International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03082
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

DEEP LEARNING BASED SKIN CANCER DETECTION SYSTEM INTEGRATED WITH IoT AND RASPBERRY PI

[1] P.Ramya Kumari,[2] P.Akshaya,[3] P.Bhuvana Venkata Sai,[4] S.Harsha Manideep Patnaik,
[5] K.Anu Vaishnavi,[6] Mrs. D. Prasanna Kumari, [7] Dr. B. Siva Prasad
[1,2,3,4,5] B.Tech student, Department of ECE, NSRIT, Vizag, AP, India
[6]Assistant Professor, Department of ECE, NSRIT, Vizag, AP, India
[7]Professor, Head of Department of ECE, NSRIT, Vizag, AP, India

ABSTRACT

Skin cancer is one of the most common forms of cancer worldwide, and early detection plays a vital role in improving treatment outcomes and saving lives. However, access to timely and accurate diagnosis can be limited, especially in remote or resource-constrained regions. In response to this challenge, this project presents the development of an intelligent skin cancer detection system powered by Raspberry Pi. The aim is to build a low-cost, portable, and efficient solution that leverages the power of deep learning and IoT to assist in the preliminary screening of skin lesions.

Rather than relying on expensive diagnostic equipment or manual interpretation, the system processes pre-acquired images of skin lesions using advanced image processing techniques to enhance quality and isolate regions of interest. These refined images are then classified using a trained Convolutional Neural Network (CNN) model capable of distinguishing between benign, malignant, and potentially precancerous lesions with significant accuracy. The outcome of the diagnosis is displayed locally on a 16x2 LCD screen, while the data is also transmitted to a connected Android-based IoT application, enabling remote access for patients or healthcare professionals. Diagnostic records are saved in structured formats for future analysis, review, or integration into larger medical systems. By integrating deep learning with embedded systems and IoT technology, this project highlights a step toward decentralized, intelligent, and accessible skin cancer screening offering potential to bridge the gap in healthcare delivery, especially in underserved communities.

KEYWORDS

Raspberry Pi, Skin Cancer Detection, Internet of Things, Convolutional Neural Network, Smart Healthcare, LCD Display Interface, Medical IoT Application, Dermoscopy Images.

1. INTRODUCTION:

1.1 Background and Motivation

Skin cancer is one of the most common forms of cancer globally, and its early detection significantly increases the chances of successful treatment. However, in many regions, especially rural or underdeveloped areas, access to dermatologists and specialized diagnostic equipment is limited. This project aims to bridge that gap by developing a low-cost, portable Skin Cancer Detection System using Raspberry Pi.

The system leverages the capabilities of image processing and machine learning to classify skin lesions as benign or malignant. Images of skin lesions are input into the Raspberry Pi system, where they are preprocessed and analyzed using a trained deep learning model. The compact size, low power consumption, and affordability of the Raspberry Pi make it an ideal platform for this healthcare application. By integrating artificial intelligence with embedded systems, the project delivers an accessible, real-time diagnostic tool that can assist healthcare professionals or even be used for preliminary self-assessment. The ultimate goal is to promote early detection, improve healthcare accessibility, and reduce the mortality rate associated with skin cancer.

Skin cancer is one of the fastest-growing types of cancer worldwide, with millions of cases diagnosed every year. Early detection plays a critical role in increasing survival rates and reducing the severity of treatment. Traditional diagnostic methods, which rely heavily on expert dermatological assessment and biopsy, can be time-consuming, expensive, and inaccessible to many people in remote or underserved regions. In recent years, Deep Learning has emerged as a powerful tool in medical image analysis, offering high accuracy in detecting various diseases, including skin cancer. This project presents a Skin Cancer Detection System based on Deep Learning techniques, designed to automatically classify skin lesions from dermoscopic images. The system uses Convolutional Neural Networks (CNNs), a class of deep learning models particularly well-suited for image recognition tasks. These models are trained on large datasets of labeled skin lesion images to learn complex patterns and features that distinguish between benign and malignant lesions. Once trained, the model can analyze new images and provide fast, reliable predictions. By integrating deep learning into the diagnostic process, this system aims to support dermatologists, improve early diagnosis, and potentially save lives. It can be deployed in hospitals, clinics, or mobile health units, and even integrated with embedded systems like Raspberry Pi for portable, real-time analysis in resource-limited settings. Skin cancer, particularly melanoma, is a life-threatening disease that can be effectively treated if detected early. Traditional diagnostic methods involve manual examination by dermatologists, which can be subjective and time-consuming. With the advancement of artificial intelligence, particularly Deep Learning, automated skin cancer detection has become a promising field of research. This project focuses on the development of a Skin Cancer Detection System using Deep Learning in Python. The system is designed to analyze dermoscopic images of skin lesions and classify them as either benign or malignant. Using Convolutional Neural Networks (CNNs), a class of deep learning models optimized for image analysis, the system can learn visual patterns from large datasets and make accurate predictions on unseen images.

The project workflow begins with data collection, which involves using public datasets such as the HAM10000 or ISIC archive. These datasets provide a diverse range of dermoscopic images labeled for training and evaluation. The collected images are then preprocessed through steps such as resizing, normalization, and augmentation to enhance the generalization ability of the model. After preprocessing, the model is built using Python libraries like TensorFlow or PyTorch, where various CNN architectures are designed and trained on the prepared dataset. The trained model is rigorously evaluated using performance metrics such as accuracy, precision, recall, and confusion matrix to ensure its reliability and robustness. Once validated, the model can optionally be deployed on a Raspberry Pi for portable diagnostics, or integrated into a graphical user interface for improved usability. By leveraging Python's robust ecosystem for deep learning and image processing, this system provides a cost-effective and scalable solution for early skin cancer detection, without relying on any external imaging hardware. Its simplicity, affordability, and portability make it highly suitable for community healthcare initiatives, mobile diagnostic units, and resource-constrained environments.

1.2 Objectives

The primary objective of this project is to develop an affordable, portable, and efficient system for the early detection of skin cancer, with a focus on reaching communities where access to dermatological care is limited or unavailable. By harnessing the power of deep learning and the versatility of the Raspberry Pi, the project aims to create a tool that can assist in the automatic classification of skin lesions as benign or malignant using dermoscopic images. The goal is not only to reduce dependency on expensive diagnostic equipment and specialized professionals but also to empower healthcare workers and individuals in remote or underserved areas with a smart, real-time diagnostic aid. Ultimately, the project aspires to contribute to the global fight against skin cancer by promoting early detection, which is critical to improving treatment outcomes and saving lives. Through this integration of AI and embedded systems, the project reflects a broader vision of making life-saving healthcare technologies more accessible, inclusive, and scalable.

2. LITERATURE SURVEY

Skin cancer is one of the most prevalent malignancies globally, with both melanoma and non-melanoma variants posing a significant threat to public health. According to Siegel et al. [1], the incidence of cancer, particularly skin-related cancers, has steadily increased, emphasizing the need for improved detection methods. Sung et al. [3] further reinforce these findings through their comprehensive global analysis, revealing the widespread nature of skin cancer across 185 countries. Gordon [4] provides a foundational overview of the epidemiology and associated risk factors, highlighting exposure to ultraviolet radiation, fair skin, and genetic predisposition as key contributors. Traditional skin cancer detection relies heavily on visual inspection and dermoscopic analysis by dermatologists, followed by biopsy. However, these techniques often suffer from

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03082
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

inter-observer variability, are invasive, and time-consuming. Technological advancements have led to the development of non-invasive, AI-based tools that can analyze dermoscopic images with high accuracy [9]. Dermoscopy, combined with digital imaging and AI, significantly enhances early detection and monitoring, especially for high-risk patients [9], [11]. The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized the field of medical image analysis. Esteva et al. [10] demonstrated that CNNs could match the diagnostic accuracy of certified dermatologists when trained on large, annotated datasets. Their work marked a paradigm shift, encouraging widespread adoption of AI in dermatological diagnostics. Following this, Sharma et al. [21] presented a cascaded ensemble model that combined CNNs with handcrafted features to achieve dermatologist-level classification of various skin lesion types. Further research by Salma and Eltrass [17] focused on the development of an automated deep learning approach to distinguish between malignant melanoma and benign skin lesions, emphasizing the model's clinical applicability. Tiwari [18] proposed an innovative hybrid model using multi-layer perceptron (MLP), CNN, and capsule networks to enhance the precision of malignant melanoma detection. These approaches leverage the hierarchical feature extraction capabilities of CNNs, enabling the system to detect subtle variations in lesion structure, color, and texture. Olayah et al. [16] advanced this area by combining multiple CNN-derived features to improve early detection accuracy. This ensemble strategy reduces the risk of false positives and negatives, which are critical concerns in real-world deployment. Transfer learning, another vital deep learning strategy, was effectively employed by Barhoumi and Khelifa [12], enabling the reuse of pretrained models on skin lesion datasets to reduce training time and enhance performance. Hair occlusions in dermoscopic images often interfere with lesion boundary detection. Li et al. [2] tackled this challenge by proposing a deep learning-based digital hair removal technique, significantly improving skin lesion segmentation outcomes. To further combat the scarcity of annotated medical images, Rashid et al. [27] utilized GAN-based data augmentation techniques, thereby enhancing the model’s robustness and generalization capabilities on smaller datasets.

The survey by Alzubaidi et al. [19] provides a comprehensive overview of deep learning and CNN architectures, their evolution, and application across domains including healthcare. Similarly, Shin et al. [20] delve into various CNN models, dataset characteristics, and the role of transfer learning in medical image detection. LeCun et al. [24], the pioneers in deep learning, outline the core principles and strengths of deep architectures, setting a strong theoretical foundation. Beyond detection, prevention is a crucial aspect of skin cancer management. Perez et al. [7], [8] explored primary, secondary, and tertiary prevention strategies, advocating for integrated technological support in skin cancer care. These

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03082
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

preventive strategies can be enhanced through smart diagnostic tools integrated into healthcare systems.The potential of deploying deep learning models on embedded platforms like Raspberry Pi is another growing research area. Maksimović et al. [23] evaluated the computational power and constraints of Raspberry Pi as an IoT device, highlighting its capability to run lightweight AI models using frameworks such as TensorFlow Lite. Such setups allow real-time, low-cost, portable diagnostics in resource-limited settings, making AI accessible beyond hospitals and into remote areas.

The use of IoT and cloud-based services in healthcare further extends the reach of these systems. Ray et al. [13] proposed secure object tracking protocols for IoT applications, which can be adapted to ensure the secure handling of sensitive medical data in skin cancer detection systems. Jatin Borana [14] discussed the broader applications of AI and associated technologies in biomedical fields, reinforcing the idea of interdisciplinary solutions. The widespread availability of open-source datasets and platforms has significantly accelerated research and experimentation. Fanconi [22], via Kaggle, provides a widely used dataset for malignant vs. benign skin lesion classification, enabling consistent benchmarking of models. Moreover, recent studies have explored deep learning in related domains such as cervical [26] and thyroid [25] cancer, reaffirming the adaptability of CNN architectures in various types of histopathological and dermatoscopic analysis. These studies strengthen the case for expanding AI-based diagnostic tools across different medical specialties. Lastly, foundational work by Dai et al. [28] and Minaee et al. [29] has driven forward the application of CNNs in object detection and classification, demonstrating techniques that have been directly or indirectly applied in medical imaging tasks. Li et al. [30] provide a thorough review of visual tracking using deep learning, an area that also influences lesion tracking in longitudinal skin cancer monitoring.

3. METHODOLOGY

3.1 Hardware Design

3.1.1 Regulated Power Supply

Power supply is a supply of electrical power. A device or system that supplies electrical or other types of energy to an output load or group of loads is called a power supply unit or PSU. The term is most commonly applied to electrical energy supplies, less often to mechanical ones, and rarely to others.

A power supply may include a power distribution system as well as primary or secondary sources of energy such as

- Conversion of one form of electrical power to another desired form and voltage, typically involving converting AC line voltage to a well-regulated lower-voltage DC for electronic devices. Low voltage, low power DC power supply units are commonly integrated with the devices they supply, such as computers and household electronics.
- Batteries.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03082
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

- Chemical fuel cells and other forms of energy storage systems.
- Solar power.
- Generators or alternators.

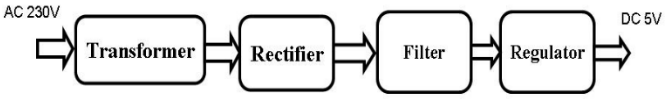


Fig 1: Regulated Power Supply

The basic circuit diagram of a regulated power supply (DC O/P) with led connected as load is shown in fig: 2.

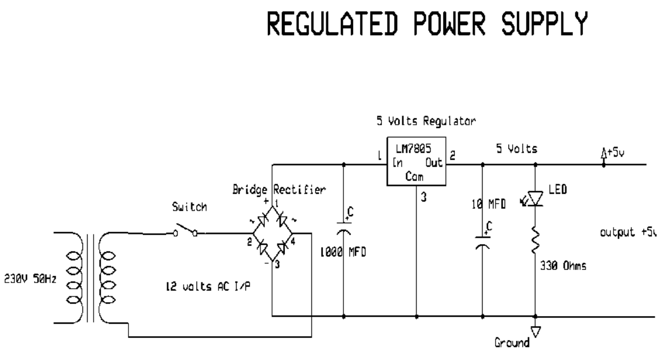


Fig 2: Circuit diagram of Regulated Power Supply with Led connection

The components mainly used in above figure are

- 230V AC MAINS
- TRANSFORMER
- BRIDGE RECTIFIER(DIODES)
- CAPACITOR
- VOLTAGE REGULATOR(IC 7805)
- RESISTOR
- LED(LIGHT EMITTING DIODE)

The detailed explanation of each and every component mentioned.

3.1.2 Transformers:

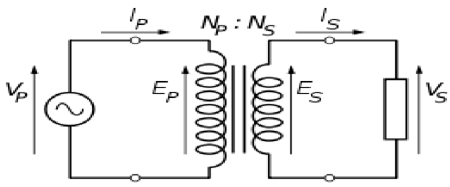
A transformer is a device that transfers electrical energy from one circuit to another through inductively coupled conductors without changing its frequency. A varying current in the first or primary winding creates a varying magnetic flux in the transformer's core, and thus a varying magnetic field through the secondary winding. This varying magnetic field induces a varying electromotive force (EMF) or "voltage" in the secondary winding. This effect is called mutual induction.

If a load is connected to the secondary, an electric current will flow in the secondary winding and electrical energy will be transferred from the primary circuit through the transformer to the load. This field is made up from lines of force and has the same shape as a bar magnet.
If the current is increased, the lines of force move outwards from the coil. If the current is reduced, the lines of force move inwards.
If another coil is placed adjacent to the first coil then, as the field moves out or in, the moving lines of force will "cut" the turns of the second coil. As it does this, a voltage is induced in the second coil. With the 50 Hz AC mains supply, this will happen 50 times a second. This is called MUTUAL INDUCTION and forms the basis of the transformer.
The input coil is called the PRIMARY WINDING; the output coil is the SECONDARY WINDING. Fig:3 shows step-down transformer.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03082
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Step down transformer:

Incase of step down transformer, Primary winding induces more flux than the secondary winding, and secondary winding is having less number of turns because of that it accepts less number of flux, and releases less amount of voltage.



$$\frac{V_P}{V_S} = \frac{I_S}{I_P} = \frac{N_P}{N_S}$$

Fig 3: Step-Down Transformer

3.1.3 Battery power supply:

A battery is a type of linear power supply that offers benefits that traditional line-operated power supplies lack: mobility, portability and reliability. A battery consists of multiple electrochemical cells connected to provide the voltage desired. Fig: 4 shows Hi-Watt 9V battery

Fig 4: Hi-Watt 9V Battery

The most commonly used dry-cell battery is the carbon-zinc dry cell battery. Dry-cell batteries are made by stacking a carbon plate, a layer of electrolyte paste, and a zinc plate alternately until the desired total voltage is achieved. The most common dry-cell batteries have one of the following voltages: 1.5, 3, 6, 9, 22.5, 45, and 90. During the discharge of a carbon-zinc battery, the zinc metal is converted to a zinc salt in the electrolyte, and magnesium dioxide is reduced at the carbon electrode. These actions establish a voltage of approximately 1.5 V.

3.1.4 Rectifiers:

A rectifier is an electrical device that converts alternating current (AC) to direct current (DC), a process known as rectification. Rectifiers have many uses including as components of power supplies and as detectors of radio signals. Rectifiers may be made of solid-state diodes, vacuum tube diodes, mercury arc valves, and other components.

A device that it can perform the opposite function (converting DC to AC) is known as an inverter.

When only one diode is used to rectify AC (by blocking the negative or positive portion of the waveform), the difference between the term diode and the term rectifier is merely one of usage, i.e., the term rectifier describes a diode that is being used to convert AC to DC. Almost all rectifiers comprise a number of diodes in a specific arrangement for more efficiently converting AC to DC than is possible with only one diode. Before the development of silicon semiconductor rectifiers, vacuum tube diodes and copper (I) oxide or selenium rectifier stacks were used.

Bridge full wave rectifier:

The Bridge rectifier circuit converts an ac voltage to dc voltage using both half cycles of the input ac voltage. The Bridge rectifier circuit is shown in the figure. The circuit has four diodes connected to form a bridge. The ac input voltage is applied to the diagonally opposite ends of the bridge. The load resistance is connected between the other two ends of the bridge.

For the positive half cycle of the input ac voltage, diodes D1 and D3 conduct, whereas diodes D2 and D4 remain in the OFF state. The conducting diodes will be in series with the load resistance R_L and hence the load current flows through R_L. For the negative half cycle of the input ac voltage, diodes D2 and D4 conduct whereas, D1 and D3 remain OFF. The conducting diodes D2 and D4 will be in series with the load resistance R_L and hence the current flows through R_L in the same direction as in the previous half cycle. Thus a bi-directional wave is converted into a unidirectional wave.

3.1.5 DB107:

Now -a -days Bridge rectifier is available in IC with a number of DB107. In our project we are using an IC in place of bridge rectifier.

Features:

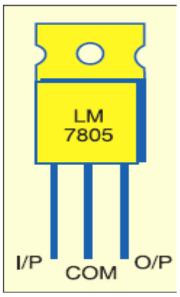
- Good for automation insertion
- Surge overload rating - 30 amperes peak
- Ideal for printed circuit board
- Reliable low cost construction utilizing molded
- Glass passivated device
- Polarity symbols molded on body
- Mounting position: Any

Filters:

Electronic filters are electronic circuits, which perform signal-processing functions, specifically to remove unwanted frequency components from the signal, to enhance wanted ones.

3.1.6 Voltage Regulator:

A voltage regulator (also called a 'regulator') with only three terminals appears to be a simple device, but it is in fact a very complex integrated circuit. It converts a varying input voltage into a constant 'regulated' output voltage. Voltage Regulators are available in a variety of outputs like 5V, 6V, 9V, 12V and 15V. The LM78XX series of voltage regulators are designed for positive input. For applications requiring negative input, the LM79XX series is used. Using a pair of 'voltage-divider' resistors can increase the output voltage of a regulator circuit. It is not possible to obtain a voltage lower than the stated rating. You cannot use a 12V regulator to make a 5V power supply. Voltage regulators are very robust. These can withstand over-current draw due to short circuits and also over-heating. In both cases, the regulator will cut off before any damage occurs. The only way to destroy a regulator is to apply reverse voltage to its input. Reverse polarity destroys the regulator almost instantly

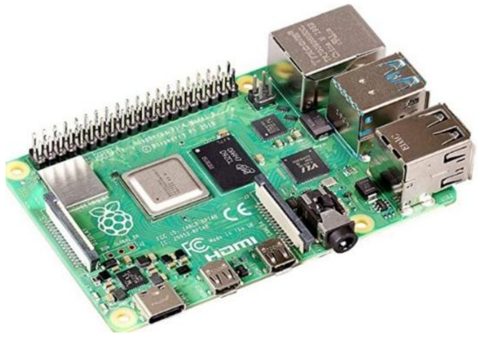


International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03082
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Fig 5: Voltage Regulator

3.1.7 <u>Raspberry-Pi Processor:</u>

The Raspberry Pi 3 Model B+ is an enhanced version of the third-generation Raspberry Pi boards, offering a balanced combination of performance and connectivity in the familiar credit-card-sized form factor. It supersedes the earlier Raspberry Pi 3 Model B and maintains compatibility with previous models while improving speed and wireless capabilities. Powered by a 1.4GHz 64-bit quad-core ARM Cortex-A53 processor, the Raspberry Pi 3 Model B+ delivers reliable computing performance suitable for a wide range of applications including home automation, IoT systems, educational tools, and lightweight desktop



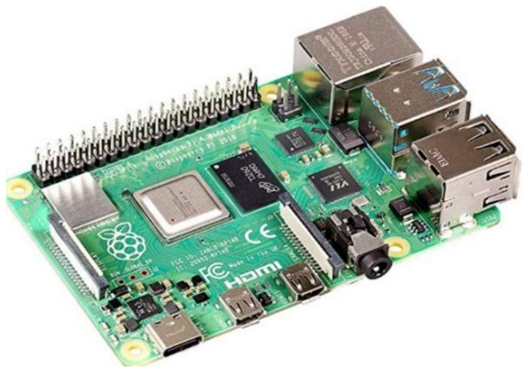
computing.

One of the key improvements in the Model B+ is the inclusion of dual-band 2.4GHz and 5GHz IEEE 802.11ac Wi-Fi, along with Bluetooth 4.2 and Gigabit Ethernet (via USB 2.0 interface),

Fig 6: Raspberry-Pi 3 Processor

Features :

- **Processor-** Broadcom BCM2837 chipset. 1.2GHz Quad-Core ARM Cortex-A53802.11 b/g/n Wireless LAN and Bluetooth 4.1 (Bluetooth Classic and LE)
- **GPU-** Dual Core Video Core IV® Multimedia Co-Processor. Provides Open GLES 2.0, hardware-accelerated OpenVG, and 1080p30 H.264 high-profile decode. Capable of 1Gpixel/s, 1.5Gtexel/s or 24GFLOPs with texture filtering and DMA infrastructure
- **Memory-**1GB LPDDR2
- **Operating System** Boots from Micro SD card, running a version of the Linux operating system or Windows 10 IoT
- **Dimensions-** 85 x 56 x 17mm
- **Power-** Micro USB socket 5V1, 2.5A



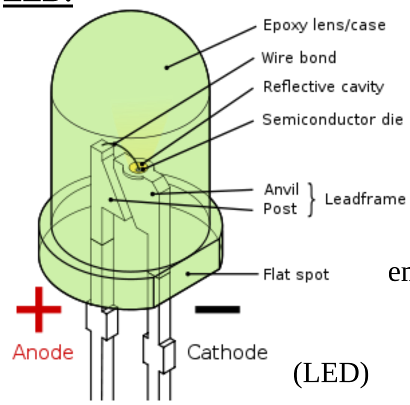
Connectors :

- **Ethernet-** 10/100 BaseT Ethernet socket
- **Video Output-** HDMI (rev 1.3 & 1.4 Composite RCA (PAL and NTSC).
- **Audio Output-** Audio Output 3.5mm jack, HDMI USB 4 x USB 2.0 Connector.
- **GPIO Connector-** 40-pin 2.54 mm (100 mil) expansion header: 2x20 strip Providing 27 GPIO pins as well as +3.3 V, +5 V and GND supply lines.
- **Camera Connector-** 15-pin MIPI Camera Serial Interface (CSI-2).
- **Display Connector-** Display Serial Interface (DSI) 15 way flat flex cable connector with two data lanes and a clock lane.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03082
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

- **Memory Card Slot-** Push/pull Micro SDIO

3.1.8 <u>LED:</u>



A light-emitting diode (LED) is a semiconductor light source. LED's are used as indicator lamps in many devices, and are increasingly used for lighting. Introduced as a practical electronic component in 1962, early LED's emitted low-intensity red light, but modern versions are available across the visible, ultraviolet and infrared wavelengths, with very high brightness. The internal structure and parts of a led are shown in figure 7 respectively.

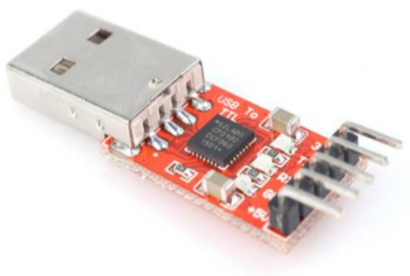


Fig 7: Parts of a LED

3.1.9 <u>USB Serial Connector:</u>

A USB serial connector is a compact and convenient device used to establish communication between a computer and microcontrollers or embedded systems like the Raspberry Pi. It typically converts USB signals from a host device into serial communication protocols such as UART (Universal Asynchronous Receiver/Transmitter), allowing easy data exchange and debugging. These connectors are especially useful for programming, monitoring, and interfacing with devices that lack standard USB ports, enabling developers to access the system's console, transfer data, or upload code directly via a USB interface.

Fig 8: USB Serial Connector

<u>Software Architecture:</u>

The software architecture of the Skin Cancer Detection System follows a modular and layered design to ensure efficient image analysis and accurate predictions. At the initial input layer, the Raspberry Pi interfaces with a USB webcam or Pi Cam to capture images of skin lesions. These images are automatically saved in a designated directory for processing. The system is configured to accept input either from a live camera feed or from stored images, making it adaptable for both real-time and offline usage.

Following the input stage, the captured image enters the processing layer, where several preprocessing operations are performed using Python-based libraries like OpenCV and NumPy. The image is resized to a standardized dimension suitable for model input, typically 224x224 pixels. It is then converted from RGB to grayscale or normalized RGB, depending on the model requirements. Image augmentation techniques such as rotation, flipping, or brightness adjustments may be applied to enhance model generalization and reduce overfitting. These preprocessing steps ensure that the images fed into the neural network are clean, consistent, and representative of various real-world conditions.

The core of the system lies in the deep learning model integrated into the recognition layer. A Convolutional Neural Network (CNN), trained on publicly available skin lesion datasets like HAM10000 or the ISIC archive, is responsible for feature extraction and classification. This model is capable of distinguishing between benign and malignant lesions by learning subtle visual patterns. The pre-trained model, optimized and converted to a lightweight format like TensorFlow Lite or PyTorch Mobile, is deployed on the Raspberry Pi for efficient inference. When a new image is passed through the model, it generates a classification result along with a confidence score.

Once the prediction is obtained, the result is passed to the output and decision layer. Here, the prediction is displayed on a connected touchscreen or through a web-based GUI using Flask or Django. Additionally, results can be logged locally or pushed to a cloud service like Firebase for record-keeping and remote access. If integrated with IoT features, the system can send alerts or updates via MQTT or HTTP protocols, enabling remote monitoring by healthcare professionals. This layered architecture ensures a seamless workflow from image capture to real-time diagnosis, making the system a reliable and accessible tool for early skin cancer detection.

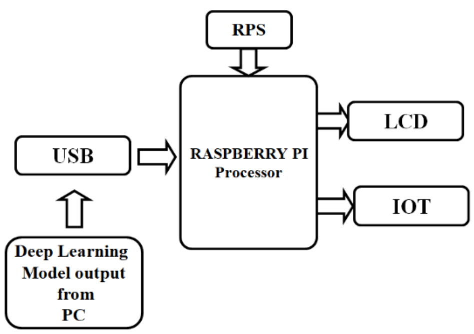
4. WORKING:

Fig 9: Block Diagram

4.1 Image Acquisition:

- A standard USB webcam is connected to one of the four USB ports on the Raspberry Pi 3 Model B+.
- The webcam captures high-resolution images of skin lesions when manually triggered through a physical button or GUI interface.
- Image acquisition is handled using Python libraries such as OpenCV (cv2.VideoCapture) which interfaces with the webcam to capture live frames.

4.2 Image Preprocessing:



- The captured image is processed on the Raspberry Pi using OpenCV or PIL (Python Imaging Library).
- Resizing the image to fit the model's input shape (e.g., 224×224).

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03082
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

- Normalization of pixel values to standardize inputs (e.g., scaling pixel intensity to 0-1).
- Contrast enhancement and denoising using filters (like Gaussian Blur) to improve image clarity.
- Optional segmentation to isolate the lesion from the background skin if needed, enhancing classification accuracy.

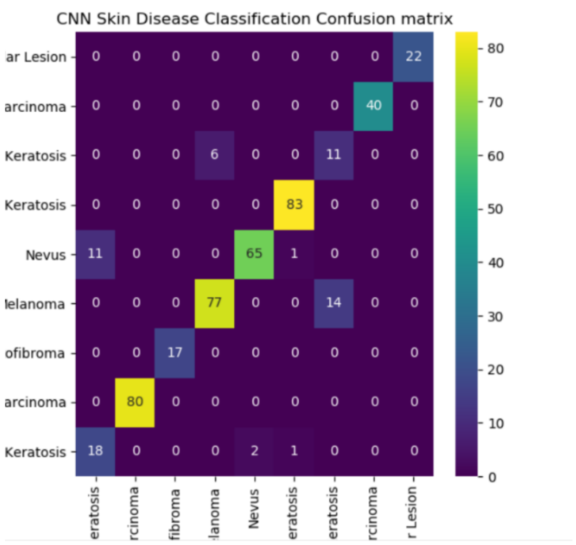


Fig 10: CNN Skin Disease Classification Matrix

4.3 Deep Learning Inference:

- A pretrained Convolutional Neural Network (CNN) model such as MobileNetV2, EfficientNet-lite, or a custom CNN is deployed onto the Raspberry Pi using TensorFlow Lite or ONNX Runtime.
- These models are chosen for their low computational footprint, enabling efficient execution on the Raspberry Pi 3 Model B+.
- The preprocessed image is fed to the CNN, which returns:
- Predicted class: whether the lesion is benign or malignant.
- Confidence score: a percentage indicating the certainty of the prediction.

4.4 Result Display:

- The prediction result is displayed on a touchscreen display or a monitor connected via HDMI.
- The GUI (developed using Python Tkinter or Flask for a web-based UI) shows:
- Captured lesion image.
- Classification result.
- Confidence level.
- Suggestive message (e.g., “Please consult a doctor if classified as malignant”).

4.5 IoT Integration for Remote Monitoring:

- The Raspberry Pi 3 Model B+ connects to the internet using its built-in Wi-Fi capability.
- Results, including image snapshots, timestamp, and prediction data, are sent to a remote server or cloud platform.
- Communication protocols such as MQTT, HTTP REST API, or services like Firebase/ThingSpeak are used for seamless data transmission.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03082
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

- This allows remote viewing by doctors or health professionals via an online dashboard.

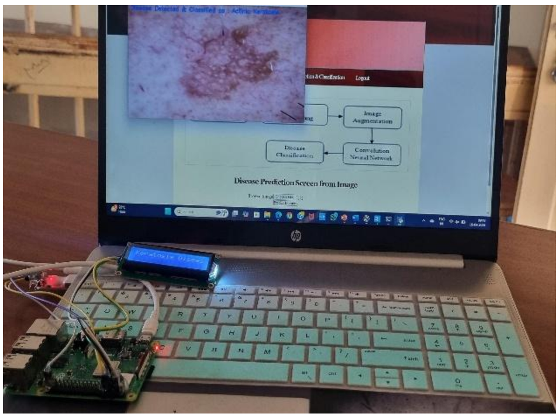
4.6 Data Logging and Alert System:

- Each diagnostic session is logged on the Raspberry Pi’s local storage (SD card) and optionally synced with the cloud database.
- These alerts ensure timely intervention and can notify both patients and medical practitioners.

Fig 11: Project Output

5. FUTURE SCOPE:

The future scope for the CNN-based skin cancer detection system in applications such as clinical diagnostics, tele dermatology, public health screening, and personalized medicine is vast and promising. By leveraging advancements in artificial intelligence, edge computing, and medical imaging, this system



has the potential to revolutionize dermatological care and extend its impact to global healthcare systems. Integrating multimodal data sources beyond dermoscopic images can significantly enhance the system’s diagnostic capabilities. By incorporating clinical metadata such as patient age, family history, skin type, UV exposure, and genetic predispositions, the system can provide more personalized risk assessments. Additionally, combining imaging with other diagnostic modalities, such as spectroscopy or confocal microscopy, could improve the detection of subtle or early-stage lesions. These advancements would enable the system to emulate the holistic reasoning of dermatologists, offering comprehensive insights that improve accuracy and patient outcomes. Developing autonomous diagnostic algorithms with real-time processing capabilities can make the system more responsive and scalable. By optimizing CNN architectures for low-latency inference on edge devices like Raspberry Pi, the system could deliver instant results in point-of-care settings, such as rural clinics or mobile health units. Incorporating adaptive learning mechanisms would allow the system to refine its predictions over time, adjusting to variations in imaging conditions, skin types, or lesion presentations.

Beyond its clinical applications, the system can serve as an educational platform for training healthcare professionals and engaging communities. By providing open-source access to its codebase and datasets, the project can inspire students and researchers to explore AI in medicine, fostering innovation and collaboration. Public-facing applications, such as mobile apps with educational content on skin cancer prevention, could raise awareness and encourage proactive health behaviors.

Overall, the future of the CNN-based skin cancer detection system is characterized by continuous innovation and a commitment to equitable healthcare. By leveraging advancements in deep learning, edge computing, multimodal data integration, and privacy-preserving techniques, the system can evolve into a cornerstone of dermatological care. Its potential to enhance early detection, support personalized medicine, and empower communities underscores its role in addressing the global burden of skin cancer. With sustained collaboration among researchers, clinicians, technologists, and policymakers, this system will continue to break new ground, ensuring that life-saving diagnostics are accessible, accurate, and inclusive for all.

8. CONCLUSION:

This project not only addresses a critical challenge in skin cancer diagnostics but also lays the foundation for future advancements in AI-driven healthcare solutions. The successful integration of Convolutional Neural Networks (CNNs) with robust datasets and innovative methodologies highlights the immense potential for automated, accurate, and accessible detection systems. By bridging cutting-edge technology with real-world clinical needs, this work paves the way for further research and enhancements, contributing to the evolution of dermatology and global health equity. The CNN-based skin cancer detection system developed in this project represents a pioneering effort at the intersection of artificial intelligence and medical diagnostics. Designed to automate the identification of melanoma and other skin lesions, this system leverages the computational power of deep learning to analyze dermoscopic images with precision and reliability. By utilizing a low-cost, versatile platform like Raspberry Pi, the project delivers a scalable solution that can be deployed in diverse settings—from urban hospitals to remote clinics addressing the urgent need for early detection in regions with limited access to dermatological expertise.

The system operates through a seamless workflow that mirrors the diagnostic process of human clinicians. It begins with image acquisition, where a high-resolution camera captures dermoscopic images of skin lesions. Finally, classification determines whether the lesion is benign or malignant, with results displayed to clinicians or patients in real time. This end-to-end pipeline ensures that the system is both intelligent and user-friendly, capable of delivering rapid assessments without compromising accuracy.

9. REFERENCES:

[1] R. L. Siegel, K. D. Miller, H. E. Fuchs, and A. Jemal, “Cancer statistics, 2022,” *CA: A Cancer Journal for Clinicians*, vol. 72, no. 1, pp. 7–33, Jan. 2022, doi: 10.3322/caac.21708.

[2] *Pattern Recognition*, vol. 117, p. 107994, Sep. 2021, doi: 10.1016/j.patcog.2021.107994.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03082
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

[3] H. Sung *et al.*, “Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries,” *CA: A Cancer Journal for Clinicians*, vol. 71, no. 3, pp. 209–249, Feb. 2021, doi: 10.3322/caac.21660.

[4] R. Gordon, “Skin Cancer: An Overview of Epidemiology and Risk Factors,” *Seminars in Oncology Nursing*, vol. 29, no. 3, pp. 160–169, Aug. 2013, doi: 10.1016/j.soncn.2013.06.002.

[5] G. N. K. Babu and V. J. Peter, “Skin cancer detection using support vector machine with histogram of oriented gradients features,” *ICTACT Journal on Soft Computing*, vol. 11, no. 2, pp. 2301–2305, 2021, doi: 10.21917/ijsc.2021.0329.

[6] M. Q. Khan *et al.*, “Classification of Melanoma and Nevus in digital images for diagnosis of skin cancer,” *IEEE Access*, vol. 7, pp. 90132 – 90144, 2019, doi: 10.1109/access.2019.2926837.

[7] M. Perez, J. A. Abisaad, K. D. Rojas, M. A. Marchetti, and N. Jaimes, “Skin cancer: Primary, secondary, and tertiary prevention. Part I,” *Journal of the American Academy of Dermatology*, vol. 87, no. 2, pp. 255–268, Aug. 2022, doi: 10.1016/j.jaad.2021.12.066.

[8] K. D. Rojas, M. E. Perez, M. A. Marchetti, A. J. Nichols, F. J. Penedo, and N. Jaimes, “Skin cancer: Primary, secondary, and tertiary prevention. Part II,” *Journal of the American Academy of Dermatology*, vol. 87, no. 2, pp. 271–288, Aug. 2022, doi: 10.1016/j.jaad.2022.01.053.

[9] L. Thomas and S. Puig, “Dermoscopy, digital dermoscopy and other diagnostic tools in the early detection of Melanoma and follow-up of high-risk skin cancer patients,” *Acta Dermato Venereologica*, vol. 97, 2017, doi: 10.2340/00015555-2719.

[10] A. Esteva *et al.*, “Dermatologist-level classification of skin cancer with deep neural networks,” *Nature*, vol. 542, no. 7639, pp. 115–118, Jan. 2017, doi: 10.1038/nature21056.

[11] A. T. Young *et al.*, “The role of technology in melanoma screening and diagnosis,” *Pigment Cell & Melanoma Research*, vol. 34, no. 2, pp. 288–300, Aug. 2020, doi: 10.1111/pcmr.12907.

[12] W. Barhoumi and A. Khelifa, “Skin lesion image retrieval using transfer learning-based approach for query-driven distance recommendation,” *Computers in Biology and Medicine*, vol. 137, p. 104825, Oct. 2021, doi: 10.1016/j.compbiomed.2021.104825.

[13] B. R. Ray, M. U. Chowdhury, and J. H. Abawajy, “Secure object tracking protocol for the internet of things,” *IEEE Internet of Things Journal*, vol. 3, no. 4, pp. 544–553, Aug. 2016, doi: 10.1109/jiot.2016.2572729.

[14] Jatin Borana, “Applications of artificial intelligence & associated technologies,” in *Proceeding of International Conference on Emerging Technologies in Engineering, Biomedical, Management and Science* , 2016, pp. 64–67.

[15] M. Sohail *et al.*, "Racial identity-aware facial expression recognition using deep convolutional neural networks," *Applied Sciences*, vol. 12, no. 1, p. 88, Dec. 2021, doi: 10.3390/app12010088.

[16] F. Olayah, E. M. Senan, I. A. Ahmed, and B. Awaji, "AI techniques of dermoscopy image analysis for the early detection of skin lesions based on combined CNN Features," *Diagnostics*, vol. 13, no. 7, p. 1314, Apr. 2023, doi: 10.3390/diagnostics13071314.

[17] W. Salma and A. S. Eltrass, "Automated deep learning approach for classification of malignant melanoma and benign skin lesions," *Multimedia Tools and Applications*, vol. 81, no. 22, pp. 32643–32660, Apr. 2022, doi: 10.1007/s11042-022-13081-x.

[18] S. Tiwari, "Dermatoscopy using multi-layer perceptron, convolution neural network, and capsule network to differentiate Malignant Melanoma From Benign Nevus," *International Journal of Healthcare Information Systems and Informatics*, vol. 16, no. 3, pp. 58–73, Jul. 2021, doi: 10.4018/ijhisi.20210701.oa4.

[19] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data*, vol. 8, pp. 1–74, Mar. 2021, doi: 10.1186/s40537-021-00444-8.

[20] H.-C. Shin *et al.*, "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1285–1298, May 2016, doi: 10.1109/tmi.2016.2528162.

[21] A. K. Sharma *et al.*, "Dermatologist-level classification of skin cancer using cascaded ensembling of convolutional neural network and handcrafted features based deep neural network," *IEEE Access*, vol. 10, pp. 17920–17932, 2022, doi: 10.1109/access.2022.3149824.

[22] C. Fanconi, "Skin Cancer: Malignant vs. Benign.". Accessed: Oct. 25, 2023. [Online]. Available: https://www.kaggle.com/fanconic/skin-cancer-malignant-vs-benign

[23] M. Maksimović, V. Vujović, N. Davidović, V. Milošević, and B. Perišić, "Raspberry Pi as Internet of Things hardware : Performances and Constraints," in *Design Issues*, 2014, vol. 3, no. JUNE, pp. 1–6.

[24] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015, doi: 10.1038/nature14539.

[25] N. T. Duc, Y.-M. Lee, J. H. Park, and B. Lee, "An ensemble deep learning for automatic prediction of papillary thyroid carcinoma using fine needle aspiration cytology," *Expert Systems with Applications*, vol. 188, Feb. 2022, doi: 10.1016/j.eswa.2021.115927.

[26] Z. Alyafeai and L. Ghouti, "A fully-automated deep learning pipeline for cervical cancer classification," *Expert Systems with Applications*, vol. 141, Mar. 2020, doi: 10.1016/j.eswa.2019.112951.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03082
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

[27] H. Rashid, M. A. Tanveer, and H. Aqeel Khan, "Skin lesion classification using GAN based data augmentation," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Jul. 2019, pp. 916–919, doi: 10.1109/embc.2019.8857905.

[28] J. Dai, Y. Li, K. He, and J. Sun, "R-FCN: Object detection via region-based fully convolutional networks," in *Advances in Neural Information Processing Systems*, 2016, pp. 379–387.

[29] S. Minaee, N. Kalchbrenner, E. Cambria, N. Nikzad, M. Chenaghlu, and J. Gao, "Deep learning-based text classification: A comprehensive review," *ACM Computing Surveys*, vol. 54, no. 3, pp. 1–40, Apr. 2021, doi: 10.1145/3439726.

[30] P. Li, D. Wang, L. Wang, and H. Lu, "Deep visual tracking: Review and experimental comparison," *Pattern Recognition*, vol. 76, pp. 323–338, Apr. 2018, doi: 10.1016/j.patcog.2017.11.007.