-Entropy Loss: the system uses a combination of loss functions to improve the performance of neural networks.

Potential Applications:

- **Early Detection of Skin Cancer:** the system can assist doctors in the early detection of skin cancer, increasing the chances of successful treatment.
- **Skin Lesion Detection:** the system can be used to accurately detect skin lesions, aiding in diagnosis and appropriate treatment.
- **Remote Clinical Triage:** The system can be used as a front-line triage tool in rural or underserved areas where access to dermatologists is limited. It allows primary healthcare workers to screen patients and prioritize urgent cases for specialist referral.
- **Continuous Home Monitoring for Chronic Conditions:** Patients with chronic skin conditions, such as diabetic foot ulcers or psoriasis, can use the device to monitor their healing progress. The thermal sensor can detect early signs of infection (heat spikes) before they become visible to the eye.
- **Post-Surgical Site Observation:** Surgeons can provide this tool to patients recovering from skin-related surgeries to monitor incision sites for inflammation or complications, reducing the need for frequent in-person follow-ups.

- **Geriatric Care in Nursing Homes:** The device can assist caregivers in nursing homes to regularly check elderly residents for pressure ulcers (bedsores), where early thermal changes often precede visible skin breakdown.
- **Integration with Telemedicine Platforms:** The system can serve as a peripheral diagnostic tool for telemedicine, sending high-resolution images and synchronized thermal data to doctors for a more accurate remote diagnosis.
- **Public Health Screening Campaigns:** During health camps or epidemic outbreaks (like Monkeypox or other rashes), the portable nature of the device allows for rapid, non-contact mass screening in public spaces.

CHAPTER 3

Requirements Analysis and Modeling

. Requirements analysis and modeling is a vital process in software and system development. Here's a detailed explanation:

3.1 Requirements Analysis

- Requirements gathering.
- Understanding needs.
- Prioritization.

3.1.1 Requirements gathering

Collecting requirements from stakeholders, such as customers and end-users, through interviews, meetings, and documents.

3.1.2 Understanding need

- Analyzing requirements to understand the actual needs and requirements of the system, including the functions and features required.
- Determining the priority of requirements based on their importance and impact on the system, to ensure that the most important needs are met first.

3.2 Requirements Modeling

- Representing requirements.
- Analyzing relationships.
- Ensuring accuracy.

3.2.1 Representing requirements

Representing requirements using models and diagrams, such as:

- Use case diagrams: Representing scenarios of system usage. tikz

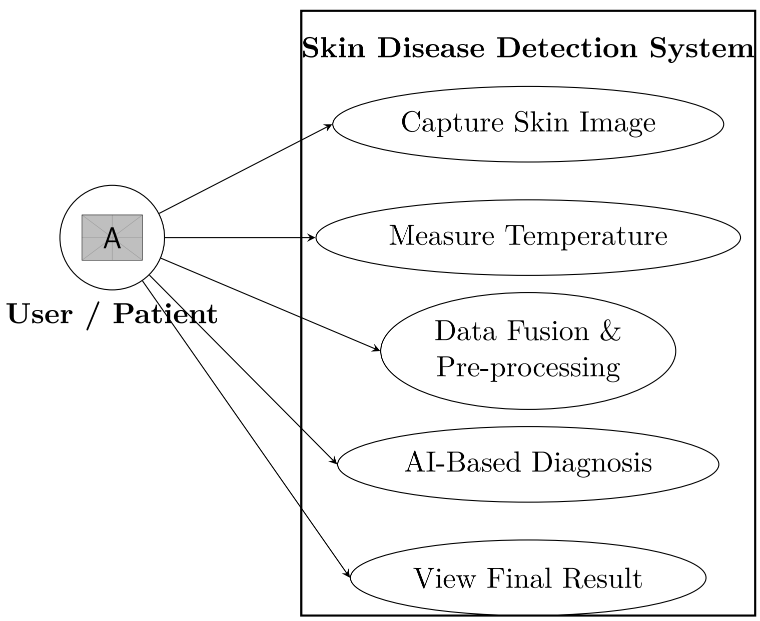


Figure 3.1: Updated Use Case Diagram for the Mobile Skin Disease Detector

  – Class diagrams: Representing entities and relationships between them.

between them.

  – Sequence diagrams: Representing the sequence of events in the system.

3.2.2 Analyzing relationships

Analyzing the rlationships between requirements and different entities in the system, to ensure a precise understanding of the relationships between components.

3.2.3 Ensuring accuracy

Ensuring the accuracy and completeness of requirements and models, to guarantee that the system meets the required needs.

Tools and Techniques:

- Use case diagrams: Used to represent scenarios of system usage, and determine the required functions and features.

- Class diagrams: Used to represent entities and relationships between them, and determine the overall structure of the system.

- Sequence diagrams: Used to represent the sequence of events in the system, and determine the interactions between components.

- Modeling languages: Such as UML (Unified Modeling Language) and BPMN (Business Process Model and Notation), used to represent requirements and models in a standardized way.

Benefits of Requirements Analysis and Modeling:

- Ensuring accuracy: Helping to ensure the accuracy and completeness of requirements, to guarantee that the system meets the required needs.

- Reducing errors: Reducing errors and subsequent improvements, which reduces the costs and time required for development.

- Improving communication: Enhancing communication between stakeholders and developers, to ensure a shared understanding of requirements and needs.

- Developing an effective system: Contributing to the development of a system that meets user needs, and achieves the desired goals.

CHAPTER 4

Project Design

4.1 Introduction

Project design is one of the most important stages in completing scientific research, as it translates theoretical requirements and previous analyses into a practical model that can be implemented and tested. This chapter explains the general structure of the proposed device, starting with the hardware components such as the sensors and processing units, moving on to the software and algorithms used for image processing and diagnosing skin diseases, and ending with the user interface that facilitates interaction with the system .

This chapter also explains the design considerations that were taken into account, such as accuracy standards, ease of use, safety, and the potential for future development of the device. It also includes block diagrams, schematics, and the interconnection mechanism of the various components, ensuring functional integration between the hardware and software to achieve the project's primary goal : early detection of skin diseases in an accurate and user-friendly manner.

4.2 Overall System Design

This section aims to provide a comprehensive overview of the overall architecture of the proposed device, presenting the main components and the relationships between them . The system relies on integrating both hardware and software components into an integrated framework that ensures efficient performance of the required functions.

The proposed system primarily consists of four interconnected modules:

4.2.1 Sensing Unit

This includes cameras and Infrared thermal sensor responsible for capturing skin images and collecting raw data. The Sensing Unit is the interface between the physical environment and the digital system. Its primary role is to gather multi-modal data (visual and thermal) from the patient's skin with high precision.

- **Visual Acquisition:** Captured via the WC-061 Camera, which provides high-resolution RGB frames to the laptop for deep learning analysis.
- **Thermal Acquisition:** Managed by the MLX90614 infrared sensor, which detects the heat radiation from the skin surface.
- **Hardware Coordination:** The ESP32 microcontroller acts as the data bridge in this unit, ensuring that thermal readings are correctly digitized and prepared for transmission via the I2C bus.

4.2.2 Processing Unit

This module is responsible for receiving raw data, performing initial processing, and applying artificial intelligence algorithms for classification and diagnosis. Unlike embedded systems with limited resources, this project utilizes a **High-Performance Laptop** as the primary Processing Unit. This choice allows for the execution of complex computational tasks that require significant RAM and GPU power.

- **Centralized Computation:** The laptop runs the core Python environment where the Convolutional Neural Network (CNN) is deployed. It handles heavy matrix multiplications required for image classification.
- **Data Fusion:** The processing unit receives thermal data from the ESP32 (via Serial-USB) and visual data from the camera simultaneously. It synchronizes these inputs to create a comprehensive diagnostic profile.
- **Real-time Analysis:** Thanks to the laptop's CPU/GPU capabilities, the system can perform image pre-processing (Resizing, Normalization) and AI inference in a matter of seconds, providing near-instantaneous results.

4.2.3 User Interface

This module enables the user to interact with the device, allowing for image capture and simplified visualization of diagnostic results. The User Interface (UI) is developed using the **Tkinter library**, which is the standard Python framework for creating Graphical User Interfaces (GUIs). It is designed to be intuitive, ensuring that even non-technical users can operate the device easily.

4.3 Hardware Design

Hardware design is a critical component of building the proposed device, encompassing the selection and integration of physical components that enable the system to perform its functions efficiently. This project focused on selecting components that strike a balance between accuracy, efficiency, and portability, in line with the primary goal of early detection of skin diseases.

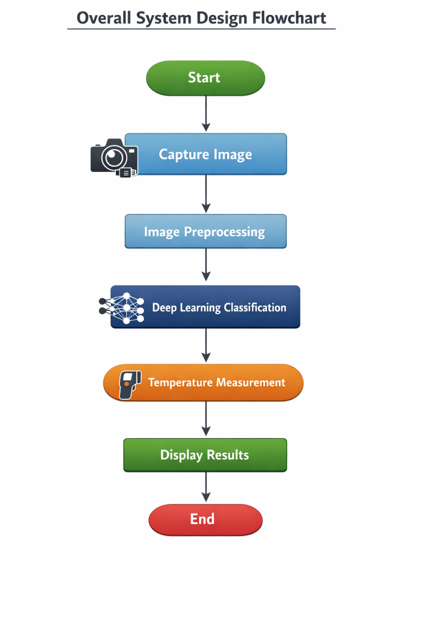


Figure 4.1: Hardware Design

4.3.1 Sensing Unit

1- Camera web wc-061 : Used to capture high-resolution images of the skin, enabling analysis of visible characteristics such as color, shape, and texture.

Table 4.1: Advanced Technical Specifications of WC-061 HD Camera

Feature	**High-Definition Specification**
Optical Resolution	Full HD Interpolated (Up to 1280 x 720p)
Sensor Technology	Advanced CMOS with High Dynamic Range (HDR)
Frame Rate	30 - 60 fps (Adaptive)
Focusing System	Precision Manual Focus (Macro support)
Color Depth	24-bit True Color RGB
Signal-to-Noise Ratio	> 48dB (Clear imaging in low noise)
Aperture	F/2.0 (High light intake for medical clarity)
Interface	USB 2.0 / 3.0 High-Speed Interface

Enhanced Diagnostic Capabilities

– **High Pixel Density:** The high-resolution sensor ensures that the "Edges" and "Texture" of the skin lesion are preserved, preventing the loss of critical

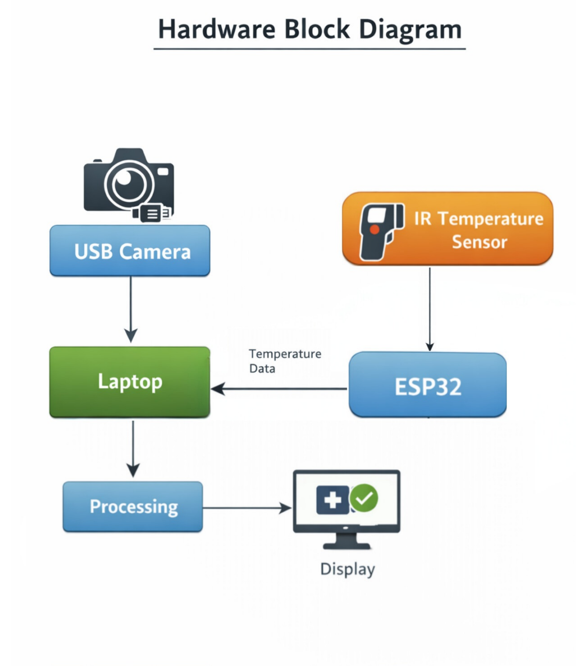


Figure 4.2: Hardware Design

diagnostic data during the image resizing process.

- **Macro Imaging Excellence:** The manual focus allows the system to operate at a close distance (3cm - 10cm) from the skin, providing a magnified view of the pathological area similar to a digital dermatoscope.
- **Low-Light Sensitivity:** The F/2.0 aperture allows more light to reach the sensor, which reduces "Digital Grain" or noise, leading to a more stable input for the Deep Learning algorithm.
- **Color Fidelity:** With a 24-bit color depth, the camera distinguishes between subtle shades of erythema (redness) and pigmentation, which are key indicators in differentiating between benign and malignant lesions.

2- Infrared Temperature Sensor (MLX90614) : Used to identify areas of inflammation or infection by measuring changes in surface temperature. The MLX90614 is an advanced, non-contact infrared thermometer designed for high-accuracy temperature measurements. It is a critical component for detecting the thermal variations associated with skin infections or inflammation.

Figure 4.3: Camera web wc-061

- **Measurement Principle:** The sensor works by detecting the infrared radiation emitted by the skin surface. This allows for a completely non-invasive diagnostic process, which is essential for medical hygiene.
- **Signal Conditioning:** It integrates an internal 17-bit Analog-to-Digital Converter (ADC) and a powerful Digital Signal Processor (DSP), ensuring that the output data is precise and filtered from external noise.
- **Thermal Range:** It can measure object temperatures ranging from -70°C to +380°C with an accuracy of 0.5°C in the medical range (35°C to 42°C).
- **Interface:** The sensor provides its data over the I2C bus, allowing the ESP32 to request and receive temperature values using only two communication lines (SDA and SCL).

Figure 4.4: IR Sensor

4.3.2 Processing Unit

Represents the heart of the system, receiving and processing data from the sensor unit.

We will use a Cumputer because It provide adequate computing power for image processing and running AI models. It has input/output (I/O) ports for connecting cameras and sensors. It has sufficient memory to support data processing of pre-trained models.

4.3.3 User Interface Hardware

screen of Labtop for live display of results.

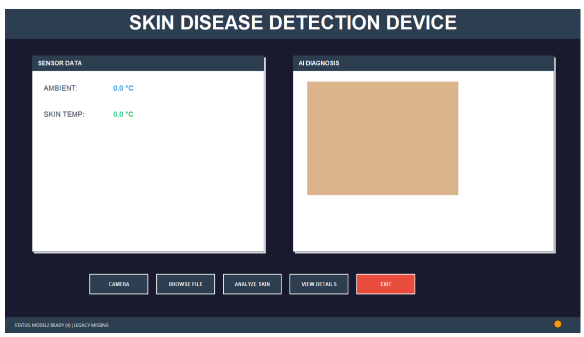


Figure 4.5: screen of Labtop

4.3.4 ESP32 Microcontroller Unit

The ESP32 is a high-performance, low-power microcontroller developed by Espressif Systems, featuring integrated Wi-Fi and dual-mode Bluetooth. In this project, it serves as the primary data acquisition and processing hub for the thermal sensing system.

– **High-Speed Processing:** Equipped with a dual-core Xtensa® 32-bit LX6 microprocessor, allowing for efficient multi-threading between sensor reading and data transmission.

- **I2C Communication:** It provides dedicated hardware pins for the Inter-Integrated Circuit (I2C) protocol, which is used to interface with the infrared sensor seamlessly.
- **Analog-to-Digital Conversion:** It features multiple 12-bit ADC channels that can be utilized for additional sensor integration if required.
- **Data Transmission:** The ESP32 is programmed to transmit the gathered data to the host computer via a high-speed Serial interface (Universal Asynchronous Receiver-Transmitter - UART) at a baud rate of 115200.

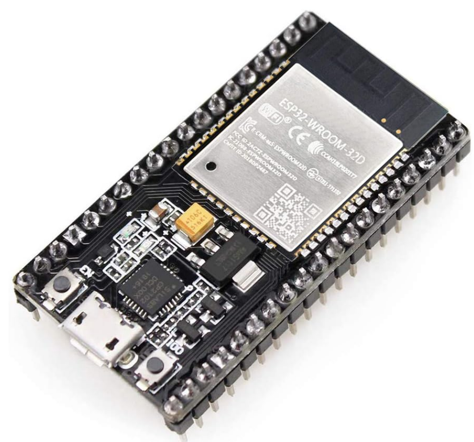


Figure 4.6: esp32

4.4 Software Design

The software design forms the backbone of the proposed device, responsible for collecting data from the sensors, processing it using computer vision techniques, analyzing it using artificial intelligence algorithms, and then displaying the results to the user in an easy and reliable manner. The system relies on the Windows operating system and the Python language, which provides powerful libraries and specialized tools, in addition to its support for integration with hardware and image processing. **The following is a detailed breakdown of the software design components:**

4.4.1 Programming Language and Environment

Python is the primary language for writing code, due to its flexibility and support for image processing and deep learning libraries. Conda the development environment.

Figure 4.7: conda

Figure 4.8: python

4.4.2 Sensor Library

Sensor Infrared Thermal are handled using proprietary libraries, typically downloaded from GitHub or from the manufacturers. The software relies on communication protocols such as Serial Communication or USB drivers to read values and convert them into processable images. This integration ensures a seamless flow of data from the hardware to the software system.

4.4.3 Data Acquisition Software

The OpenCV library is used to control the cameras and capture images. The system stores raw images in a standard format (JPEG/PNG) for processing.

4.4.4 Image Pre-processing

Images are enhanced using libraries such as OpenCV . This stage includes noise removal, contrast adjustment, and image segmentation to isolate the target skin area. The goal is to provide high-quality images that help the model achieve higher accuracy. Numpy is used for efficient numerical computations and array-based data Processing in the system .

Figure 4.9: open cv

Figure 4.10: numpy

4.4.5 Training and Experimental Tools

The Google Colab environment was used to train RESNET50 Model because it provides graphics processors (GPUs) that enable efficient model training. The Kaggle environment was used to train VGG19 Model . These models were chosen due to their proven performance in image classification tasks and their widespread use in medical image analysis research. Training the models from scratch allowed full control over the learning process and ensured that the extracted features were directly influenced by the characteristics of the skin disease dataset used in this project.

4.4.6 Artificial Intelligence & Deep Learning

The TensorFlow library was used to develop convolutional neural networks (CNNs). The training process relies on readily available data from the internet (such as the ISIC Dataset and HAM10000) in addition to locally generated data. Transfer learning is used to reduce training time and increase accuracy. Two pre-trained Convolutional Neural Network (CNN) architectures, ResNet50 and VGG19, are employed using the transfer learning approach to enhance accuracy while reducing training time and computational cost.

ResNet50 is utilized for its deep residual learning capability, which helps overcome the vanishing gradient problem and enables efficient feature extraction from complex image patterns. On the other hand, VGG19 is adopted due to its simple and uniform architecture, which relies on stacked convolutional layers to capture fine-grained visual features.

Both models are fine-tuned on the project-specific dataset, allowing the system to learn domain-relevant features effectively and achieve reliable classification performance. The extracted features are processed during the inference stage to generate accurate predictions, which are then used in the final decision-making process of the system.

4.4.7 Database

Databases are a key component of the system, used to analytical results, and confidence intervals, enabling long-term monitoring of a patient's medical condition. This project relied on two types of databases:

1. Pre-built Datasets:

Several open medical datasets were obtained from the internet, such as dermatology image databases available in scientific repositories (HAM10000 Dataset , ISIC Dataset).

These databases help train prototypes and test the performance of algorithms. The HAM10000 ISIC Dataset Contains common skin diseases and conditions, **such as :**

1 . Psoriasis / Lichen Planus

2 . Dermatofibroma (df)

3 . Benign keratosis (bkl)

4 . Eczema

5 . Acne Rosacea

6 . Melanoma

7 . Vascular Lesions (vasc)

8 . Melanocytic Nevi (nv)

9 . Vascular tumors

10 . Actinic keratoses

11 . Basal Cell Carcinoma (bcc)

2. Custom-built Datasets: A custom database was created by collecting available and reliable clinical images.

The collected images were manually organized and labeled according to the type of skin disease.

4.4.8 User Interface

A graphical interface was designed using Tkinter Library . The interface allows the user to capture images, view results .

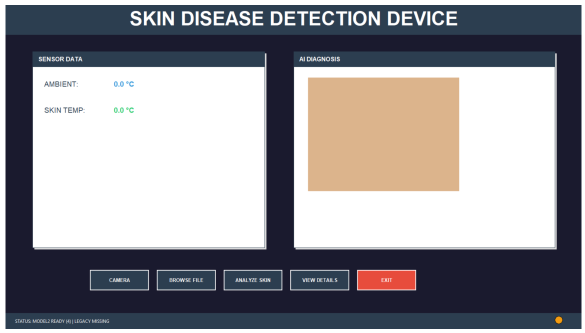


Figure 4.11: Main interface

The user interface is designed using the Python Tkinter framework, prioritizing a dark-themed, professional aesthetic. The following points detail the functional components of the dashboard:

- **Main Title Header:** The interface features a prominent top header labeled "SKIN DISEASE DETECTION DEVICE" in white uppercase typography. This provides immediate context and maintains a professional medical software branding.

- **Sensor Data Monitoring Panel:** Located on the left, this section provides real-time telemetry from the sensing unit:

- **Ambient Temperature:** Displays the surrounding environment temperature in degrees Celsius (°C).

- **Skin Temperature:** Shows the direct reading from the MLX90614 sensor for immediate thermal assessment.

- **AI Diagnosis and Image Preview:** The right-side panel is dedicated to visual output:

- It contains a viewport for displaying either the live camera stream or the uploaded skin image for visual confirmation.

- **Operational Control Bar:** A horizontal array of buttons at the bottom facilitates the system's workflow:

  - **CAMERA:** Toggles the live feed from the WC-061 web camera.
  - **BROWSE FILE:** Allows the user to import existing medical images from local storage.

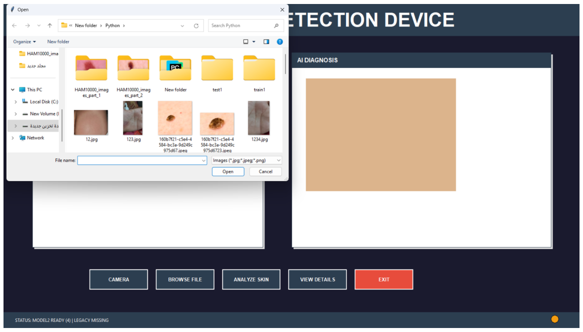


Figure 4.12: BROWSE FILE

  - **ANALYZE SKIN:** The core trigger button that sends the fused data to the Deep Learning model.
  - **VIEW DETAILS:** Opens an expanded report about the current scan , and shows the confidence scores for each disease .

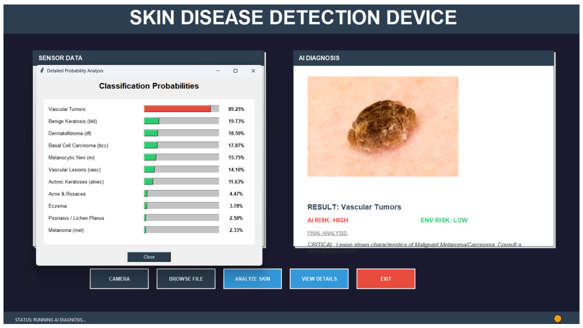


Figure 4.13: VIEW DETAILS

- **EXIT:** A highlighted red button for safe termination of the application.
- **System Status Bar:** The bottom-most strip provides low-level system feedback, such as model readiness and hardware connection status.

4.5 Algorithm Design

An algorithmic design represents the logical structure that defines how the system operates from the moment data is entered to the final output. This section helps clarify the internal flow of software processes, including the stages of data collection, processing, analysis, and output display. The algorithm is designed according to interconnected steps to ensure accuracy and efficiency, and can be represented by the flowchart shown below.

4.5.1 Algorithm Stages

1. Data Input:

   The system begins by opening sensors and cameras to capture skin images. The validity of the captured data is verified before moving on to the next step.

2. Pre-processing:

   Image quality improvement (noise removal, contrast adjustment, and brightness adjustment). Isolating the skin area from the background using segmentation techniques. Image dimensions are standardized to fit the AI model.

3. Feature Extraction

   Extracting visual features such as color, texture, and geometric patterns. These features help the model distinguish between different skin conditions.

4. AI-based Classification

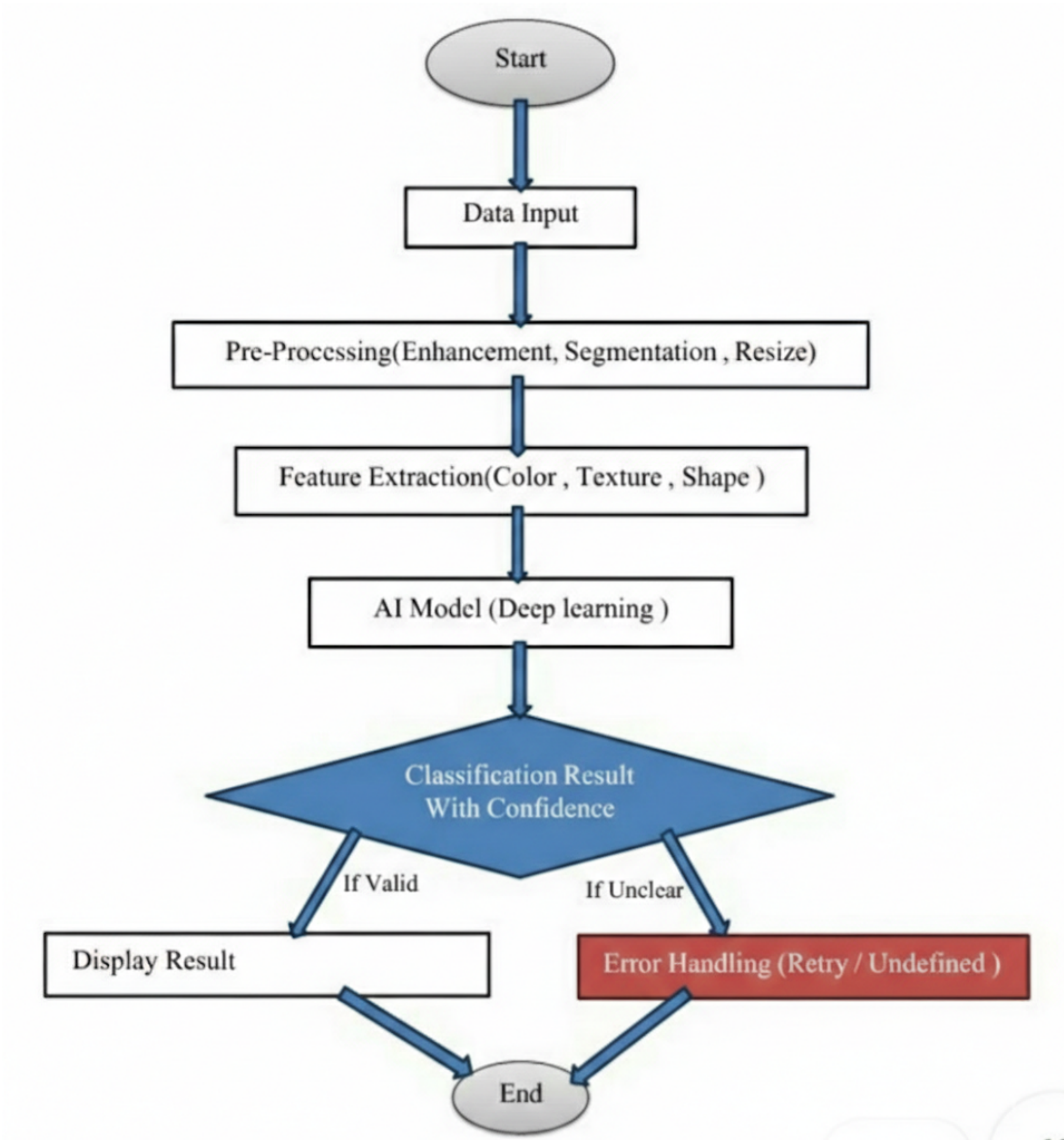
The processed images are fed into a pre-trained deep learning model. The model classifies the skin condition and outputs a diagnosis with a confidence level.

5. Results Output:

   The final diagnosis is displayed to the user via a simple graphical interface. The images and results are stored in a database for later referen.

6. Error Handling:

   If the image is unclear or the capture fails, an alert appears asking to try again. If the model fails to identify the condition, the user is presented with an "Undetermined" option, with a recommendation to consult a doctor.


Start
Data Input
Pre-Processing(Enhancement, Segmentation , Resize)
Feature Extraction(Color , Texture , Shape)
AI Model (Deep learning)
Classification Result
With Confidence
If Valid
If Unclear
Display Result
Error Handling (Retry / Undefined)
End

CHAPTER 5

Implemention And Test

5.1 Introduction

This chapter presents the practical implementation and testing phase of the proposed mobile skin disease detection system . While the previous chapters focused on the theoretical background, system requirements, and design aspects, this chapter shifts the focus toward the actual realization of the system components and their integration into a functional prototype . The implementation process involved translating the system design into a working hardware–software solution capable of capturing skin images, processing them, and producing preliminary diagnostic results . Particular attention was given to ensuring that the implemented system aligns with the design objectives, including portability, ease of use, and reliable performance under realistic operating conditions . In addition to the implementation details, this chapter also describes the testing procedures carried out to evaluate the functionality and behavior of the system . Various tests were conducted to verify that each component operates as intended, from image acquisition to result presentation. These tests aimed to identify potential issues, assess system stability, and ensure that the overall workflow performs consistently . The outcomes of this chapter provide a clear understanding of how the proposed system was built and tested in practice , forming the foundation for analyzing the experimental results and discussions presented in the following chapter .

5.2 System Implementation

5.2.1 Hardware Implementation

Hardware Components and Selection :

The hardware implementation of the proposed system represents a core element in transforming the theoretical design into a practical and functional prototype. The selection of hardware components was guided by several important factors, including availability, ease of integration, reliability, and suitability for a portable skin disease detection system. The implemented hardware configuration was designed to support real-time image acquisition and temperature measurement while maintaining a simple and flexible structure. The image acquisition process in the system relies on an external USB camera connected directly to a laptop. This type of camera was chosen due to its ease of use, wide compatibility with common operating systems, and seamless integration with image processing libraries such as OpenCV . The external USB camera enables the system to capture clear images of the skin surface, which serve as the primary input for further processing and analysis. Using a USB-based camera also allowed rapid testing and adjustment during the development phase without the need for specialized hardware drivers . In addition to visual imaging, the system incorporates an infrared temperature sensor (GY-MLX90614) to measure skin temperature and ambient environmental temperature. This sensor provides non-contact temperature measurements, which makes it suitable for medical-related applications where direct contact with the skin may not always be practical or desirable. The inclusion of temperature sensing adds an additional layer of information that can assist in identifying abnormal skin conditions associated with inflammation or infection . The processing and coordination of sensor data are handled using a laptop as the main processing unit. The laptop serves as the central platform for running the software components, receiving image data from the USB camera, and handling the data transmitted from the microcontroller. This choice provides sufficient computational power for image processing and model inference while maintaining flexibility during development and testing . To manage communication between the temperature sensor and the processing unit, a microcontroller (ESP32) was utilized. The ESP32 acts as an intermediary unit responsible for reading temperature data from the infrared temperature sensor and transmitting it to the laptop . The temperature sensor communicates with the ESP32 using a digital I^2C interface, specifically through the SDA and SCL lines . This digital communication method ensures stable data transfer and reduces noise compared to analog signaling, which is particularly important for accurate temperature readings .

- **Hardware Integration and Data Flow :**

  After selecting the hardware components, the next step focused on integrating these components into a unified system capable of operating reliably during real-time usage. The integration process aimed to ensure smooth communication between the sensing units, the microcontroller, and the main processing device, while maintaining system stability and ease of operation . The external USB camera was connected directly to the laptop through a standard USB interface. This direct connection allowed the camera to be recognized immediately by the operating system without requiring additional hardware configuration. Once connected, the camera was accessed through the software layer using image acquisition libraries, enabling continuous image capture during system operation. This setup ensured that visual data could be transferred efficiently to the processing unit with minimal latency .

  The infrared temperature sensor (GY-MLX90614) was interfaced with the ESP32 microcontroller using a digital I^2C communication protocol. The sensor transmits temperature readings via the SDA (Serial Data) and SCL (Serial Clock) lines, allowing precise and synchronized data transfer. The ESP32 was responsible for initializing the sensor, reading both skin temperature and ambient temperature values, and preparing these readings for transmission to the laptop . Using digital communication helped reduce measurement errors and ensured consistent sensor performance under different operating conditions .

Communication between the ESP32 and the laptop was established through a wired interface, allowing the processed temperature data to be sent in real time. The laptop receives this data and synchronizes it with the captured skin images, enabling the system to associate temperature readings with corresponding visual information .

This integration plays an important role in enhancing the overall analysis process by combining image-based features with thermal information .

During the implementation phase, attention was given to ensuring that all hardware components operated together without conflicts.

Several test runs were conducted to verify stable data transmission, correct sensor readings, and continuous camera operation.

Minor adjustments were made to connection parameters and timing to achieve reliable performance.

These practical considerations helped improve system robustness and reduced the likelihood of data loss or communication interruptions during testing .

5.2.2 Software Implementation

- Development Environment and Software Structure :

  The software implementation of the proposed system was carried out using a structured and lightweight development environment that supports image processing and machine learning tasks. The Windows operating system was used as the primary platform during development and testing, due to its compatibility with the selected hardware components and its support for widely used development tools . To manage dependencies and ensure a stable runtime environment, the Conda environment was utilized . Conda provided an isolated workspace in which all required libraries and packages were installed and executed consistently. This approach helped avoid compatibility issues between different library versions and ensured that the software could run reliably throughout the implementation and testing phases. The entire software system was developed using the Python programming language. Python was selected because of its flexibility, ease of integration with hardware interfaces, and strong ecosystem of libraries for computer vision and artificial intelligence applications. The simplicity of Python also facilitated rapid development and debugging during the implementation stage.

- The system relies on several core libraries that play distinct roles within the software architecture :

  1- TensorFlow was used for loading and executing the trained deep learning model responsible for skin disease classification .

  2- OpenCV was employed to handle image acquisition from the USB camera and to perform essential image processing operations .

  3- NumPy was used to convert image data into numerical arrays and matrices suitable for processing and inference within the model .

  4- Infrared Thermal sensor library was used to read temperature values received from the ESP32 microcontroller .

  From a structural perspective, the software was implemented as a single executable Python file. This design choice simplified execution and reduced complexity during testing, making it easier to manage the overall workflow of the system. All main operations—including image capture, preprocessing, model inference, temperature reading, and result display—were handled within this unified program structure . A simple graphical user interface (GUI) was developed using the Tkinter library. The interface allows the user to interact with the system in a straightforward manner, providing basic controls for image capture and result visualization. The focus of the interface design was usability rather than visual complexity, ensuring that the system could be operated easily without requiring technical expertise . The implemented system operates entirely in a local environment. All processing, analysis, and inference are performed locally on the laptop without relying on external servers or cloud services. Additionally, the system does not store patient data or medical records, which helps maintain privacy and simplifies data management during testing and demonstration .

- Software Workflow and Data Processing :

  The software workflow of the proposed system was designed to follow a clear and sequential execution process that ensures accurate data handling and reliable system behavior. Once the application is launched, all software components are initialized in a predefined order to guarantee proper communication between the hardware devices and the processing modules. At the beginning of execution, the system initializes the graphical user interface and establishes communication with the connected hardware components. The USB camera is accessed through the OpenCV library, which allows the software to verify camera availability and configure basic parameters such as resolution and frame capture mode. This step ensures that image acquisition can proceed without interruptions during runtime. In parallel, the software establishes a communication channel with the ESP32 microcontroller to receive temperature readings from the infrared sensor. The temperature data is continuously monitored to confirm sensor stability before it is used in the analysis process. Once the hardware interfaces are successfully initialized, the system enters the data acquisition phase. When the user triggers image capture through the graphical interface, the camera captures a skin image in real time. The captured image is then transferred directly into the image processing pipeline without intermediate storage, which reduces processing time and minimizes memory usage. The software ensures that each captured image is validated to confirm that it meets basic quality requirements before further processing is applied. The image preprocessing stage plays a critical role in preparing the captured data for model inference. During this stage, the system applies a series of processing steps using OpenCV, including noise reduction, normalization, and resizing of the image to match the input dimensions required by the trained model. These operations help standardize the input data and reduce the effect of variations caused by lighting conditions or camera positioning. After preprocessing, the image is converted into a numerical representation using NumPy arrays, enabling efficient computation during the classification phase. Following preprocessing, the prepared image is passed to the deep learning model loaded using the TensorFlow library. The model performs inference on the input data and produces a classification output representing the predicted skin condition. The software handles this process in a structured manner to ensure that model execution does not interfere with other system operations, such as user interface responsiveness or sensor data acquisition. In parallel with image analysis, the system retrieves temperature readings from the infrared sensor through the ESP32. These readings include both skin temperature and ambient temperature, providing contextual information that complements the visual analysis. The temperature values are synchronized with the corresponding image capture event to ensure consistency in the data presented to the user. Once the analysis is completed, the system proceeds to the result presentation phase. The classification output generated by the model, along with the associated temperature readings, is displayed through the graphical user interface. The interface presents the information in a clear and minimal format, allowing the user to understand the system output without requiring technical knowledge. No data is stored after the result is displayed, as the system operates in a local and non-persistent mode to maintain simplicity and privacy. Throughout the software execution process, error handling mechanisms were implemented to improve system reliability. The software continuously monitors the status of the camera and sensor connections, and appropriate notifications are displayed if a failure occurs, such as unsuccessful image capture or loss of sensor communication. These measures help ensure stable operation and provide feedback to the user in case corrective action is required. Overall, the implemented software workflow provides a coherent and efficient pipeline that integrates image acquisition, preprocessing, artificial intelligence inference, and result visualization into a single executable application. This design supports real-time operation and demonstrates the practical feasibility of the proposed skin disease detection system.

5.3 Dataset Description

5.3.1 Data Sources and Dataset Composition

The dataset used in this project plays a fundamental role in the performance and reliability of the proposed skin disease detection system. Since the system relies on deep learning techniques, the quality, diversity, and size of the dataset directly affect the accuracy and generalization capability of the trained model. For this reason, careful consideration was given to selecting reliable and medically recognized image sources. The primary sources of skin images were the HAM10000 dataset and the ISIC dataset. Both datasets were obtained through the Kaggle platform, which provides well-organized and publicly available medical image repositories. These datasets are widely used in dermatological research and are considered standard benchmarks in skin disease classification tasks. Using such established datasets helped ensure that the training data was credible and representative of real-world skin conditions. The combined dataset consisted of approximately 14,000 skin images. These images cover a range of different skin conditions and were collected under varying imaging conditions, including differences in lighting, skin tone, and lesion appearance. This diversity was beneficial for improving the robustness of the model and reducing overfitting to a specific visual pattern. The dataset includes images representing a total of eleven different skin diseases. Seven of these disease categories originate from the HAM10000 dataset, while four additional common skin conditions were selected from the ISIC dataset to enrich the variety of cases. The inclusion of multiple disease categories allowed the model to learn distinguishing features across a broader spectrum of skin abnormalities, which aligns with the project's objective of supporting preliminary diagnosis rather than focusing on a single condition. It is important to note that the dataset was not perfectly balanced across all disease classes. Some skin conditions were represented by more than one thousand images, while others had significantly fewer samples. This imbalance reflects the natural distribution of available medical data, where certain conditions are more frequently documented than others. Although class imbalance can affect model performance, it also mirrors realistic clinical scenarios and was therefore accepted as part of the dataset characteristics. Before training, the dataset was divided into three subsets to support model development and evaluation. The images were split as follows:

70 of the images were allocated for training the model.

15 were reserved for testing the model's performance on unseen data.

15 were used for validation to monitor model behavior during training and to support parameter tuning. This data partitioning strategy helped ensure that the model was evaluated fairly and that its performance metrics reflected its ability to generalize beyond the training data.

5.3.2 Dataset Characteristics , Preparation , and Challenges

Beyond the dataset size and sources, several important characteristics of the collected data had a direct impact on the system development and training process. The images obtained from the HAM10000 and ISIC datasets vary significantly in terms of resolution, lighting conditions, background complexity, and skin tone representation. This variability reflects realistic clinical imaging scenarios and contributes to building a more generalizable model, but it also introduces additional challenges during preprocessing and training. One of the notable aspects of the dataset is the diversity in image acquisition conditions. The images were captured using different devices and under varying illumination environments, which resulted in differences in brightness, contrast, and color distribution. While such variations can negatively affect model performance if left unaddressed, they also provide an opportunity for the model to learn invariant features that are less sensitive to environmental changes. For this reason, the dataset was considered suitable for training a model intended for real-world use rather than controlled laboratory conditions. Another important characteristic of the dataset is the presence of class imbalance. As previously mentioned, some disease categories contain a large number of samples, while others are represented by relatively fewer images. This imbalance is a common issue in medical datasets and reflects the uneven availability of clinical data for different conditions. Although class imbalance may influence the learning process, it was intentionally preserved to maintain the authenticity of the dataset. Addressing this issue through algorithmic or preprocessing techniques was considered during model development, while acknowledging that perfect balance is rarely achievable in practical medical applications. Prior to training, the dataset underwent a preparation phase to ensure compatibility with the implemented system. Images were organized into structured directories according to their respective categories, and file formats were standardized to ensure consistent loading during training and testing. Basic preprocessing steps were applied to remove corrupted or low-quality images that could negatively impact the learning process. This step helped improve the overall reliability of the dataset without altering its original medical characteristics. The dataset splitting strategy played a critical role in evaluating the performance of the trained model. By allocating separate subsets for training, validation, and testing, the system was able to learn from one portion of the data while being evaluated on unseen samples. The validation set was particularly important for monitoring model behavior during training, allowing early detection of issues such as overfitting or underfitting . Meanwhile, the testing set provided an unbiased evaluation of the final model performance after training was completed. It is also important to highlight that the dataset was used strictly for research and educational purposes within the scope of this project. No patient-identifying information was included, and all images were obtained from publicly available datasets intended for academic use. This approach ensured compliance with ethical considerations and simplified data handling during development and testing.

5.3.3 Types Of Diseases In Dataset

1. Psoriasis / Lichen Planus

Psoriasis and Lichen planus are skin conditions that share some features in common, like a red and scaly look, but they also have key differences. Psoriasis tends to thicken into patches and can last for years or decades. You'll need to manage your symptoms with your doctor. Lichen planus may stop with simple red bumps that often go away on their own, though they sometimes return. And unlike psoriasis, lichen planus can affect the inside of your mouth.

Causes :

Psoriasis seems to start with your genes. You're more likely to get it if one of your relatives has it. The condition causes your immune system – your body's defense against germs – to misfire and send faulty signals that make skin cells grow too fast. Genes don't seem to play a role in most cases of lichen planus. And it's not even clear what happens in your body to cause the condition, though doctors suspect a mistaken immune system response may have something to do with it. People with hepatitis C – an infection that causes liver problems – appear more likely to have lichen planus. Your doctor may test your blood for the virus that causes hepatitis C if you have symptoms of lichen planus. Some medications can cause skin symptoms that look like lichen planus, especially diuretics for high blood pressure, heart disease drugs, and anti-malaria medicine. If you're seeing a dermatologist, a specialist who treats skin problems, let them know about all the medicines you take.

Symptoms

Psoriasis can cause symptoms that range from simple red spots to the dry, thickened, flaky patches of skin that are the most common sign of the condition (plaque psoriasis). It also tends to cause bits of skin to flake off, sometimes enough that you notice little pieces around your home and workplace. Lichen planus is more likely to be limited to smaller lesions or spots and doesn't commonly cause flaking. But sometimes thicker, scaly, patches can show up, especially on your lower legs and ankles. Though both conditions can appear anywhere on the skin, psoriasis is most common on the knees, elbows, scalp, and the crease of your behind. Lichen planus is more common on your inner wrists and inner forearms. A type of the condition called "hyperkeratotic lichen planus" is thicker, looks more purple and wart-like, and is more common on the lower legs and ankles. Psoriasis and lichen planus are itchy, but if you have lichen planus, the itchiness is typically more intense.

2 . Dermatofibroma (df)

Dermatofibroma, also known as fibrous histiocytoma, is a common, benign, cutaneous soft-tissue lesion characterized by firm subcutaneous nodules, typically measuring 1 cm or less in diameter. Dermatofibromas are commonly found on the extremities and are prevalent across all age groups. However, they are more frequently observed in individuals aged 20 to 50, especially among females. Although the exact cause of the condition remains unknown, it is common for patients presenting with a dermatofibroma to report a history of local trauma at the site, such as from an insect bite, minor injuries, or superficial puncture wound. Dermatofibromas are typically asymptomatic but may sometimes cause pain, tenderness, or itchiness. Diagnosis involves histopathological examination, which correlates well with sonographic findings. Treatment is generally unnecessary unless the lesion is symptomatic, though excision is recommended for suspicious or atypical cases. Complications of surgical removal may include bleeding, infection, and scarring. This activity reviews the clinical manifestations, epidemiology, histopathology, diagnostic modalities, and differential diagnoses of dermatofibromas, which are crucial for accurately distinguishing dermatofibromas from other cutaneous neoplasms, notably dermatofibrosarcoma protuberans, to ensure appropriate management strategies. This activity also emphasizes the vital role of the interprofessional healthcare team in enhancing patient outcomes by raising awareness of dermatofibroma and ensuring preparedness in effectively managing these cases. A multidisciplinary approach involving healthcare professionals is essential for ensuring accurate diagnosis, effective management, and optimized patient outcomes of dermatofibroma.

The nature of dermatofibroma as either a reactive process or a true neoplasm remains unclear. Although the exact cause of the condition remains unknown, it is common for patients presenting with a dermatofibroma to report a history of local trauma at the site, such as from an insect bite, minor injuries, a rose thorn injury, or a superficial puncture wound, but not consistently. While patients diagnosed with dermatofibroma often report a history of local trauma, suggesting a reactive process, such trauma is not consistently reported and is found in only about one-fifth of cases. More often, dermatofibromas develop spontaneously without any specific inciting event or trauma. Spontaneous regression is rare, which may argue against a primarily reactive process and instead support a clonal or neoplastic model. Dermatofibroma lesions consist of proliferating fibroblasts, often with the involvement of histiocytes. Some studies have detected clonal markers in dermatofibroma cells through analysis of X chromosome inactivation, suggesting a monoclonal pattern and potentially supporting a neoplastic origin of development. Conversely, others suggest a heterogeneous derivation of dermatofibroma, positing that it represents both reactive and neoplastic processes within the same lesion. In this model, the histiocytoid component may be neoplastic, while the fibrous portion may arise from reactive fibroblastic proliferation.

3 . Benign keratosis (bkl) Benign keratosis, specifically seborrheic keratosis, is defined in clinical dermatology as a non-neoplastic proliferation of epidermal keratinocytes that results in well-circumscribed, pigmented cutaneous lesions. From a research perspective, these growths are characterized by a lack of malignancy and are not precursors to squamous cell carcinoma or melanoma, despite their sometimes concerning clinical appearance. The etiology of these lesions is primarily linked to the biological aging process and genetic predisposition, with molecular studies identifying frequent somatic mutations in the FGFR3 and PIK3CA genes which drive the localized overgrowth of skin cells without progressing to systemic disease. Physiologically, these lesions manifest as "stuck-on" papules or plaques that vary in color from pale tan to deep black, often exhibiting a waxy or verrucous texture. A key diagnostic feature identified through dermoscopy is the presence of milia-like cysts and comedo-like openings, which serve as definitive markers to differentiate benign keratosis from melanocytic nevi or malignant melanoma. Because these lesions are confined to the epidermis and do not penetrate the dermal-epidermal junction, they rarely result in scarring unless subjected to significant trauma or aggressive surgical intervention. Management of benign keratosis is generally elective, as the condition poses no physiological threat to the patient. Treatment is typically sought for symptomatic relief of pruritus or irritation, or for cosmetic improvement. Current medical standards favor minimally invasive destruction techniques such as cryosurgery using liquid nitrogen, which induces thermal shock to the keratinocytes, or curettage, which involves the physical scraping of the lesion from the skin surface. While the prognosis is excellent and the recurrence rate for individual treated lesions is low, patients with a genetic predisposition will likely continue to develop new lesions over time, necessitating periodic dermatological evaluation to monitor for any atypical changes.

4 . Eczema Eczema is the name for a group of inflammatory skin conditions that cause dry skin, itchiness, rashes, scaly patches, blisters and skin infections. There are seven types of eczema that affect the skin. There is no cure for eczema but there are many treatments available to help you manage it. Many people with eczema use the phrase "flare" to describe a phase of eczema that can last many days or even several weeks when they are experiencing one or more exacerbated eczema symptoms or side effects from prolonged itchiness. Severe eczema can come with additional complications beyond itchy skin and rashes, such as infections that can lead to hospitalization if left untreated. Sometimes eczema is confused with other skin conditions like psoriasis, so it's important to see a doctor to get a proper diagnosis.

Causes :

The exact cause of eczema is unknown. In fact, each type of eczema can have different causes. Some of the most common causes are:

- A family history of eczema
- Being exposed to certain environmental triggers
- Stress
- A combination of these triggers

In general with eczema, when an irritant or an allergen from outside or inside the body "switches on" the immune system, it produces inflammation. It is this inflammation that causes the symptoms common to most types of eczema. It can affect anywhere on the body from the head to lower legs, hands and feet. In particular, creases of the skin, especially the flexural areas behind the knees, elbows, lower legs and other areas of skin that rub against each other can lead to irritation, increased sweat and other possible contributing factors.

Some types of eczema, such as atopic dermatitis, may be caused by various factors including:

- A weakened skin barrier (or the outer protective layer of the skin)

- An overactive immune system that leads to inflammation
- Environmental triggers
- Genetics

Symptoms Eczema almost always includes itchy skin. For many people, the itch can range from mild to moderate. Sometimes the itch gets so bad that people

scratch it until it bleeds. This is called the “itch-scratch cycle.” Symptoms of eczema often include:

- Itchy skin
- Dry skin
- Rash
- Inflamed skin
- Discolored skin
- Rough, leathery skin
- Scaly patches
- Oozing or crusting skin
- Swelling

5 . Acne Rosacea Acne is an inflammatory skin disease that affects a majority of people at some point in their lifetime. Although acne is popularly associated with teens, the disease occurs in infants and adults, too. A number of factors can contribute to the inflammation that causes the papules and pustules—commonly called pimples, whiteheads, and blackheads—of acne.

Rosacea is an inflammatory skin disease that can cause redness of the face, which may be persistent or may come and go. This is known as flushing or blushing. Rosacea is also characterized by the presence of pimple-like bumps called papules and pustules. Over time, untreated rosacea can lead to skin changes, such as a dry, rough feel, visible blood vessels, and/or swelling. Persistent swelling of the nose and ears can occur and can lead to “phymas” or permanent changes in the size and shape of affected sites. Rosacea occurs in people of both sexes and usually appears in adulthood.

6 . Melanoma Melanoma is a type of skin cancer that originates in melanocytes. Melanocytes are responsible for producing the pigment that gives skin its color. This pigment is called melanin.

Melanoma usually develops on skin that is frequently exposed to the sun. This includes the skin of the arms, back, face, and legs. Melanoma can also develop in the eyes. Rarely, it occurs inside the body, such as in the nose or throat.

Causes : The exact cause of all types of melanoma is unclear. Most melanomas are caused by exposure to ultraviolet (UV) radiation . UV radiation comes from sunlight or tanning beds and lamps . Limiting your UV exposure may help reduce your risk of developing melanoma . Melanoma is more common in people under 40, especially women. Knowing the symptoms of skin cancer can help ensure that cancerous changes are detected and treated before the cancer spreads. Successful treatment of melanoma is possible if the tumor is detected early .

Symptoms :

The first signs and symptoms of melanoma are usually:

- A change in an existing mole.
- The development of a new pigmented or unusually shaped growth on the skin.

Melanoma doesn’t always start as a mole. It can also occur on healthy skin Melanoma symptoms can appear anywhere on the body. They most often affect areas that have been exposed to the sun. This includes the arms, back, face, and legs.

Melanomas can also affect areas that are not as exposed to the sun. This includes the soles of the feet, palms of the hands, and the base of the fingernails. Melanomas can also occur anywhere inside the body. These tumors are more common in people with brown or dark skin.

7 . Vascular Lesions (vasc)

Vascular lesions are a broad category of skin lesions and malformations affecting blood vessels. Medically, they are classified as hemangiomas or vascular malformations resulting from abnormalities in the formation of capillaries, veins, or arteries. Research-wise, these lesions arise from abnormal proliferation of the cells lining the vessels (endothelial cells) or dilation of pre-existing vessels. They range from congenital birthmarks present in infants to acquired conditions that appear with age or as a result of sun exposure and hormonal changes. Most of these lesions are considered benign, but they require careful evaluation to ensure they are not associated with deeper systemic syndromes.

Causes :

- Genetic Mutations: Many congenital vascular malformations arise from localized somatic mutations during embryonic development that disrupt the signaling pathways responsible for vessel formation.

- Hormonal Fluctuations: Elevated levels of estrogen, particularly during pregnancy or through the use of oral contraceptives, can trigger the development of lesions like Spider Angiomas.

- Chronic UV Exposure: Long-term sun damage weakens the perivascular connective tissue and the walls of superficial capillaries, leading to permanent dilation known as Telangiectasia.

- Biological Aging: As the skin ages, the vascular walls lose elasticity and the surrounding dermal support diminishes, often resulting in the formation of Cherry Angiomas.

- Hepatic Dysfunction: Certain vascular manifestations, such as prominent spider nevi, are clinical indicators of underlying liver disease or portal hypertension.

- Physical Trauma: Minor injuries can sometimes trigger a reactive overgrowth of vascular tissue, leading to conditions like Pyogenic Granuloma.

Symptoms :

- Color Variation: Lesions typically present in shades of bright red, deep purple, or blue, depending on the depth of the vessel and the oxygenation of the blood within.
- Blanching: A classic diagnostic sign where the lesion temporarily loses its color (turns pale) when pressure is applied, due to the displacement of blood within the vessels.
- Morphological Diversity: Appearances range from flat, non-palpable macules to raised, dome-shaped papules or soft, spongy masses.
- Friability and Bleeding: Because the vessel walls in these lesions are often thin or fragile, they may bleed easily even with minimal friction or minor trauma.
- Pulsation and Warmth: In high-flow vascular malformations (arteriovenous), a physical "thrill" or pulse may be felt, accompanied by localized warmth.
- Rapid Proliferative Phase: In infantile hemangiomas, a small precursor mark may rapidly expand in size and volume during the first few weeks or months of life.

8. Melanocytic Nevi (nv) Melanocytic nevi, commonly referred to as moles, are benign clinical neoplasms characterized by the localized proliferation of melanocytes, the pigment-producing cells of the skin. From a histopathological perspective, these lesions are classified based on the architectural location of the melanocyte nests within the skin layers: junctional, compound, or intradermal. While the vast majority of melanocytic nevi follow a stable, benign biological course, they remain a primary focus of dermatological research because certain atypical variants can serve as potential precursors or phenotypic markers for an increased risk of cutaneous melanoma.

Causes :

- Genetic predisposition and family history.
- Cumulative and intermittent UV radiation exposure.

- Somatic genetic mutations (e.g., BRAF gene mutation).
- Hormonal fluctuations during puberty or pregnancy.
- Phenotypic skin type (higher prevalence in fair-skinned individuals).
- Immunosuppression or immune system modulation.

Symptoms :

- Pigmentation changes (shades of brown, black, or flesh-colored).
- Geometric symmetry (round or oval shapes).
- Well-defined and regular borders.
- Small diameter (typically less than 6 mm).
- Surface texture variations (flat, macule-like, or raised papules).
- Stability in appearance over long periods .

9 . Vascular tumors

Vascular tumors are clinically defined as neoplasms arising from the active neoplastic proliferation of endothelial cells. Unlike vascular malformations, which are structural errors in vessel formation, vascular tumors exhibit true cellular hyperplasia and increased mitotic activity. These lesions range from common benign growths, such as infantile hemangiomas, to rare, highly aggressive malignancies like angiosarcomas. Research emphasizes the importance of distinguishing these tumors based on their biological behavior, as many benign variants undergo a predictable cycle of rapid proliferation followed by gradual involution, whereas others may require aggressive medical or surgical intervention.

Causes :

- Active endothelial cell hyperplasia.
- Somatic genetic mutations.
- Localized tissue hypoxia triggering growth.
- Overexpression of angiogenic factors (e.g., VEGF).

- Hormonal signaling dysregulation.
- Rare hereditary predisposition syndromes.

Symptoms :

- Emergence of a colored cutaneous mass (red, purple, or blue).
- Rapid and progressive increase in size.
- Alteration in skin texture (rubbery or firm consistency).
- Surface ulceration or skin breakdown.
- Propensity for bleeding with minor trauma.
- Localized pain or tenderness (in aggressive subtypes).

10 . Actinic keratoses

Actinic keratosis (AK), also known as solar keratosis, is a common pre-cancerous skin lesion that develops as a direct result of chronic, cumulative exposure to ultraviolet (UV) radiation from the sun or tanning beds. From a research and pathological perspective, AK represents an early-stage intraepidermal proliferation of atypical keratinocytes. While most lesions remain superficial and benign, they exist on a biological continuum with Squamous Cell Carcinoma (SCC); if left untreated, a significant percentage of these lesions can progress to invasive malignancy. Because of this potential for transformation, actinic keratoses are often managed as "field cancerization," where the entire sun-damaged area is treated rather than just the visible spots.

Causes

- Chronic and cumulative ultraviolet (UVB) radiation exposure.
- DNA damage and mutations in the tumor suppressor gene (p53).
- Phenotypic susceptibility (fair skin, light eyes, and blonde/red hair).
- History of frequent or severe sunburns during childhood and adolescence.
- Immunosuppression (e.g., organ transplant recipients or HIV).

- Advanced age and long-term environmental occupational exposure.

Symptoms :

- Rough, scaly, or sandpaper-like texture on the skin surface.
- Development of small, dry, or crusty patches (macules or papules).
- Color variations ranging from flesh-toned to red, brown, or yellowish- gray.
- Localized stinging, burning, or itching in the affected area.
- Persistent or recurrent lesions that flake off and then reappear.
- Occasional tenderness or pain when the lesion is touched or rubbed.

11 . Basal Cell Carcinoma (bcc)

Basal Cell Carcinoma (BCC) is the most common form of skin cancer globally, arising from the basal cells located in the deepest layer of the epidermis. From a clinical and research standpoint, BCC is characterized by slow growth and a very low rate of metastasis (spreading to distant organs); however, it is considered "locally invasive," meaning it can cause significant destruction to surrounding skin, cartilage, and bone if neglected. The malignancy is primarily driven by the dysregulation of the Hedgehog signaling pathway, a cellular mechanism that controls cell growth and differentiation. While rarely life-threatening, early diagnosis and surgical intervention are critical to prevent extensive tissue damage and disfigurement, particularly when lesions appear on the face.

Causes :

- Chronic and intense exposure to ultraviolet (UV) radiation.
- Genetic mutations in the PTCH1 or SMO genes (Hedgehog pathway).
- Fair skin phenotype (Fitzpatrick skin types I and II).
- History of therapeutic radiation (radiotherapy) for other conditions.
- Long-term exposure to arsenic or other environmental carcinogens.
- Immune system suppression (e.g., organ transplant patients).

- Genetic syndromes such as Gorlin Syndrome (Basal Cell Nevus Syndrome).

Symptoms :

- Appearance of a pearly, translucent, or "waxy" bump.
- Presence of visible, tiny blood vessels on the surface (Telangiectasia).
- Development of a flat, scaly, flesh-colored or brown patch.
- Central ulceration that may bleed, crust over, and fail to heal (the "rodent ulcer").
- Raised, rolled borders around a central indentation.
- A white, scar-like lesion with an ill-defined border (morpheaform subtype).

5.4 Model Training

5.4.1 Computing Optimized Circle

The model training phase represents one of the most critical stages in the development of the proposed skin disease detection system. The objective of this phase was to evaluate the effectiveness of deep learning models trained from scratch on the selected dataset and to analyze their ability to learn discriminative features from skin images. Instead of relying on a single architecture, two different convolutional neural network models were trained independently to enable performance comparison and deeper analysis. Two well-known deep learning architectures were selected for this task: ResNet50 and VGG19. These models were chosen due to their proven performance in image classification tasks and their widespread use in medical image analysis research. Training the models from scratch allowed full control over the learning process and ensured that the extracted features were directly influenced by the characteristics of the skin disease dataset used in this project. The training process was conducted using two different cloud-based platforms. The ResNet50 model was trained using the Google Colab environment, which provides access to GPU acceleration and sufficient computational resources for deep learning experiments. On the other hand, the VGG19 model was trained using the Kaggle platform, which also offers GPU support and an integrated environment for dataset management and experimentation. Using two platforms helped validate the flexibility of the training workflow and ensured that the training process was not dependent on a single execution environment. Both models were trained using a batch size of approximately 32 images per iteration. The batch size defines the number of training samples processed by the model before updating its internal parameters. Selecting a batch size of 32 represents a practical balance between memory usage and training stability. Smaller batch sizes can lead to noisy gradient updates, while very large batch sizes may require excessive memory and reduce generalization performance. The chosen batch size allowed efficient utilization of available computational resources while maintaining stable convergence during training. During training, each model learned to adjust its weights by minimizing the classification error across the training dataset. The training process involved multiple epochs, during which the models repeatedly analyzed the dataset to refine their feature representations. Model performance was continuously monitored using the validation dataset to ensure that learning progressed appropriately and to detect potential issues such as overfitting. The final training results demonstrated noticeable differences in model performance. The ResNet50 model achieved an overall classification accuracy of approximately 80This result indicates that the model was able to learn meaningful patterns from the dataset, although its performance was influenced by factors such as dataset imbalance and the complexity of skin lesion variations. In contrast, the VGG19 model achieved a higher classification accuracy of approximately 95, suggesting stronger feature extraction capability and better adaptation to the dataset used in this project. It is important to note that accuracy alone does not fully describe model behavior, especially in medical classification tasks. However, the observed accuracy values provide a useful indicator of each model's learning effectiveness and serve as a basis for further evaluation and comparison. The difference in performance between the two models highlights the impact of architectural design and training dynamics on classification outcomes.

5.4.2 Training Behavior, Performance Analysis, and Practical Observations

During the training phase, close attention was given to the behavior of both deep learning models in order to understand how each architecture responded to the characteristics of the dataset. Monitoring the training and validation performance over multiple epochs provided valuable insights into model convergence, stability, and generalization capability. The ResNet50 model demonstrated a gradual and stable learning behavior throughout the training process. The residual connections within the architecture helped mitigate issues related to vanishing gradients, allowing the model to continue learning as training progressed. However, despite this structural advantage, the model's overall accuracy converged at approximately 80This behavior suggests that while ResNet50 was capable of extracting meaningful features from the dataset, its performance was affected by factors such as dataset complexity, class imbalance, and variations in lesion appearance. In some training iterations, minor fluctuations between training and validation accuracy were observed, indicating sensitivity to certain image patterns within the dataset. In contrast, the VGG19 model exhibited a more rapid convergence and achieved a higher final accuracy of approximately 95The deeper and more uniform convolutional structure of VGG19 allowed the model to capture fine-grained visual features such as texture and color variations, which are particularly important in skin disease classification. The training curves showed a consistent increase in accuracy with relatively smaller gaps between training and validation results, suggesting better generalization on unseen data. This behavior indicates that VGG19 was more effective in learning discriminative features from the given dataset under the chosen training configuration. Batch size selection played an important role in shaping the training dynamics of both models. Using a batch size of approximately 16 images provided a balanced learning process by allowing frequent weight updates without introducing excessive noise into the optimization process. This batch size also ensured that memory usage remained within acceptable limits on both training platforms. The consistency of this configuration across both models allowed a fair comparison of their learning behavior and final performance. Several practical challenges were encountered during the training process. One of the primary challenges was the class imbalance present in the dataset, which influenced the learning behavior of the models. Classes with a large number of samples tended to dominate the learning process, while underrepresented classes contributed less to the optimization of model weights. Although this issue was expected given the nature of medical datasets, it required careful monitoring to ensure that the model did not overfit dominant classes. Another challenge was related to training resource limitations. Training deep learning models from scratch requires significant computational power and time. Differences in hardware availability and execution environments between Google Colab and Kaggle resulted in variations in training duration and system responsiveness. Despite these constraints, both platforms provided sufficient resources to complete the training process and obtain meaningful results. Overfitting was also considered during training analysis. Validation performance was continuously observed to ensure that improvements in training accuracy did not come at the expense of generalization. While minor signs of overfitting were observed in later epochs for some configurations, the models overall maintained acceptable generalization behavior within the scope of this project. This outcome suggests that the dataset size and preprocessing steps were adequate for training deep learning models without severe overfitting. The comparative training results of ResNet50 and VGG19 highlight the importance of model architecture selection in medical image classification tasks. While ResNet50 offered stable training behavior and moderate accuracy, VGG19 demonstrated superior performance under the same dataset conditions. These observations support the decision to evaluate multiple models rather than relying on a single architecture, as different models may respond differently to the same data. the training phase provided valuable experimental evidence regarding model behavior, performance differences, and practical limitations. Training two models from scratch enabled a comprehensive evaluation of the system's learning capability and contributed to a deeper understanding of how architectural choices influence classification outcomes. These findings form a strong foundation for the result analysis and discussion presented in the next chapter.

5.5 System Testing

5.5.1 Functional Testing and Operational Behavior

The system testing phase was conducted to verify the correct operation of the implemented system under real usage conditions. This phase focused on evaluating the functional behavior of the system components and ensuring that the overall workflow—from data acquisition to result generation—operates as intended. Functional testing confirmed that the system is capable of performing its primary tasks in a sequential and integrated manner. When the system is activated, it successfully captures an image using the external USB camera. The acquired image is then processed through the image preprocessing and classification pipeline. At the same time, the infrared temperature sensor measures the skin temperature and transmits the digital readings to the microcontroller, which forwards the data to the software system. Based on the processed image and the received temperature value, the system generates a diagnostic output representing the predicted skin condition. During testing, the interaction between hardware and software components was observed to be stable. Image acquisition, temperature measurement, and model inference occur within a single execution cycle, allowing the system to provide results without noticeable delay. This confirms that the integration between the camera, infrared sensor, microcontroller, and software environment was implemented correctly. However, system testing also revealed limitations related to input quality. The system does not include an automated validation or alert mechanism to detect invalid or low-quality images. As a result, when images are captured under poor lighting conditions or with insufficient focus, the system may still attempt to process the image and produce a classification result. In such cases, the diagnosis may be inaccurate due to the degradation of visual features required by the model. Testing under different lighting scenarios showed that image quality plays a critical role in classification accuracy. Images captured in environments with uneven illumination, shadows, or low resolution were more likely to lead to incorrect predictions. This behavior highlights the dependency of the trained models on clear and well-lit input images, which is a common characteristic of computer vision-based medical systems. Despite this limitation, the system continued to operate without crashing or producing execution errors during testing. Even when image quality was suboptimal, the system maintained functional continuity by completing the processing pipeline and returning a result. This indicates that the software implementation is robust from an execution standpoint, although the accuracy of results depends heavily on input conditions.

5.5.2 Performance Testing

Performance testing was conducted to evaluate how efficiently and consistently the proposed system operates during continuous and repeated usage. This type of testing focuses on execution speed, system stability over time, and the impact of varying input conditions on overall performance rather than on classification accuracy alone. The system demonstrated relatively fast performance during operation. Once the image was captured by the USB camera, the processing pipeline—including image preprocessing, model inference, and temperature reading—was completed within a short time frame. This allowed the system to provide diagnostic results without noticeable delay from the user's perspective. The use of local processing on the laptop contributed significantly to this responsiveness, as no external communication or cloud-based computation was involved. Performance stability was also evaluated by running the system under consistent conditions for multiple iterations. The system showed stable behavior across repeated executions, with no significant variation in processing time when image quality and lighting conditions remained unchanged. This indicates that the software implementation and hardware integration were efficient and well-suited for real-time operation within the limits of the project. However, minor performance variations were observed when environmental conditions changed. Specifically, when images were captured under poor lighting conditions or when image quality was degraded, a slight increase in processing time was noticed. This variation can be attributed to the additional computational effort required by the image processing stage to handle unclear or noisy visual data. Despite this, the system continued to operate smoothly, and the changes in performance were minimal and did not affect system usability. Long-duration testing was also performed to assess system reliability over extended periods of operation. During these tests, the system was executed continuously for a prolonged time without restarting the software or hardware components. The results showed that the system could operate for long periods without crashes, freezing, or memory-related issues. Communication between the camera, temperature sensor, microcontroller, and software remained stable throughout these tests. The absence of system failures during extended usage reflects a robust software structure and reliable hardware communication. It also confirms that the selected development environment and implementation approach are suitable for sustained operation, which is an important requirement for practical deployment scenarios. the performance testing results indicate that the proposed system achieves a satisfactory balance between speed, stability, and reliability. While slight performance variations occur under suboptimal image capture conditions, the system maintains consistent operation and remains responsive.

These findings support the suitability of the system as a functional prototype for skin disease detection and provide confidence in its operational performance under normal usage conditions.

5.6 System Limitations

Despite the successful implementation and testing of the proposed system, several limitations were identified during the development and evaluation phases. These limitations are mainly related to hardware constraints, environmental conditions, dataset characteristics, and model behavior. Identifying such constraints is essential for providing a realistic assessment of the system's current capabilities and for guiding future improvements. One of the primary limitations of the system is its strong dependency on image quality. Since the diagnosis relies heavily on visual features extracted from skin images, variations in lighting conditions, camera focus, and image resolution can significantly affect classification results. Images captured under poor illumination or with shadows may lead to incorrect predictions, even though the system continues to operate normally from a functional perspective. This limitation highlights the importance of controlled image acquisition conditions. Another limitation is the absence of an automated image validation or error notification mechanism. The system does not detect whether the captured image is unsuitable for diagnosis, such as images that are blurred or poorly lit. As a result, the model may generate a diagnosis based on suboptimal input without warning the user, which can reduce the reliability of the output in real-world usage. The dataset used for training also introduces certain constraints. Although the dataset size is relatively large, the distribution of images across different disease classes is not balanced. Some diseases are represented by a large number of images, while others have significantly fewer samples. This imbalance may bias the model toward more frequent classes and reduce its ability to accurately classify underrepresented conditions. In addition, the system was trained using images collected from publicly available datasets, which may differ in quality, imaging conditions, and patient demographics. These variations can limit the model's generalization when applied to real-world images captured using different cameras or under different environmental settings. From a hardware perspective, the use of a standard USB camera limits the consistency of image acquisition. Unlike specialized medical imaging devices, the camera does not provide controlled lighting or fixed focal distance, which may result in variability between captured images. Similarly, the temperature measurement depends on correct positioning of the infrared sensor, and inaccurate positioning can affect the reliability of temperature readings. The system also operates entirely in a local environment without data storage or historical tracking. While this design choice supports privacy, it limits the ability to analyze trends over time or compare current results with previous measurements. This constraint restricts the system's usefulness in long-term monitoring scenarios. Finally, the system is intended as a prototype and decision-support tool rather than a fully validated medical diagnostic system. The generated results should not be considered a replacement for professional medical evaluation. This limitation reflects the scope of the project and aligns with ethical considerations in medical application development.

Chapter 6

Results And Discussions

6.1 Results Overview

This section presents an overview of the results obtained from testing the proposed system. The focus of this section is on how the system outputs results, how information is presented to the user, and how classification outcomes from the implemented models are interpreted under different testing conditions.

The system was designed to generate diagnostic results using both deep learning models implemented in the project. For each input image, the system produces classification outputs from the two models, allowing comparative observation of their predictions. This approach enhances transparency and provides a clearer understanding of model behavior during diagnosis.

For every analyzed image, the system displays the predicted disease class along with descriptive notes indicating whether the detected condition is considered dangerous or non-dangerous. These notes are intended to support interpretation and do not influence the classification decision itself. The result presentation focuses on clarity and usability rather than displaying technical metrics only.

6.1.1 Confidence Score Presentation

In addition to textual diagnostic results, the system provides a confidence visualization mechanism. A dedicated button within the graphical user interface allows the user to access a separate view displaying confidence scores for all supported disease classes. These scores are presented as percentage values, representing the probability distribution generated by the model.

Displaying confidence scores for all classes enhances result interpretability by allowing users to assess the certainty of the prediction. When a single class shows a dominant confidence value, the result can be interpreted with higher reliability. In contrast, closely distributed confidence values across multiple classes indicate uncertainty and highlight ambiguous cases.

The confidence visualization feature is available for both models, enabling users to compare confidence behavior and better understand the internal decision process of each model.

6.1.2 Testing Scenarios and Image Sources

The system results were obtained through multiple testing iterations using different image sources. Two primary image types were used during evaluation. The first type consisted of images taken from the same datasets used during the training phase. These images generally produced more stable predictions and higher confidence values, as their visual characteristics closely matched the training data.

The second type consisted of new images captured using the system's USB camera. These images introduced real-world variability in terms of lighting conditions, focus, and positioning. While the system continued to operate correctly, confidence values for camera-captured images were often more variable, reflecting the influence of environmental factors on model performance.

Testing multiple images rather than relying on a single evaluation instance allowed a more realistic assessment of system behavior and consistency.

6.1.3 Multi-Model Output Interpretation

The simultaneous presentation of results from both models allows users to observe agreement or disagreement between predictions. In many cases, both models identified the same disease class, which increased confidence in the diagnostic result. In other cases, particularly under suboptimal image conditions, the models produced different predictions.

When disagreement occurred, confidence scores provided valuable insight into the level of uncertainty associated with each prediction. Disagreements were typically accompanied by lower confidence values, indicating ambiguity rather than definitive misclassification.

This dual-model result presentation supports informed interpretation and aligns with the experimental nature of the system. The system does not enforce a final decision based on a single model but instead provides sufficient information for the user to evaluate the output critically.

6.1.4 User-Oriented Result Interpretation

From a user perspective, the result presentation strategy emphasizes clarity, transparency, and practical usability. By combining disease identification, severity-related notes, and confidence visualization, the system offers a comprehensive output that supports informed understanding of the diagnostic process.

The results also demonstrated that proper image capture plays a significant role in output quality. Clear images captured under good lighting conditions resulted in higher confidence predictions, while poor image quality led to reduced confidence and increased variability.

Overall, the results overview reflects the system's ability to provide interpretable and informative outputs under both controlled and real-world conditions, supporting its role as an experimental and decision-support tool.

6.2 Model Performance Analysis

This section provides a comprehensive analysis of the performance of the two deep learning models implemented in the proposed system. The evaluation focuses on practical system behavior, confidence distribution, and model interaction during classification rather than relying solely on numerical accuracy metrics.

The system was designed to utilize both models in a sequential and complementary manner. During operation, the classification process begins with the ResNet50 model. If the model successfully identifies the input image and produces a valid output, the result is presented to the user. In cases where the ResNet50 model fails to confidently classify the image, the system proceeds to analyze the same input using the VGG19 model. This approach improves system robustness by reducing reliance on a single model and enhancing result reliability.

Both models were evaluated using images from the training dataset as well as images captured directly using the USB camera. While dataset images generally resulted in more stable predictions, camera-captured images introduced greater variability due to differences in lighting and image quality. Despite this variability, the system continued to operate reliably across all test scenarios.

Environmental factors, particularly lighting conditions, were found to affect the performance of both models. Poor lighting and unclear images reduced classification confidence and increased uncertainty in the predicted results. However, this effect was observed in both models, indicating that image quality plays a critical role in deep learning-based skin disease classification.

Table 6.1 summarizes the main performance characteristics observed during system testing for both models.

Table 6.1: Comparative Performance Analysis of ResNet50 and VGG19

Aspect	**ResNet50**	**VGG19**
Training Accuracy	Approximately 80%	Approximately 90%
Model Role in System	Primary classification model	Secondary classification model
Execution Order	First-stage analysis	Fallback analysis
Sensitivity to Lighting Conditions	Affected	Affected
Confidence Stability	Moderate	Higher
Performance on Dataset Images	Stable	Highly stable
Performance on Camera-Captured Images	Variable	More consistent

The comparative analysis indicates that ResNet50 performs effectively as an initial classifier, particularly when image quality is sufficient and visual features are clear. Its relatively faster initial evaluation allows the system to produce results efficiently under favorable conditions.

The VGG19 model demonstrated stronger performance in terms of confidence stability and overall classification accuracy. Its ability to extract detailed visual features made it more reliable in challenging scenarios, such as images captured under suboptimal lighting or with lower clarity.

Confidence score behavior further supported these observations. ResNet50 often produced broader confidence distributions in difficult cases, indicating uncertainty, while VGG19 typically generated more concentrated confidence peaks for the predicted class. These differences highlight the complementary strengths of the two models.

By presenting outputs from both models and displaying confidence values for all disease classes, the system provides transparent and interpretable results. The sequential dual-model strategy enhances system reliability without enforcing a single definitive decision, aligning with the experimental and decision-support nature of the proposed system.

6.3 Temperature Measurement Results

The temperature measurement component was integrated into the proposed system as an additional informational feature rather than a primary factor in the diagnostic decision-making process. The main purpose of including skin temperature measurement was to provide supplementary data that may assist medical professionals in confirming and evaluating skin conditions, particularly in cases where certain diseases are associated with elevated temperature levels.

In the implemented system, temperature readings do not influence the classification results produced by the deep learning models. Instead, the measured temperature value is displayed alongside the visual diagnosis to enhance result interpretation. This separation between image-based classification and temperature measurement ensures that the system maintains a clear operational structure while avoiding over-reliance on a single diagnostic parameter.

During testing, the temperature readings were observed to be general and consistent across different measurements. The system does not attempt to associate specific temperature ranges with individual disease classes, nor does it perform detailed thermal analysis. The temperature value serves as an indicative measurement that provides contextual support to the visual diagnostic output.

The measurement process is performed instantly. Once the infrared temperature sensor is positioned correctly, the system acquires the temperature value in real time without requiring prolonged contact or repeated sampling. This immediate response contributes to overall system responsiveness and allows temperature data to be collected seamlessly during the diagnostic process.

The inclusion of temperature measurement enhances the completeness of the system output while maintaining simplicity in system design. By presenting temperature as supplementary information, the system supports informed interpretation of results without increasing classification complexity.

6.4 Discussion of System Behavior

This section discusses the observed behavior of the proposed system during experimental usage and testing. The discussion focuses on practical system performance, input conditions, and usability within the scope of the implemented prototype.

During testing, it was clearly observed that the quality of the diagnostic results was strongly influenced by image acquisition conditions. The system produced more accurate and reliable outputs when the camera was positioned correctly and adequate lighting conditions were provided. Under these conditions, visual features of the skin were clearer, allowing the deep learning models to extract meaningful patterns and generate higher confidence predictions.

In contrast, improper camera positioning or insufficient lighting resulted in reduced image clarity, which negatively affected classification confidence and, in some cases, led to incorrect predictions. This behavior highlights the dependency of image-based diagnostic systems on controlled capture conditions and emphasizes the importance of proper setup during system usage.

From a usability perspective, the system proved suitable for experimental and demonstration purposes. It functioned as intended during testing and allowed users to observe the diagnostic process and results effectively. However, the system was primarily designed as a prototype for testing and evaluation rather than a fully optimized clinical tool.

6.5 Comparison with Related Works

This section presents a theoretical comparison between the proposed system and similar skin disease detection systems discussed in related literature. The comparison is qualitative in nature and focuses on general system characteristics rather than specific numerical benchmarks.

Table 6.2: Theoretical Comparison Between the Proposed System and Related Works

Comparison Aspect	Related Works	Proposed System
Diagnostic Approach	Image-based classification using a single deep learning model	Image-based classification using two deep learning models
Model Architecture	Often relies on a single CNN architecture	Utilizes ResNet50 and VGG19 models
Model Training	Pre-trained or partially trained models are commonly used	Models trained from scratch
Decision Strategy	Single-model output	Sequential dual-model evaluation
Confidence Presentation	Confidence values are sometimes not displayed	Confidence scores displayed for all disease classes
Temperature Measurement	Not commonly integrated	Integrated as an additional informational parameter
Image Acquisition	Dataset-based images only	Dataset images and real-time camera-captured images
System Execution	Often cloud-based or server-dependent	Fully local execution
Data Storage	Patient data may be stored for analysis	No data storage to preserve privacy
System Purpose	Diagnostic or research-oriented systems	Experimental and decision-support prototype

The comparison highlights that the proposed system emphasizes transparency, dual-model analysis, and local execution. Unlike many related systems that rely on a single classification model, the proposed approach offers a complementary evaluation mechanism through sequential model usage. Additionally, the inclusion of confidence visualization and temperature measurement provides richer contextual information without increasing system complexity.

CHAPTER 7

Conclusions and Recommendations

This chapter summarizes the overall outcomes of the project and presents the main conclusions derived from the system implementation and evaluation. It reflects on the extent to which the project objectives were achieved and assesses the effectiveness of the proposed system as an experimental prototype.

In addition, this chapter outlines recommendations and possible directions for future work. These recommendations are based on the observed system behavior, identified limitations, and potential improvements that could enhance system performance and applicability in future developments.

7.1 Conclusions

This project presented the design and implementation of an experimental system for skin disease detection based on deep learning and image processing techniques. The system integrated image-based classification with auxiliary temperature measurement to support diagnostic interpretation.

Based on the implementation and testing results, the project can be considered successful as an experimental study. The system operated as intended, allowing image acquisition, model-based classification, confidence visualization, and temperature measurement within a unified framework. The experimental setup enabled the evaluation of system behavior under different input conditions and demonstrated the feasibility of the proposed approach.

The project also achieved its primary objective. The developed system was able to analyze skin images, identify potential disease classes using deep learning models, and present the results in an interpretable manner. The inclusion of confidence scores and descriptive output enhanced result transparency and supported informed interpretation of the diagnostic outcomes.

the conclusions drawn from this work reflect the effectiveness of the proposed system as a functional prototype and an experimental platform for evaluating deep learning-based skin disease detection.

7.2 Recommendations for Future Work

Although the proposed system achieved its primary objectives as an experimental prototype, several improvements and extensions can be considered to enhance its performance, reliability, and practical applicability in future work.

One important recommendation is to improve the image acquisition hardware. Using a higher-quality camera with better resolution and controlled focus would significantly enhance image clarity and reduce the impact of poor lighting conditions. Improved image quality would directly contribute to more reliable feature extraction and classification accuracy.

Another recommended improvement is to increase the size of the training dataset. Expanding the number of images for each disease class, particularly for under-represented conditions, would help improve model generalization and reduce classification bias caused by dataset imbalance. A larger and more diverse dataset would also allow the models to better handle real-world variations.

Future versions of the system could also include an image quality validation mechanism. Such a mechanism could detect poor lighting, blur, or improper camera positioning before classification is performed, prompting the user to recapture the image.

This enhancement would reduce incorrect diagnoses caused by low-quality inputs.

In addition, improving the graphical user interface could enhance usability and user interaction. A more informative and user-friendly interface could provide clearer guidance during image capture and result interpretation, making the system easier to use for non-technical users.

Further development may also include optimizing model performance and exploring additional deep learning architectures. Evaluating other convolutional neural network models or fine-tuning existing architectures could lead to improved accuracy and robustness under challenging conditions.

Finally, future work could investigate the integration of secure data storage and result logging mechanisms, provided that privacy and ethical considerations are carefully addressed. This would enable long-term analysis and performance evaluation while maintaining user data protection.

These recommendations aim to guide future enhancements and highlight potential directions for extending the proposed system beyond its current experimental scope.

Bibliography

@articlelitjens2017dlmedical, title=A Survey on Deep Learning in Medical Image Analysis, author=Litjens, Geert and Kooi, Thijs and Bejnordi, Babak Ehteshami and Setio, Arnaud A A and Ciompi, Francesco and Ghafoorian, Mohsen and van der Laak, Jeroen A W M and van Ginneken, Bram and Sanchez, Clara I, journal=Medical Image Analysis, volume=42, pages=60–88, year=2017, publisher=Elsevier

@articlelecun2015deeplearning, title=Deep Learning, author=LeCun, Yann and Bengio, Yoshua and Hinton, Geoffrey, journal=Nature, volume=521, number=7553, pages=436–444, year=2015, publisher=Nature Publishing Group

@inproceedingshe2016resnet, title=Deep Residual Learning for Image Recognition, author=He, Kaiming and Zhang, Xiangyu and Ren, Shaoqing and Sun, Jian, booktitle=Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages=770–778, year=2016

@articlesimonyan2014vgg, title=Very Deep Convolutional Networks for Large-Scale Image Recognition, author=Simonyan, Karen and Zisserman, Andrew, journal=arXiv preprint arXiv:1409.1556, year=2014

@articletschandl2018ham10000, title=The HAM10000 Dataset: A Large Collection of Multi-Source Dermatoscopic Images of Common Pigmented Skin Lesions, author=Tschandl, Philipp and Rosendahl, Cliff and Kittler, Harald, journal=Scientific Data, volume=5, pages=180161, year=2018, publisher=Nature Publishing Group

@articlecodella2018isic, title=Skin Lesion Analysis Toward Melanoma Detection, author=Codella, Noel C F and Gutman, David and Celebi, M Emre and Helba, Brian and Marchetti, Michael A and Dusza, Stephen W and Kalloo, Ashfaq and Liopyris, Konstantinos and Mishra, Nabin and Kittler, Harald and Halpern, Allan, journal=IEEE Journal of Biomedical and Health Informatics, volume=22, number=2, pages=437–450, year=2018, publisher=IEEE

@misckaggle$_d ataset, title = SkinCancerandDermatoscopicImageDatasets, author = Kaggle, howpublished =$, year=2023

@inproceedingsabadi2016tensorflow, title=TensorFlow: A System for Large-Scale Machine Learning, author=Abadi, Martín and Barham, Paul and Chen, Jianmin and Chen, Zhifeng and Davis, Andy and Dean, Jeffrey and others, booktitle=Proceedings of the 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI), pages=265–283, year=2016

@articlebradski2000opencv, title=The OpenCV Library, author=Bradski, Gary, journal=Dr. Dobb's Journal of Software Tools, year=2000

@manualesp32manual, title=ESP32 Technical Reference Manual, author=Espressif Systems, year=2023, organization=Espressif Systems

@manualmlx90614datasheet, title=MLX90614 Infrared Thermometer Datasheet, author=Melexis Technologies, year=2022, organization=Melexis

@articleesteva2017dermatologist, title=Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks, author=Esteva, Andre and Kuprel, Brett and Novoa, Roberto A and Ko, Justin and Swetter, Susan M and Blau, Helen M and Thrun, Sebastian, journal=Nature, volume=542, number=7639, pages=115–118, year=2017, publisher=Nature Publishing Group

@articlepham2020skinreview, title=A Review of Skin Disease Detection Using Deep Learning, author=Pham, Trung and Tran, Hai and Pham, Van, journal=Journal of Healthcare Engineering, volume=2020, pages=1–12, year=2020, publisher=Hindawi

@articlecelebi2015lesion, title=Lesion Border Detection in Dermoscopy Images, author=Celebi, M Emre and Wen, Qi and Iyatomi, Hitoshi and Shimizu, Kazuyuki and Zhou, Huiyu and Schaefer, Gerald, journal=Computerized Medical Imaging and

Graphics, volume=40, pages=83–92, year=2015, publisher=Elsevier

@articleshorten2019augmentation, title=A Survey on Image Data Augmentation for Deep Learning, author=Shorten, Connor and Khoshgoftaar, Taghi M, journal=Journal of Big Data, volume=6, number=1, pages=1–48, year=2019, publisher=Springer

@articlepowers2011evaluation, title=Evaluation: From Precision, Recall and F-Measure to ROC, Informedness, Markedness and Correlation, author=Powers, David M W, journal=Journal of Machine Learning Technologies, volume=2, number=1, pages=37–63, year=2011

@articlezhou2019cnnmedical, title=A Review on Deep Learning in Medical Image Analysis, author=Zhou, Shuiwang and Greenspan, Hayit and Shen, Dinggang, journal=Medical Image Analysis, volume=69, pages=101–123, year=2019, publisher=Elsevier

@articlehan2021skinreview, title=Skin Disease Classification Using Deep Learning: A Review, author=Han, Seung Hoon and Kim, Minsoo and Park, Jae Young, journal=Sensors, volume=21, number=6, pages=1–20, year=2021, publisher=MDPI

@articlemasood2020dermoscopy, title=Computer-Assisted Decision Support System for Skin Cancer Classification, author=Masood, Ammara and Ali Al-Jumaily, Adel, journal=Computers in Biology and Medicine, volume=124, pages=103–111, year=2020, publisher=Elsevier

@articlegoodfellow2016dlbook, title=Deep Learning, author=Goodfellow, Ian and Bengio, Yoshua and Courville, Aaron, journal=MIT Press, year=2016

@articleopencv2021vision, title=Open Source Computer Vision Library: Applications and Use Cases, author=OpenCV Team, journal=OpenCV Documentation, year=2021