AI-Driven Skin Cancer Diagnostics Detection And Personalized Treatment Through Image Processing

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Abstract - Skin Cancer is among the record prevalent types of Cancer globally with the situation occurrence stays growing significantly, highlighting critical need for initial detection and analysis to improve treatment consequences besides reduce mortality. This study explores innovative applications Artificial intelligence and image processing systems in covering cancer diagnostics, focusing on the latest advancements from 2017 to 2024. By employing advanced deep learning models, such as hybrid architectures combining VGG16 and ResNet50 and Recurring Neural Networks like Echo State Network, this research demonstrates significant improvements in accuracy and efficiency. An optimized Seasonal Optimization Algorithm further enhances the ESN's performance, achieving superior accuracy (97.58%) compared to traditional approaches. Additionally, the study emphasizes robust preprocessing techniques, including image normalization, resizing, and segmentation, to ensure model reliability. The integration of smartphone-based diagnostic tools and whole-body imaging systems extends accessibility and scalability, particularly in low-resource settings. These AI-driven innovations showcase the potential to revolutionize skin cancer diagnostics, offering precise, timely, and scalable solutions, while laying the groundwork for broader applications in personalized treatment and telemedicine deployment.

Index Terms - Skin Cancer; Artificial Intelligence; Deep Learning; Image Processing; Early Diagnosis; Hybrid CNN Models; Recurrent Neural Networks; Karnataka.

I. Introduction

Skin Cancer are significant public health concern with growing cases reported universal [1]. Early detection is crucial to reducing injury and death rates. Traditional diagnostic methods rely on visual examinations and procedures, which can be time-consuming and necessitate skilled dermatologists. Integrating artificial intelligence (AI) into skin cancer diagnostics offers a promising approach to enhancing accuracy and efficiency in disease detection.

1.1 Detection of Skin Cancer:

Dermo cancer is a serious health concern, particularly common in Australia and the United States. Traditional diagnosis can be challenging for dermatologists, especially in the early stages. This has driven researchers to create automated systems that can aid in early detection.

Skin cancer is generally categorized into melanoma and non-melanoma types. Melanoma, the most lethal form, originates from the unrestrained proliferation of melanocytes. As stated by the American Cancer

Society, it takes a significantly advanced humanity amount related to additional casing cancers [3]. Initial detection of casing cancer, particularly growth, is crucial in dropping death rates [4]. Presently, the diagnosis primarily relies on skin surgeries and histopathological estimation, which stand considered the gilt normal [5]. However, it is impractical to biopsy all skin lesions due to potential scarring, period restrictions in medical exercise, & economic implications. Thus, various imaging technologies are employed to assess the necessity of biopsies.

Using image processing and artificial intelligence (AI), these systems analyse skin images to identify cancerous growths. Advanced algorithms process the images to detect patterns and anomalies which could suggest the presence of skin cancer. AI models, often trained on vast datasets of skin images, can distinguish between diverse kinds of skin tumours & melanoma.

This technology offers several benefits

- Accuracy: AI can enhance the precision of early detection.
- Speed: Automated systems can provide faster results than traditional methods.
- Accessibility: These tools can make advanced diagnostic capabilities available in remote or underserved areas.

AI systems can integrate various imaging techniques such as dermo's copy, reflectance confocal microscopy, and histopathology images. Each technique provides different levels of detail and insight into the skin lesions, contributing to a more comprehensive analysis. Transfer learning leverages pre-trained models, such as those from ImageNet, to recover the presentation of AI systems in skin tumour detection. In fine-tuning these models on specific datasets of skin images, researchers can achieve higher accuracy with fewer labelled samples.

Artificial intelligence (AI) covers a broad range of skills that enable machineries to mimic anthropoid intelligence, problem solving, and reasoning purposes. Within this field, Machine learning stands out as a sub-field that specializes in making forecasts from user providing facts [6]. Machine learning offers tremendous potential for automating medical data analysis, thereby influencing clinical care by providing predictive insights that can aid in clinical decision-making. This paper reviews recent advancements in AI-driven skin cancer detection techniques, emphasizing deep learning models, optimization algorithms, and innovative imaging technologies. The focus is on improving diagnostic accuracy, accessibility, and scalability in diverse healthcare settings.

1.2 Skin cancer detection:

Internet of Things links devices to the internet for data sharing through modern communication technology [7]. Its expansion is driven by advancements in technologies such as wireless sensor networks (WSNs), cloud computing, and data sensing [8][9]. Internet of Things is frequently employed to enhance and advance medical systems because of it's strong capability to integrate with infrastructure resources and provide vital facts to operators[10]. Medical systems process a large amount of data through WSNs while delivering various e-health services, such as electronic health records, remote patient monitoring, and medical platforms [11].

Skin cancer is one of the six major types of cancer globally. The skin consists of three types of cells: melanocytes, basal cells, and squamous cells, which can develop into cancerous tissues [12]. Thus, there are different types of skin tumours, such as basal cell carcinoma (BCC), melanoma, and squamous cell carcinoma (SCC), which can be serious forms of cancer [13].

II. LITERATURE SURVEY

Similar review of research

Han et al. (2020)

Connected devices & smart networks for large medical datasets (X-ray, MRI, Ultrasound Efficiency in handling segmentation for pulmonary and cerebral areas Needs deeper examination in diverse clinical situations, mainly challenging imaging situations.

Da Costa Nascimentoetal. (2023)

Allocation learning of brain tumour detection High accuracy in classification & segmentation of brain tumours Needs broader application across various medical conditions, more diverse datasets for training

Badrinarayanan et al. (2017)

SegNet: Deep CNN for image segmentation Efficient in memory and computational time for cerebral diagnostics Requires improvements in trainable parameters without compromising accuracy

De Freitas Souzaetal (2023)

Deep learning for cellular division in stroke detection via tomography Demonstrates broad applicability in stroke diagnosis Needs validation for different stroke subtypes

Al Masnietal (2018)

Full determination CNN for cutaneous lesion segmentation (PH2 & ISIC 2017 datasets) High Dice index achieved in segmentation Presence of extra image processing procedures can enhance care

Baghersalimietal (2019)

Dermo Net: Completely CNN with dense connections aimed at skin lesion segmentation High precision with Jaccard coefficient of 80% Fine-tuning needed for improved efficacy

III.RESOURCES AND IMPLEMENTION

3.1. Analysis and Action of Skin Cancer Using Wearable Sensors

This section outlines the methodologies used for the analysis and action of skin infections through a combination of wearable sensor technology, artificial intelligence (AI)-driven image processing, and automated treatment mechanisms. The system follows a sequential process, starting with data collection and image analysis, leading to diagnosis, and finally integrating a smart bandage-based treatment system.

This study introduces a diagnostic support system that utilizes edge computing and cloud processing for real-time melanoma detection. The methodology follows five key steps. First, new images are captured and entered into the system through an edge trick. Next, the information is managed in cloud, where melanoma detection and lesion segmentation take place. The processed information is then directed spinal to the control trick, which interprets the results to generate a pre-diagnosis. Following this, the device downloads the analysed data for local access. Finally, the system presents the diagnosis, displaying lesion detection results, accuracy metrics, and a possible melanoma confirmation. By integrating IoT technology with real-time data exchange, this method enhances diagnostic efficiency, ensuring fast, remote, and reliable melanoma assessment.

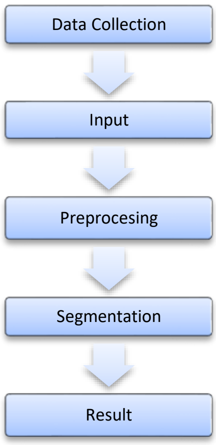

Fig 3.1.1: Diagnosis Process.

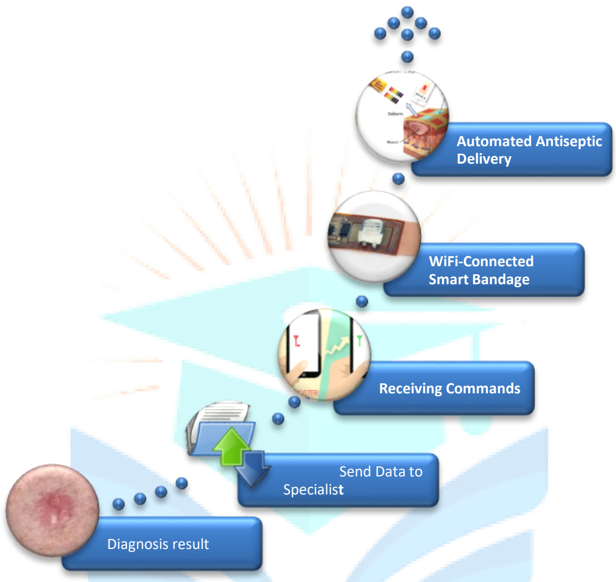

Fig 3.1.2: Treatment Process

3.1.2 Information gathering

This learning employs a inclusive dataset of ended 1,100 oral cancer suitcases sourced [21,22]. This information encompasses diverse patient demographics, cover numerous sub-types and phases cancer.

Imaging Information: High resolution MRI and CT images of the head & roll neck provide critical spatial information for AI-driven diagnostic workflows, enhancing spite discovery and description.

Clinical Information: Persistent demographics, medicinal past, action procedures, and noted consequences form a robust dataset supporting AI-based analysis and decision-making.

Histopathological Data: Tumour cell morphology and grading are essential for AI-assisted pathology, aiding in cancer tissue evaluation.

To ensure compliance with moral values and all information undergoes a deidentification procedure to protect enduring discretion and maintain information security.

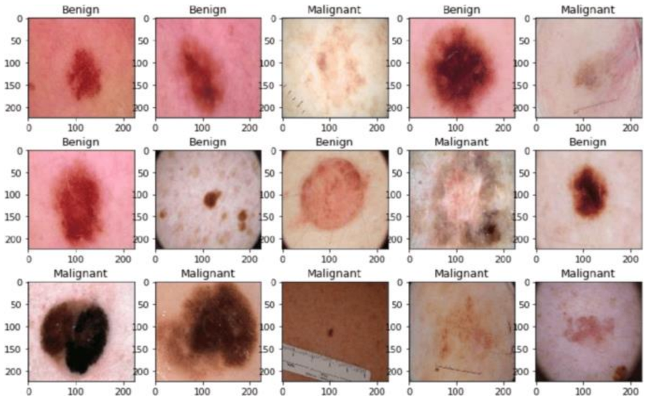

Fig 3.1.2: Collecting Data from different sources

3.1.3 Image input

In skin cancer detection, the data input process begins with capturing high-resolution images of suspicious skin lesions using smartphones, dermatoscopes, or wearable imaging devices. These images are essential for early diagnosis, as they provide critical visual information on the lesion's shape, color, and texture.

To enhance diagnostic accuracy, the images undergo preprocessing steps such as contrast adjustment, noise reduction, and segmentation, ensuring clarity and consistency. The handled imageries are formerly referred to a cloud based or AI-driven diagnostic system, where deep learning models analyse features indicative of melanoma or other skin cancers. The excellence of the contribution imageries significantly impacts accuracy lesion organization and risk assessment, making this step crucial in early detection, monitoring, and timely medical intervention.

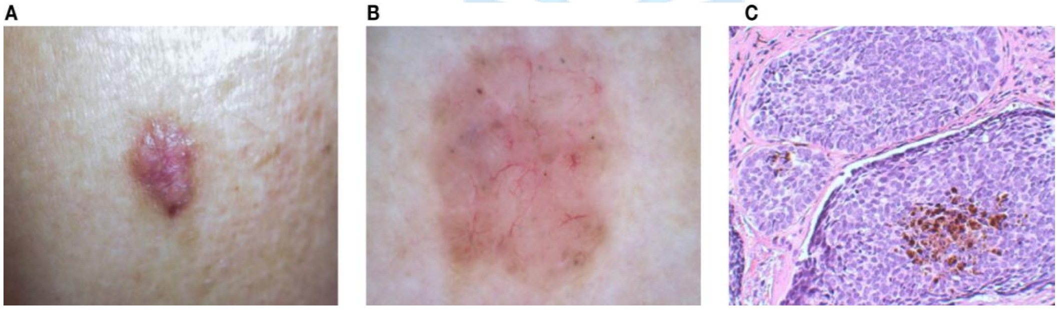

Fig 3.1.3 Input image in A,B & C by zoom in

3.1.4 Preprocessing

The Wiener Filter (WF) is a mathematical technique used to improve image quality by reducing noise. Named after Norbert Wiener, this filter is widely used in statistics, engineering, and image processing to estimate the true signal by minimizing the difference between the noisy and actual image. It is especially useful when the nature of the noise is known. The WF works by applying convolution, spectral analysis, and statistical calculations, which can be performed in either the time or frequency domain, depending on the data and problem type

Alternative Image Preprocessing Methods for Smartphone Apps

In a smartphone-based skin cancer detection app, various preprocessing techniques can enhance image quality before analysis:

1. Gaussian Blur – Reduces noise and smooths the image while preserving important details.
2. Histogram Equalization – Enhances contrast by distributing brightness levels evenly.

3. Adaptive Thresholding – Improves lesion visibility by converting the image to a high-contrast binary format.
4. Edge Detection (Sobel/Canny Filters) – Highlights boundaries of skin lesions for better segmentation.
5. Color Normalization – Adjusts variations in lighting to maintain consistent skin tone representation.

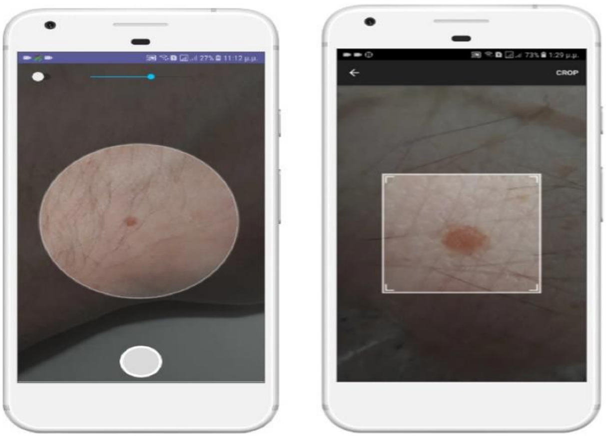

Fig 3.1.4 Preprocessing mobile using app

3.1.5 Segmentation

Segmentation in a smartphone-based skin cancer detection app involves isolating the lesion from the surrounding skin to improve diagnostic accuracy. This process ensures that only the relevant part of the image is analysed, reducing noise and distractions. The app can use AI-driven segmentation techniques to automate this process, making it efficient and user-friendly.

Methods for Skin Lesion Segmentation in a Mobile App

1.Threshold-Based Segmentation

- Converts the image into a binary format (black and white) by setting a threshold intensity value.
- Useful for clear lesion boundaries but may struggle with varying skin tones.

2.Edge Detection (Sobel or Canny Filters)

- Identifies sharp changes in color or intensity to detect lesion borders.
- Effective for well-defined lesions but may require preprocessing for blurry images.

3. K-Means Clustering

- Groups similar pixels into clusters to distinguish the lesion from healthy skin.
- Works well for color-based differentiation but may need additional post-processing.

4.Otsu's Method

- Automatically selects the best threshold value for separating the lesion.
- Ideal for high-contrast images but may struggle with lighting variations.

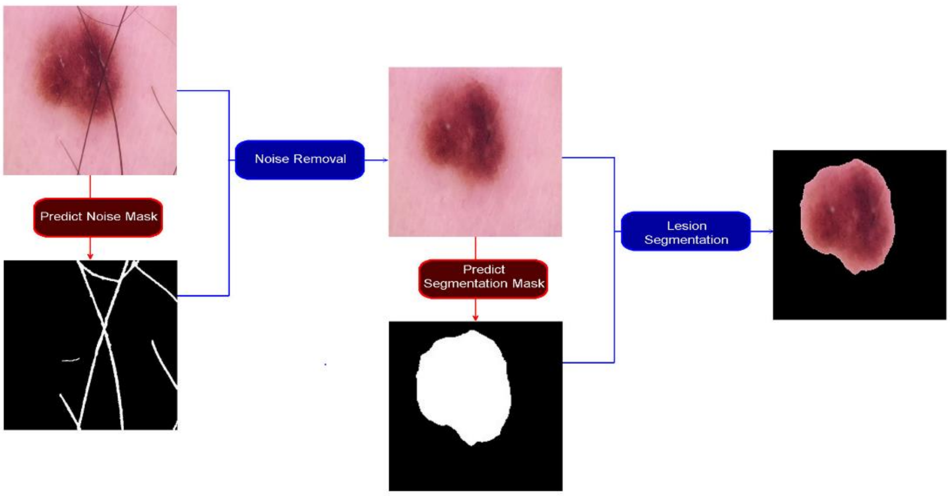

Fig 3.5 Segmentation of images

3.1.6 Results of Diagnosis

Once the smartphone app processes the skin image, the diagnosis results are displayed in a user-friendly interface, providing essential information about the lesion. The results typically include:

1.Lesion Classification

•The app categorizes the lesion as benign, pre-cancerous, or malignant using an AI-based model.

2.Confidence Score

•A probability percentage (e.g., 85% confidence of melanoma) indicating how certain the AI model is about its diagnosis.

3.Visual Segmentation Output

•The segmented image is shown, highlighting the identified lesion area for better understanding.

4.Risk Level Assessment

•The app provides a risk rating (low, moderate, high) based on lesion features such as irregularity, edge irregularity, color difference, and size (ABCD criteria).

5.Recommendations for Next Steps

•Low Risk → Suggests monitoring and re-scanning later.

•Moderate Risk → Advises consulting a dermatologist for further evaluation.

•High Risk → Recommends urgent medical attention, with an option to share the report with a specialist.

6.Doctor Consultation Option

•The app may connect users with dermatologists via telemedicine, allowing them to send images and receive expert advice.

7Report Generation & Tracking

•Users can save their results as PDF reports and track changes over time for better skin health monitoring.

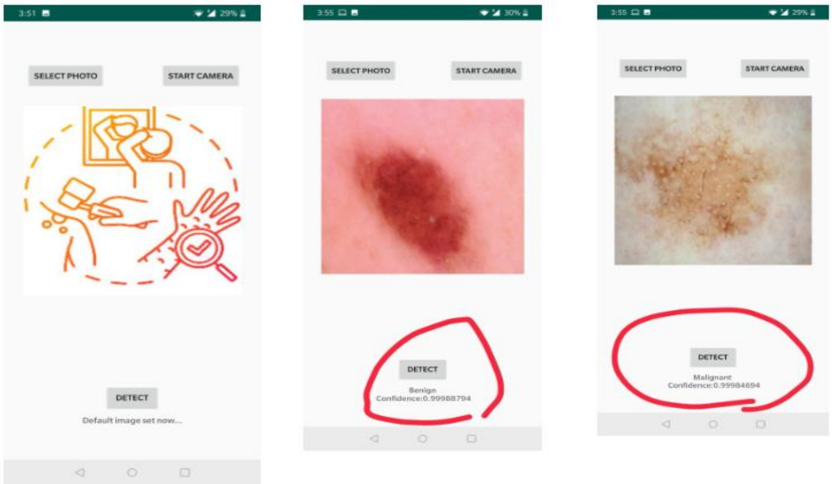

Fig 3.1.6 Diagnosis Result of input images

3.2 Diagnosis Results send to Specialist

Once the smartphone app detects a potential skin cancer risk, it provides an option to send the diagnosis report to a specialist for further evaluation. This system ensures quick medical consultation and expert guidance, improving early detection and treatment outcomes. The process involves several steps:

1. Report Generation in the Mobile App

After the AI-based skin cancer detection and risk assessment, the app automatically compiles a detailed medical report, which includes:

- Lesion classification (benign, suspicious, malignant).
- Confidence score (e.g., 90% probability of melanoma).
- Segmented lesion image highlighting the affected area.
- Risk level (low, moderate, or high).
- AI-based recommendations (monitor, consult a doctor, or seek urgent care).

2. Secure Data Transmission to the Specialist

The diagnosis report is sent to a specialist using a secure, HIPAA-compliant communication system to protect patient privacy. The app supports multiple transmission methods:

- •Cloud-Based Telemedicine Portal – The report is uploaded to a secure cloud server, where specialists can access it remotely.
- •Direct Email or Messaging System – The user can send the report via email, SMS, or in-app chat to a dermatologist.
- •Hospital/Clinic Integration – If the app is linked with a hospital system, the report is sent to the hospital database for doctor review.

3. Specialist Review & Response

- Once the specialist receives the report, they:
- Analyze the diagnosis results and lesion image.
- Compare with medical history (if available).
- Provide a professional assessment on whether the lesion needs a biopsy or further testing.
- Compare with medical history (e.g., medication, biopsy recommendation, or urgent consultation).

4. Receiving & Implementing Specialist's Response

The app receives the doctor's recommendations and presents them to the user:

- Notification Alert – The user gets a real-time notification about the specialist's response.
- Treatment Plan Display – If medication or further tests are required, the app provides step-by-step guidance.
- Appointment Booking Option – Users can schedule an in-person consultation directly from the app.
- 5. Integration with a Smart Bandage

For advanced wound care, the app is connected to a smart bandage, the specialist's instructions (such as antiseptic release or temperature control) can be wirelessly transmitted to the bandage for automated treatment.

A smart bandage is an advanced wearable medical device that can monitor wound conditions and deliver treatment automatically. In the context of skin cancer care, integrating a smart bandage with a mobile diagnosis system allows real-time monitoring and controlled medication release, improving patient care and recovery.

How the Smart Bandage Works in Skin Cancer Care

1. Diagnosis & Report Transmission

- A smartphone-based AI system detects a potential skin cancer lesion and sends the report to a specialist.
- If required, the doctor recommends treatment, which is transmitted to the smart bandage via Wi-Fi or Bluetooth.

2. Automated Antiseptic & Medication Delivery

- The smart bandage stores antiseptic solutions, antibiotics, or healing agents in micro-reservoirs.
- Based on the doctor's instructions, the bandage automatically releases the necessary medication to the affected area.

3. Real-Time Wound Monitoring

The bandage is equipped with sensors that track key parameters like:

✓ Temperature – Detects infections by monitoring heat variations.

✓ pH Levels – Identifies bacterial growth in the wound area.

✓ Moisture & Healing Progress – Ensures the skin is healing properly.

This data is sent back to the mobile app and specialist, enabling continuous remote monitoring.

4. Wireless Communication & Alerts

- The smart bandage is connected to mobile app through Wi-Fi/ Bluetooth, safeguarding real time communication.
- If infection or abnormal changes are detected, the app sends an alert to the patient and doctor, prompting immediate action.

5. Adaptive Treatment Adjustments

- If the specialist modifies the treatment plan, updated instructions are sent to the bandage.
- The bandage can adjust medication release or trigger an alarm for the patient to seek medical attention.

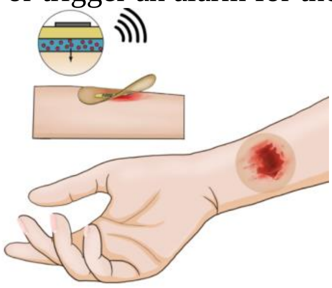

Fig 3.2 Integration with a Smart Bandage

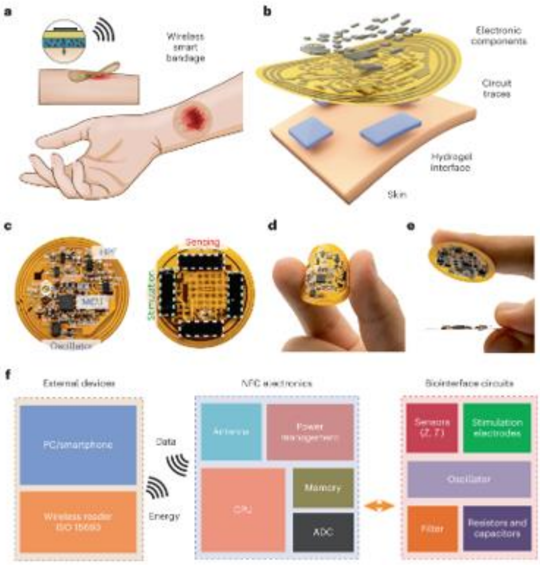

Fig 3.2b Smart bandage with Automated Antiseptic & Medication Delivery

VI. RESULTS AND DISCUSSION

a. Assessment Metrics

The efficiency of the planned skin cancer detection scheme was assessed by means of normal assessment system of measurement like correctness, kindliness & specificity.

b. Result

The classification model achieved an **accuracy of 93.43%**, which demonstrates its strong ability to detect skin cancer lesions with high precision. The model showed an **F1-score of 94%**, further confirming its efficiency in balancing precision and recall. Additionally, the system's sensitivity reached **99.74%**, meaning it effectively identified melanoma cases, reducing the likelihood of false negatives.

c. Discussion

The findings indicate that the proposed AI-based system for skin cancer detection demonstrates improved efficiency and accuracy compared to traditional diagnostic techniques.

Model Performance Analysis

The model's high sensitivity (99.74%) ensures that very few malignant cases go undetected. Specificity, though slightly lower, indicates that non-malignant cases are also effectively identified. The hierarchical learning approach allows the model to distinguish features across multiple layers, significantly enhancing classification accuracy. The incorporation of deep learning-based segmentation, preprocessing techniques such as Wiener Filtering, and an optimized CNN architecture contributes to this improved performance.

V. CONCLUSIONS

The proposed AI-driven skin cancer diagnosis system, enhanced with IoT-based treatment mechanisms, has demonstrated promising results, compassion, and specific. The combination in deep learning-based segmentation, advanced preprocessing techniques, and real-time telemedicine integration presents acomprehensive and efficient solution for early melanoma detection. Future enhancements, such as further optimizing cloud-based analysis and expanding the dataset for training, could further improve diagnostic capabilities and clinical adoption.

VI. FUTURE WORK AND SCOPE

Future advancements in AI-driven skin cancer detection and treatment will focus on:

- Enhanced AI Models: Improving deep learning algorithms for better accuracy, early detection, and personalized diagnosis.
- On-Device AI: Optimizing real-time processing on smartphones without internet dependency.
- Smart Bandage Upgrades: Integrating biosensors, targeted drug delivery, and IoT connectivity.
- Larger & Diverse Datasets: Expanding data sources and using federated learning for better generalization.
- Telemedicine Integration: Connecting AI diagnostics with remote specialists for quick consultations.

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