SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V10I7P111

Volume 10 Issue 7, 108-129, July 2023

Original Article

IoT-Driven Image Processing Framework for Accurate Skin Diseases Diagnosis and Classification

S. Umarani[1], Sunitha Y N[2], V Nuthan Prasad[3], KDV Prasad[4], Chanakya Kumar[5], Yogesh Mahajan[6]

[1]*Department of Computer Science and Applications (BCA), College of Science and Humanities, SRM Institute of Science and Technology, Ramapuram, Chennai, Tamilnadu, India.*
[2]*Department of Electronics and Communication, SJB Institute of Technology, No 67, BGS Health and Education City, Dr. Vishnuvardhana road, Kengeri, Bangalore, Karnataka, India.*
[3]*Department of Electronic and Communication, M S R I T, Bangalore, Karnataka, India.*
[4]*Symbiosis Institute of Business Management, Hyderabad, Symbiosis International (Deemed University), Pune, India.*
[5]*Department of Faculty of Marketing, Indira School of Business Studies PGDM, Pune, Maharashtra, India.*
[6]*Symbiosis Centre for Management & Human Resource Development, Symbiosis International University, Pune, Maharashtra, India.*

[4]*Corresponding Author : kdv.prasad@sibmhyd.edu.in*

Received: 02 May 2023 Revised: 28 June 2023 Accepted: 18 July 2023 Published: 31 July 2023

Abstract *- Skin diseases affect millions worldwide, and accurate diagnosis and classification are critical for effective treatment. The Internet of Things (IoT) has emerged as a powerful technology that can be used to improve healthcare systems in recent years. This paper proposes an image processing framework based on IoT for accurate skin disease diagnosis and classification. To enable remote and real-time skin disease diagnosis, the proposed framework combines the capabilities of IoT devices, such as smartphones or wearable cameras, with advanced image processing techniques. The framework uses the cameras built into IoT devices to capture high-resolution images of the affected skin areas. After that, the images are securely transmitted to a central server or cloud-based platform for processing and analysis. The framework's image-processing component employs cutting-edge algorithms for image enhancement, feature extraction, and classification. Deep learning techniques, such as convolutional neural networks (CNNs), automatically extract relevant features from skin images. These characteristics are then used to classify skin diseases accurately. The framework incorporates robust encryption and authentication mechanisms during data transmission and storage to ensure the privacy and security of sensitive medical data. Patient consent and data anonymization techniques are also used to address privacy concerns. The proposed framework has several advantages over traditional methods for diagnosing skin diseases. It enables remote diagnosis by leveraging IoT devices, reducing the need for patients to travel to healthcare facilities. The real-time analysis allows for prompt intervention and treatment planning. Extensive experiments are carried out using a diverse dataset of skin disease images to assess the performance of the proposed framework. The findings show that the framework is highly accurate in diagnosing and classifying various skin diseases.*

Keywords *- IoT (Internet of Things), Image processing, Skin diseases, Diagnosis, Authentication, Remote healthcare and Real-time analysis.*

1. Introduction

Skin diseases are a primary global health concern, affecting millions worldwide. Accurate diagnosis and classification of these diseases are critical for effective treatment and management. Traditional diagnosis methods, primarily based on dermatologists' visual examination, have limitations such as subjectivity, inter-.

Observer variability and reliance on healthcare professionals' expertise. IoT devices such as smartphones and wearable cameras can capture high-resolution images of affected skin areas in the context of skin disease diagnosis[1]. Advanced image processing techniques can then process and analyze these images for accurate diagnosis and classification. This paper proposes an image-processing framework based on IoT for accurate skin disease diagnosis and classification[2]. The framework combines IoT device capabilities with cutting-edge image processing algorithms to enable remote and real-time diagnosis. The framework enables individuals to easily capture images of their skin lesions by leveraging the built-in cameras of smartphones or wearable cameras[3]. The proposed framework's image-processing component employs advanced algorithms for image enhancement, feature extraction, and classification. Deep learning algorithms improve diagnosis accuracy and reliability by leveraging large-scale training datasets and learning complex patterns and representations. In any healthcare system, ensuring the privacy and security of sensitive medical data is critical. The proposed framework employs strong encryption and authentication mechanisms to protect patient information during data transmission and storage[4]. In addition, patient consent and data anonymization techniques address privacy concerns while adhering to ethical guidelines. Comparative analyses of existing methods and techniques validate the proposed framework's superiority.

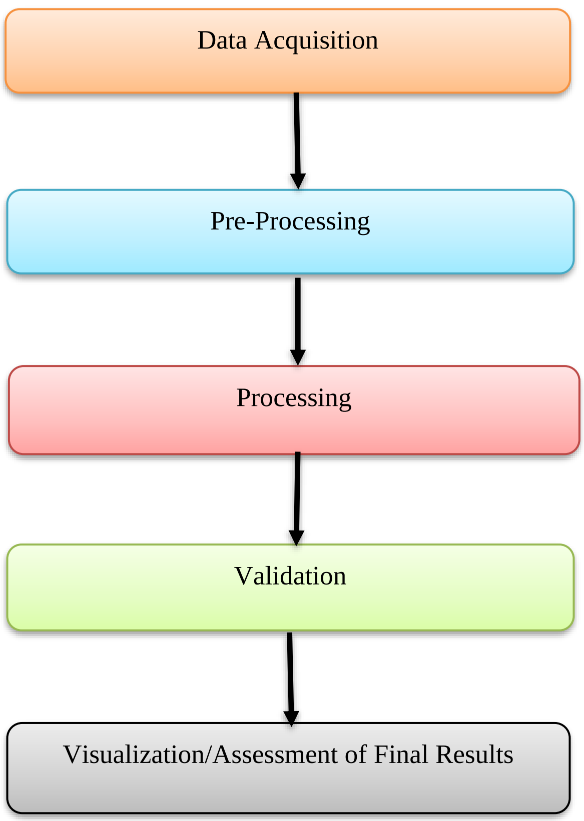


Fig. 1 Typical CAD model pipeline

As cutting-edge modules facilitating intelligence methods, CAD models have become indispensable tools in healthcare and computer-related studies. These models assist well-trained professionals in clinical decision-making by applying diagnosis rules[5]. In healthcare applications, CAD models serve as experts, continually examining medical data and gaining new experiences. This acquired knowledge is then utilized to optimize diagnostic rules and improve system performance within a limited timeframe[6]. Feedback mechanisms are integrated into the systems to facilitate this learning process, allowing for acquiring new experiences from diverse clinical data sets, particularly regarding successes and failures. With their effective learning capabilities, CAD systems can be considered intelligent [7].

These methods enable decision-making across a wide range of diseases and clinical conditions. The model for skin disease diagnosis consists of several stages and processes, as depicted in Figure.1. The specifics may vary based on the model's architecture and methodology. The CAD model pipeline is iterative, and based on feedback, new data, and advancements in algorithms and technologies, continuous improvement and refinement are typically performed[8]. The ultimate objective is to develop a reliable and accurate tool to aid healthcare professionals in diagnosing and effectively treating skin diseases. These factors create a fertile environment for developers to create expert models that effectively aid healthcare and computer science. In the past, biomedical studies focused on exploring the feasibility of applying systems to address issues in biology and medicine.

The demand for capable CAD systems became evident, leading developers to initially focus on creating fully automated CAD methods[9]. The seminal work of Karp in theoretical computer science, specifically "Reducibility among Combinatorial Problems," highlighted the challenges faced in developing techniques to address processing issues. The significant evolution of CAD has guided physicians in reducing clinical failures and negligence, thereby lowering healthcare expenses[10]. Overall, the development and deployment of CAD methods in the clinical sector are driven by the need to improve diagnostic accuracy, reduce medical errors, and leverage advancements in computer science to enhance healthcare outcomes while managing costs. In order to provide precise and effective medical diagnoses, medical experts need to thoroughly examine various aspects, as mentioned by the authors in the paper[11]. Medical records, including lab reports and other findings, serve as symptoms that may indicate a particular disease.

Additionally, a patient's clinical history, encompassing past medical information and relevant issues, is crucial in the diagnostic process. Genetic factors also play a significant role; therefore, a patient's family history is considered in the diagnosis. Furthermore, a patient's social behaviour and lifestyle are essential for disease diagnosis. Habits, residence, diet, and other aspects contribute to understanding the patient's condition[39]. To facilitate the exchange of patient information, many hospitals, medical services, and clinics have implemented Electronic Health Records (EHR), which enable the sharing of digital documents. CAD models incorporating disease-related information or patient details provide valuable guidance in examining diseases[13]. However, as clinical information has become more sophisticated and complex, its volume has dramatically increased. Overall, integrating various data sources and advanced computational techniques through CAD models holds promise for enhancing medical diagnoses. However, the increasing complexity and size of clinical information present challenges that need to be addressed for optimal utilization of these systems.

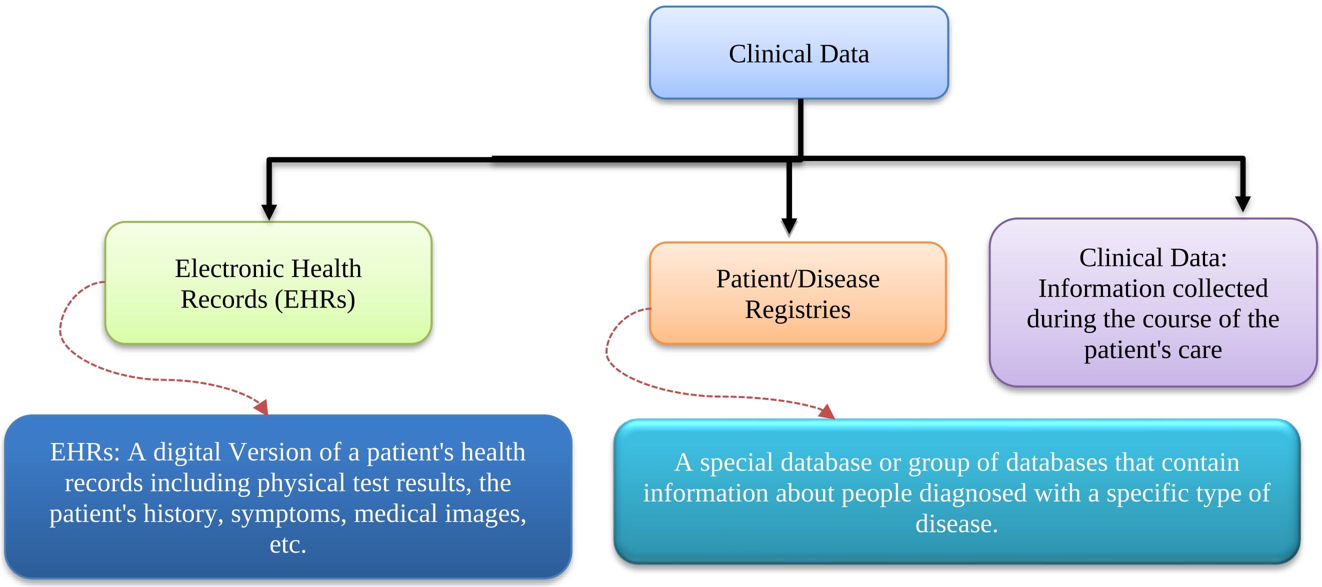


Fig. 2 Models in CAD systems rely on variable data

As depicted in the figure.2, Computer-Aided Diagnosis (CAD) models for skin disease diagnosis can utilize numerous pieces of information to improve precision and dependability. The following data types are frequently used in CAD models for skin disease diagnosis: Dermoscopy is a noninvasive imaging method that magnifies images of the skin. Dermoscopy captures skin lesions' surface and subsurface characteristics, allowing for a comprehensive analysis and characterization[14]. In skin disease diagnosis, these images frequently serve as the primary data source for CAD models. Clinical images are conventional or high-resolution images of the skin captured by conventional cameras. They offer a more comprehensive view of the affected area and can capture skin lesions' color, texture, and morphology. Clinical images are beneficial when dermoscopy images are unavailable or additional information is required for a more accurate diagnosis. Patient History and Metadata: CAD models can incorporate patient-related data. This additional information facilitates the comprehension of the context and potential risk factors associated with skin diseases[15]. The patient's medical history and metadata provide valuable insights that can aid in developing accurate diagnoses and individualized treatment plans. Biopsy and Histopathology Information: Sometimes, skin biopsies are performed to confirm the diagnosis and examine skin lesions' cellular and tissue-level characteristics. Histopathological data, such as micrographs and pathology reports, can be incorporated into CAD models to enhance diagnostic precision[16]. This data type permits a more thorough examination of particular skin diseases' cellular and structural characteristics. Annotations and Actuality of the Lesion Labels: Training and validating CAD models heavily rely on annotated data. Dermatologists or other specialists manually annotate images of skin lesions by outlining their borders, indicating distinct regions, and highlighting specific characteristics. These annotations provide ground truth labels for training the model and can be used to assess the CAD system's performance. Multispectral Data: Multispectral imaging entails capturing skin images at various wavelengths, enabling the visualization of specific characteristics such as melanin distribution, vascular patterns, and tissue oxygenation levels[17]. By incorporating multispectral data, CAD models can gain additional insight into skin lesions that may not be visible on standard images alone. It is important to note that different CAD models may utilize different data types. Some models rely solely on dermoscopic images, whereas others combine multiple data sources to enhance diagnostic precision. The availability and integration of diverse data types contribute to developing comprehensive and dependable CAD systems for diagnosing skin diseases. In summary, incorporating IoT devices and advanced image processing techniques in skin disease diagnosis is a promising solution for improving accuracy and efficiency. The proposed Internet of Things-powered image processing framework enables remote and real-time diagnosis, reducing the need for patients to travel to healthcare facilities. The framework improves the accuracy and reliability of diagnosis and classification by leveraging deep learning algorithms. Secure data transmission and storage address privacy concerns while maintaining the confidentiality of sensitive medical information.

2. Literature Survey

In recent years, skin disease diagnosis and classification have seen tremendous developments, with researchers and healthcare professionals experimenting with numerous methodologies and procedures to increase accuracy and efficiency. The following is a summary of related work in this field: Image Analysis of Dermoscopic Images: Dermoscopy has long been used to diagnose skin diseases. Using dermoscopic pictures, researchers created algorithms. These methods classify skin lesions using hand-produced characteristics or manufactured representations. Deep learning technologies, notably convolutional neural networks (CNNs), have lately outperformed classic machine learning methods in skin disease identification[18]. CNNs automatically develop hierarchical representations from raw pictures, reducing the need for handcrafted features. Ensemble approaches: To increase the accuracy and robustness of skin disease detection, ensemble approaches, which mix many models to create collective predictions, have been investigated. To generate a final diagnosis, ensemble models combine the outputs of numerous classifiers or feature extractors[19]. Bagging, boosting, and stacking approaches were used to construct diverse and accurate ensemble models. Transfer learning takes pre-trained models from large-scale datasets like ImageNet and fine-tunes them on skin disease datasets. This method allows for using learned characteristics from different domains, minimizing the need for substantial labelled data while enhancing generalization performance in skin disease detection. Fusing of Multiple Modalities: To improve the diagnostic capacities of CAD models, the fusing of multiple modalities, such as dermoscopy images, clinical images, patient metadata, and histopathology data, has been examined. Combining data from several sources can provide additional insights and increase the accuracy of skin disease classification.

Mobile Applications and Platforms: Online and mobile applications have arisen as tools for remote diagnosis and telemedicine in skin disease diagnosis. These services allow individuals to upload photos of their skin lesions for dermatologists or CAD systems to analyze. Mobile applications with AI-powered skin disease diagnosis capabilities enable quick and easy self-assessment and early screening options.

Large-scale and diversified datasets are essential for training and assessing skin disease diagnosis models. Researchers have contributed to creating publically available datasets such as ISIC (International Skin Imaging Collaboration), HAM10000, and PH2, which contain a broad spectrum of skin lesions and serve as standards for assessing the performance of CAD models.

Clinical Integration and Validation: Several research have been conducted to analyze the impact of CAD models on dermatologists' decision-making processes. These studies evaluate the efficacy of CAD systems in real-world settings and look into how they might help dermatologists improve diagnostic accuracy and efficiency.

In [20], authors implemented a multi-resolution collection of CNNs, incorporating techniques such as EN (EfficientNet), SENet (Squeeze-and-Excitation Network), and ResNeXt, for predicting skin lesions. Despite using a small dataset comprising HAM10000 and ISIC 2018, their approach demonstrated significant performance in skin lesion prediction. By leveraging TL techniques and utilizing pre-trained DNN models, the researchers achieved improved classification accuracy on the applied datasets. These studies highlight the effectiveness of DL-based approaches, CNN architectures, and TL models in accurately classifying and predicting skin lesions. By leveraging advanced techniques and incorporating pre-existing knowledge from pre-trained models, researchers have made notable progress in enhancing the performance of skin lesion identification systems. TL is beneficial for addressing issues related to limited labelled datasets. However, TL may not be optimal for healthcare image analysis due to the significant discrepancies between this domain's source and target data [40]. TL methods typically pre-train models on diverse datasets, such as images of animals, automobiles, nature, etc., which exhibit different characteristics compared to clinical images.

Consequently, implementing TL methods in this context can be computationally demanding and requires substantial computational resources. Overall, DL methods, such as RBM, DBN, and DNN, along with TL techniques, have been employed effectively in various clinical image analysis tasks, demonstrating promising results and outperforming existing approaches. In [22], authors employed a feature aggregation system using ResNet34 as the backbone network. The encoder module utilized dense connections to facilitate the flow of information between high-level and low-level features, aiding in effective feature aggregation and spatial data recovery. The decoder module comprised various deconvolutional processors for recovering the spatial resolution of feature maps.

Additionally, an auxiliary loss was applied in the encoding portion to reduce the complexity of model training. These studies highlight the application of DL techniques in skin lesion segmentation[23]. Various network architectures, such as DeepLab, PSPNet, SegAN, and ensemble methods, have been utilized to improve segmentation accuracy and achieve state-of-the-art performance. Researchers have made significant advancements in accurately segmenting skin lesions by leveraging pre-trained weights, feature aggregation, and post-processing techniques like CRF.

Transfer Learning (TL) is a widely used model, but it may not be optimal for clinical image analysis due to significant discrepancies in the target data. TL relies on pre-training models on diverse clinical images and biases the source data for feature extraction.

A study suggests an IoT-based intelligent skin disease diagnosis system that captures skin photos using smartphone cameras[24]. Deep learning algorithms are being used to construct an IoT-based dermatology diagnosis system. The system incorporates wearable cameras to capture skin images, which are then processed using deep-learning models for automatic skin condition diagnosis and classification. Based on the collected skin scans, the suggested method allows for remote diagnosis and individualized therapy suggestions.

An IoT-based smart system for skin disease diagnosis and prevention is presented in this study. The system employs image processing algorithms and machine learning approaches to evaluate skin photos captured by IoT devices. It provides real-time diagnosis and preventive strategies to promote skin disease identification and treatment[25]. Using transfer learning techniques, the system extracts information from skin photos taken by IoT sensors and conducts accurate diagnosis and categorization. The technology uses IoT sensors to gather skin photos and deep learning algorithms to diagnose and classify skin conditions accurately. This research focuses on an IoT-based skin disease detection and classification system employing machine learning algorithms. The technology uses IoT devices to record skin photos and machine learning algorithms for accurate diagnosis and classification[26]. The study provides an Internet of Things-enabled skin disease diagnostic and categorization system that uses machine-learning techniques[41]. The technology uses IoT devices to record skin photos and machine learning algorithms for accurate diagnosis and categorization. The availability of large-scale datasets and the incorporation of CAD models into clinical processes have significantly improved the accuracy and practicality of skin disease detection[28]. Future research will undoubtedly continue to investigate fresh methodologies, use developing technologies, and address issues such as interpretability, applicability to varied populations, and robustness to differences in picture quality.

3. Detection of Skin Lesions

The process of recognizing and characterizing abnormal growths or alterations in the skin is known as skin lesion diagnostics. It is critical in detecting and managing a variety of skin illnesses, including skin cancer. Skin lesion diagnosis employs a variety of procedures and techniques, including Visual inspection: Dermatologists examine the skin visually for anomalies such as changes in size, shape, colour, or texture. They make a diagnosis or prescribe additional tests or procedures based on their expertise and clinical experience. Dermoscopy: Dermoscopy allows physicians to study subsurface structures and identify specific features linked with various skin disorders by magnifying the skin. Dermoscopy can help distinguish benign lesions from possibly cancerous ones.

A skin biopsy may be conducted when a definitive diagnosis is necessary. A small skin lesion sample is taken during a biopsy and sent to a pathology laboratory for investigation[29]. To assess the presence and type of disease, the pathologist examines the biopsy specimen under a microscope, evaluating the cellular and tissue-level characteristics. Computer-Aided diagnostic (CAD): Computer-aided diagnostic systems enable by utilizing computational algorithms and machine learning approaches. CAD systems analyze dermoscopic or clinical photos of skin lesions to extract features for automatic categorization.

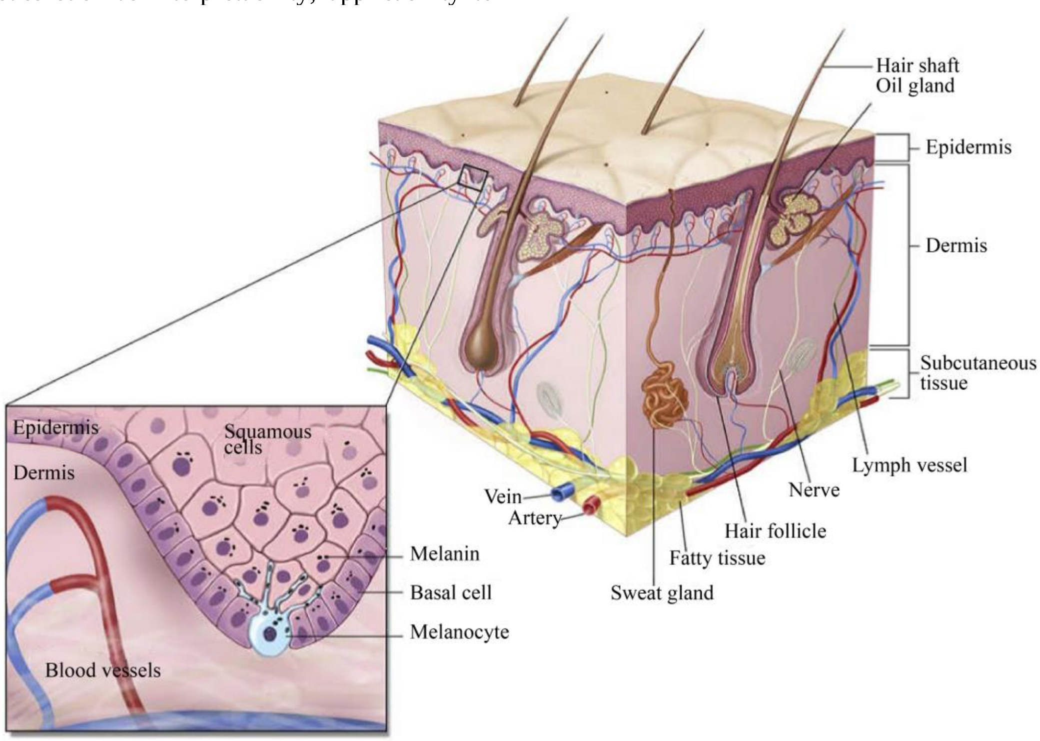


Fig. 3 Anatomical structure of human skin

These technologies offer clinical decision-makers an objective and reliable assessment of skin lesions. Artificial Intelligence (AI): Algorithms can automatically diagnose and classify skin lesions by learning patterns and features from massive datasets of skin lesion snaps and promising results in detecting benign and malignant skin lesions with high accuracy and sensitivity[30]. Mobile Applications: As smartphones have become more popular, mobile applications have arisen as tools for skin lesion diagnostics. Image analysis algorithms and AI approaches are frequently used in these apps to assess user-uploaded photos of skin lesions. They can provide preliminary assessments, risk assessments, or recommendations for additional medical consultation. Teledermatology is the remote diagnosis and management of skin problems through telecommunication technologies. Dermatologists can remotely check skin lesions using teledermatology by evaluating photos or recordings of the affected areas.

This technique increases access to expert dermatological care in underserved areas and improves dermatology service efficiency. Imaging technologies, computer algorithms, and artificial intelligence (AI) advancements have considerably improved the accuracy and efficiency of skin lesion identification[31]. These various procedures and techniques are complementary and frequently used to provide reliable diagnosis and treatment recommendations for patients with skin lesions. Figure 3 depicts the Anatomical Structure of Human Skin. The human skin is the body's largest organ and is a protective barrier between the internal organs and the exterior environment. Understanding the anatomical nature of the human skin is critical for dermatological evaluations, diagnosis, and treatment. The many layers and structures work together to keep the skin healthy and to perform vital duties such as protecting and regulating the body. Keratinocytes are the most abundant cells in the epidermis and are responsible for producing a tough protein called keratin[32]. Keratinocytes provide structural strength to the skin and contribute to its waterproofing properties.

Melanocytes: These cells produce a pigment called melanin, which gives colour to the skin and helps protect it from harmful UV radiation. Melanocytes transfer melanin to neighbouring keratinocytes, protecting them against UV damage. Langerhans cells: These specialized immune cells are involved in the body's defence against pathogens. They capture and process antigens present in the skin, playing a crucial role in the skin's immune response. Merkel cells: Located in the deepest layer of the epidermis, they detect pressure and tactile sensations. These four types of cells work together to maintain the integrity and function of the epidermis, ensuring the skin's protection and sensory capabilities. The dermis, located beneath the epidermis, provides structural support, blood supply, and nerve endings to the skin.

4. Critical Challenges in Diagnosis

Skin lesion diagnosis involves several issues that healthcare providers and researchers must overcome. Among these difficulties are: Visual Similarity: Because many skin tumours have similar visual characteristics, it can be difficult to distinguish between benign and malignant lesions based solely on visual examination. Lesions of similar colours, forms, or textures may necessitate additional diagnostic equipment and techniques to ensure an accurate diagnosis. Subjectivity: Because dermatologists rely on their expertise and experience, skin lesion diagnosis can be subjective. Discrepancies in diagnosis might result from discrepancies in interpretation and inter-observer variability, especially in complicated or confusing instances[33]. Achieving high levels of consistency and agreement among dermatologists is still challenging.

Lesion Type Variability is High: Skin lesions include a variety of disorders such as benign moles, skin malignancies, infections, inflammatory conditions, and more. Because of the wide range of lesion forms, dermatologists must have extensive knowledge and experience to diagnose and classify various illnesses[34] effectively. Image Quality and Variability: The quality of skin lesion images can vary greatly, affecting diagnosis accuracy. Lighting conditions, picture resolution, image artifacts, and patient characteristics (e.g., skin tone, hair) can complicate image interpretation, and image acquisition protocol standardization and image quality enhancement are active research topics. Dermatologists are difficult to find: Access to dermatologists may be limited in some places, resulting in delayed diagnosis and treatment[35]. Telemedicine and teledermatology programs address this issue by allowing remote consultation and diagnosis, although infrastructure and connectivity limitations can still be a hurdle.

Some skin illnesses are exceedingly rare, making it difficult for dermatologists to encounter and gain significant experience identifying and managing them. When facing these unusual illnesses, this can result in delays or misdiagnosis[36]. Overlapping Clinical symptoms: Some skin disorders have overlapping clinical symptoms, making differentiation difficult. Differentiating between benign and malignant skin tumours or different types of dermatitis, for example, might be difficult, necessitating further testing or histological examination for a conclusive diagnosis[42].

Lack of Objective Diagnostic Criteria: There is a lack of well-defined and broadly accepted objective diagnostic criteria for certain skin disorders. This can lead to differences in diagnosis and management techniques, potentially leading to discrepancies in patient care. The diverse range of skin colours among individuals further complicates the prediction of skin lesions. These challenges are illustrated in Figure 4. Some of the specific challenges associated with the visual features of skin lesion images are highlighted by [38]. Shape and Border Irregularities: Skin lesions can exhibit irregular shapes and borders, making accurately identifying their boundaries challenging. The presence of asymmetry, jagged edges, or blurred borders can indicate malignancy.

Colour Variation: Skin lesions can display a wide range of colours, including shades of brown, black, red, blue, or white. Analyzing and distinguishing between different colour variations within a lesion can be complex.

Texture and Surface Features: The texture of a skin lesion, such as smoothness, roughness, or the presence of scales or ulcers, can provide important clues for diagnosis. However, capturing and interpreting these textural features accurately is a challenge.

Size and Depth: Skin lesions can vary significantly in size and depth, ranging from small, superficial lesions to larger and deeper ones. Determining the size and depth accurately is crucial for appropriate diagnosis and treatment planning.

Heterogeneous Patterns: Skin lesions can exhibit diverse patterns, such as reticular, globular, homogeneous, or multicomponent patterns. Analyzing and characterizing these patterns can be complex, requiring expertise and advanced image analysis techniques.

Image Quality: The quality of skin lesion images can vary due to factors like image resolution, lighting conditions, and image artifacts. Poor image quality can affect the accuracy of lesion analysis and interpretation.

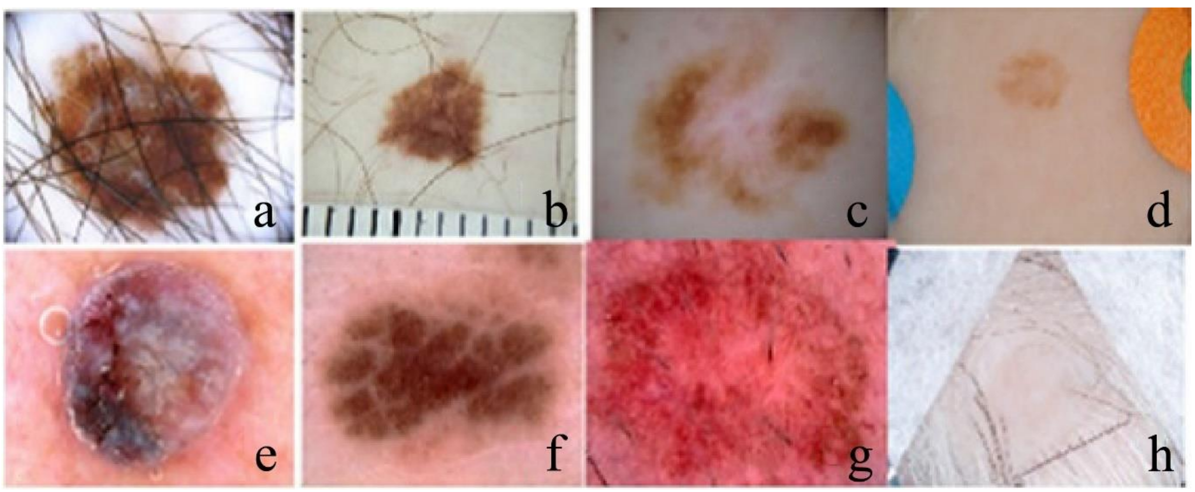


Fig. 4 Skin lesion identification

(a)Hair Artefact: Hair on the skin can obscure the view of skin lesions, making precise analysis and identification difficult. Hair artefacts can obstruct visualization and require close inspection or image processing procedures to reduce their impact. (b) Ruler Mark Artefact: Ruler marks or other artefacts in the image can sometimes interfere with the assessment of skin lesions. These markings might be distracting or obscure vital details; therefore, they must be correctly detected and removed for appropriate diagnosis. (c) Low Contrast: Low-contrast skin lesion photos make it difficult to see minute details and characteristics of the lesion. The absence of contrast can make it difficult to distinguish between different sections of the lesion or identify it from healthy skin around it. (d) Colour Illumination: Changes in lighting or colour illumination can impact the appearance of skin lesions. Uneven or non-standard lighting might change the colour and texture of the lesion, potentially affecting diagnosis accuracy. (e) Bubbles: If the imaging technique uses gel or water, bubbles can occur, obscuring the clear view of the skin lesion. These bubbles may need to be eliminated or decreased to generate a higher-quality image for examination. (f) Irregular Boundaries: Skin lesions frequently have irregular boundaries that might be difficult to distinguish correctly. The irregularity can be caused by the lesion's shape, colour changes, or the properties of the surrounding tissue. Careful examination and image analysis techniques are required to establish the precise limits of the lesion. (g) Blood Vessels: Blood vessels may appear in some skin lesions, such as vascular or melanomas. The presence of blood vessels within or around the lesion can affect diagnostic interpretation and demand additional study or imaging modalities. (h) Frame Artefacts: Frame artefacts are any undesirable elements or artefacts around the image's edges or borders. These artefacts may be introduced during the imaging process or due to the image-capturing system's limitations. Such artefacts should be recognized and removed to avoid interfering with lesion diagnosis. These issues demand continual research and technology. AI and machine learning algorithms, standardized imaging methods, image analysis improvements, and easier access to dermatologists can improve skin lesion detection. Dermatologists, academics, and technology developers must collaborate to overcome these hurdles and improve skin lesion diagnosis outcomes.

5. Proposed Model

A skin lesion identification CAD (Computer-Aided Diagnosis) model is presented in Figure.5. which is an automated system that uses computational methods and machine learning approaches to diagnose and classify skin lesions. These models seek to increase the accuracy, efficiency, and objectivity of identifying skin disorders, including benign and malignant lesions. A CAD model for skin lesion identification includes the following components and processes:

Data Collection: A dataset of annotated skin lesion photos is required to train and validate the CAD model. These photos can be obtained from various sources, such as dermatology clinics, research databases, or publically available datasets like ISIC (International Skin Imaging Collaboration). Preprocessing: Skin lesion photos are preprocessed to improve their quality and make further analysis more accessible. To improve image quality and standardize data, preprocessing techniques may include image scaling, normalization, noise reduction, and contrast enhancement.

Feature Extraction: This is an essential stage in which significant features are extracted from preprocessed photos. These attributes capture crucial skin lesions properties such as color, texture, form, and spatial correlations. Examples of feature extraction approaches include histogram analysis, wavelet transforms, texture analysis, and CNNs.

Feature selection strategies are used in some circumstances to minimize the dimensionality of the feature space and remove irrelevant or redundant features. This phase aids in enhancing the model's efficiency and reducing overfitting.

Classification: For classification, the extracted or selected features are fed into machine learning algorithms or deep learning models. Because of their capacity to acquire hierarchical representations directly from images, deep learning models, particularly CNNs, have demonstrated extraordinary success in skin lesion categorization.

Model Development and Validation: The annotated skin lesion dataset is used to train the CAD model, and the features derived from the images are coupled with their corresponding ground truth labels.

Model Deployment: Once the CAD model has been trained and verified, it may be used to detect skin lesions in real-time. The CAD model can assess new skin lesion photos and produce a categorization or probability score for various skin disorders, assisting in the diagnosis process.

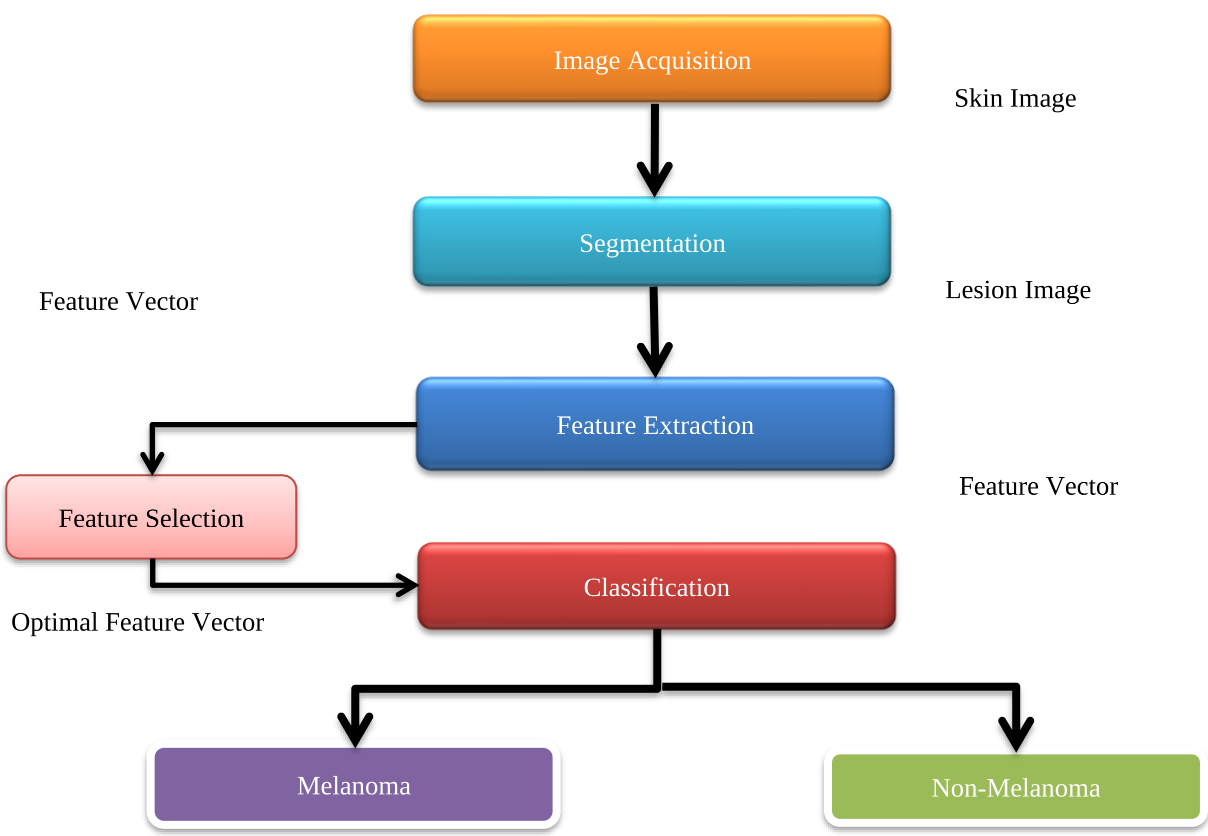


Fig. 5 Proposed model workflow

While dermoscopy improves accuracy, the prediction of melanoma still presents significant challenges. Additionally, medical analysis of melanoma is subjective and can vary between observers, leading to inter and intra-observer differences. These challenges highlight the need for in vivo second opinions, which can enhance diagnostic accuracy, prolong the patient's lifespan, reduce false negatives, and minimize the clinical and emotional burden of unnecessary interventions. They also enable automatic diagnosis and streamline the diagnostic process for physicians, reducing redundancy and irregularities. These developments in CAD systems offer promising solutions to improve the accuracy and objectivity of melanoma prediction. By incorporating IP and CV methods, CAD systems can help address the challenges associated with skin lesion analysis, enhance diagnostic accuracy, and optimize patient care. It should be noted that developing a CAD model for skin lesion diagnosis necessitates a large and diversified dataset, robust feature extraction methods, proper feature selection strategies, and thorough training and validation procedures. Continuous improvement and refining of CAD models and advances to identify skin lesions more accurately and reliably in clinical practice.

5.1. Image Acquisition

In CAD models, the initial step involves the acquisition of digital images. Various techniques and applications are used for this process, including Digitized colour slides: This technique was commonly used in earlier melanoma detection, where colour slides were digitized to obtain digital images for analysis. Medical image acquisition: Digital images and video clips are acquired using imaging modalities specific to the medical field, such as dermatoscopes, which capture high-resolution images of skin lesions. Epiluminescence microscopy (ELM): This technique involves briefly contacting a lesion's surface with a glass plate and capturing images using a microscope. It provides detailed information about the surface features of a lesion. The existence and application of CSLM in melanoma prediction have been explored in recent literature, highlighting its potential as a valuable tool in CAD models for the analysis and diagnosis of melanoma.

Ultrasound is used in medical dermatology, particularly in Europe, but it is not as widely preferred in the United States. Ultrasound operates based on acoustic features within the skin tissue. It can be used for imaging and analyzing skin lesions. C-mode: C-mode ultrasound is still under development and aims to produce three-dimensional images using computer guidance. This mode provides a more comprehensive and detailed view of the skin tissue. These modalities offer alternative approaches to visualize and analyze skin lesions, each with advantages and limitations. For melanoma detection, PET using FDG has demonstrated high sensitivity and specificity.

5.2. Image Segmentation

In computer-aided diagnosis (CAD) models, image segmentation is a critical component of skin lesion identification. It entails dividing an image into discrete sections or segments to isolate and analyze specific areas of interest within a skin lesion. Image segmentation is critical in skin lesion detection because it delineates the boundaries of the lesion, separates it from the surrounding healthy skin, and aids in extracting critical information. Here are some picture segmentation methods used in skin lesion identification: Thresholding is a fundamental and commonly used picture segmentation technique. It entails defining a threshold value to divide pixels in an image into two categories: foreground (lesion) and background (healthy skin). This method presupposes that the lesion and surrounding skin have a distinct intensity or colour difference. Region-based Region-based segmentation algorithms divide an image into discrete regions by grouping pixels with similar features. One prominent way is the watershed algorithm, which simulates water flow over a terrain to detect borders. Starting with a seed point, region-growing algorithms iteratively group surrounding pixels with similar attributes to generate regions. Edge-based segmentation seeks to discover sharp transitions or edges between various parts of an image. These lines illustrate the borders between the skin lesion and the healthy skin around it. Edge detection techniques such as the Canny edge detector and the gradient-based approach are extensively utilized in skin lesion segmentation. Graph-cut Segmentation: Graph-cut algorithms depict the image as a graph, with pixels acting as nodes and edges reflecting relationships between them.

The graph is then partitioned to minimize the energy function, considering pixel intensities and edge connections. Graph-cut algorithms can accurately segment complicated tumours with uneven borders. Segmentation based on Deep Learning: Deep learning algorithms, notably convolutional neural networks (CNNs), have shown great potential in the segmentation of skin lesions. CNNs are trained from start to finish to learn hierarchical representations from skin lesion images and automatically segment the lesion based on learned features. Skin lesions have been successfully segmented using U-Net, a prominent architecture for medical picture segmentation. Due to changes in lesion appearance, texture, colour, and uneven lesion boundaries, image segmentation in skin lesion detection can be difficult. Depending on the precise characteristics of the lesion and the imaging modality employed, different segmentation algorithms and approaches may perform better or worse. Approaches that combine different segmentation techniques or use domain-specific knowledge frequently produce more accurate results.

5.3. Feature Extraction

Feature extraction is critical in detecting skin lesions for computer-aided diagnostic (CAD) models. It entails extracting essential and discriminative elements from skin lesion photos that can be utilized to distinguish between different types of lesions or categorize them as benign or malignant. Colour, texture, shape, and spatial relationships are just a few of the properties captured by these attributes. Here are several ways to extract features often utilized in skin lesion identification: To capture the colour distribution and fluctuations within the lesion, statistical metrics such as mean and standard deviation and histogram-based features such as colour histograms or colour moments can be produced. Texture represents the spatial organization and patterns of pixels inside an image. Texture-based features gather data on changes in intensity, gradients, or spatial frequencies inside a skin lesion. Shape-based characteristics: The geometric properties and contour characteristics of skin lesions are described by shape features. These characteristics include area, perimeter, circularity, symmetry, convexity, and eccentricity. Shape-based features can be extracted from the lesion's boundary or region and provide information on the general shape and structure of the lesion. Statistical features capture statistical aspects of pixel intensities within a skin lesion. These characteristics include mean, variance, skewness, kurtosis, and higher-order moments. Statistical features give information about the distribution and statistical aspects of the pixel intensities in the lesion. Texture Gradient Features: Texture gradient features capture differences in local contrast inside a skin lesion. These features are obtained from gradient or edge information and detail textural changes inside the lesion. Features of Convolutional Neural Networks (CNNs): With the introduction of deep learning, pre-trained CNN models can be employed as feature extractors. These models, trained on big datasets, learn hierarchical representations that automatically capture discriminative information. Features can be recovered from the CNN's intermediate layers to capture low-level and high-level features. Shape Context Descriptors: Shape context descriptors represent the spatial relationships between a skin lesion's contour points. They provide a translation, rotation, and scale-invariant representation of the lesion's shape. Shape context descriptors have been used to match and categorize skin lesions. The feature extraction technique used is determined by the characteristics of the skin lesion, the available data, and the CAD model's unique requirements. A combination of multiple feature types is frequently used to capture a comprehensive collection of properties for reliable lesion diagnosis. Feature extraction enhances CAD models' discriminative capacity and accurately classifies skin lesions.

5.4. Feature Selection

Selecting the most valuable and relevant characteristics from a broader range of extracted features is involved. The goal of feature selection is to reduce the dimensionality of the feature space, increase model performance, and avoid overfitting. Here are some common feature selection strategies used in skin lesion identification: Selection of Univariate Features: The statistical importance of each feature is evaluated independently by univariate feature selection methods. The association between each feature and the goal variable. Features with statistically solid significance or discriminative power are chosen for further investigation. RFE continues until a predetermined number of features or a halting threshold is reached. Techniques for Regularization: Regularization approaches, such as L1 (Lasso) or L2 (Ridge), encourage sparsity in the feature space by penalizing model coefficients. These strategies encourage feature selection by decreasing less relevant features to zero and removing them from the model. Machine Learning Models' Importance of Features: Some machine learning algorithms include feature importance measurements that indicate how much each feature contributes to the model's prediction performance. The final model includes features with high significance scores. Correlation Analysis: Correlation analysis investigates the links between features and discovers highly connected features. Highly correlated characteristics may provide redundant or duplicate information, and choosing only one can minimize dimensionality without compromising performance. Domain Expertise and Knowledge: Domain expertise and expert perspectives can help influence feature selection. Dermatologists or medical specialists can provide vital insight into the traits most important for identifying skin lesions. This knowledge can help guide the selection of significant traits that are clinically relevant. The dataset determines the technique used to choose features, the challenge's complexity, and the CAD model's unique requirements. It is critical to strike a compromise between the necessity for feature reduction and the need for appropriate discriminatory power for accurate lesion detection. Proper feature selection improves model interpretability, reduces computing costs, and can increase the CAD model's generalization ability.

5.5. Image Classification

Image classification is a critical problem in computer-aided diagnosis (CAD) models for identifying skin lesions. It entails labeling or classifying an input skin lesion image based on its features and characteristics. The purpose is to correctly categorize skin lesions as benign or malignant or distinguish between different skin disorders. Here are some standard picture classification algorithms used in skin lesion identification: Algorithms for Machine Learning: Machine learning methods are extensively used in CAD models for image classification on a labelled dataset of skin lesion photos. These algorithms learn to spot patterns and generate predictions based on the retrieved features. Convolutional Neural Networks (CNNs): CNNs have transformed picture categorization jobs such as skin lesion detection. CNNs are deep learning algorithms that learn hierarchical representations from incoming images directly. Because of their ability to capture complex and discriminative information, CNNs have successfully categorised skin lesions. Ensemble approaches: To increase classification accuracy, ensemble approaches mix many models. Techniques such as bagging (Bootstrap Aggregating) and boosting can generate an ensemble of classifiers that make predictions collectively. Ensemble approaches aid in reducing the danger of overfitting and increasing the CAD model's robustness. Transfer Learning: Transfer learning is a technique that solves similar tasks by using pre-trained models on big datasets. Pre-trained CNN models, such as VGGNet, ResNet, or InceptionNet, trained on big-picture datasets like ImageNet, can be utilized as a starting point in skin lesion diagnosis. The pre-trained models are refined using the specific skin lesion dataset, allowing the model to learn from the customized data and enhance classification performance. Architectures for Deep Learning: Other deep learning architectures, besides CNNs, can be utilized for skin lesion categorization. If the dataset contains sequential or time-series data, attention methods or multi-modal architectures that combine picture and textual information can be investigated for increased performance. Online Learning: Online learning techniques allow the CAD model to adapt and update continuously as new data becomes available. This is especially beneficial in fast-paced medical situations where new skin lesion data is constantly being obtained. Online learning methods can update model parameters progressively and incorporate new knowledge without retraining the entire model. The available dataset, processing resources, and the CAD model's specific requirements determine the picture classification approach. Figure 6 provides an overview of the machine learning-based classification process, where the models are trained on labelled data and subsequently used for classifying new instances based on their extracted features.

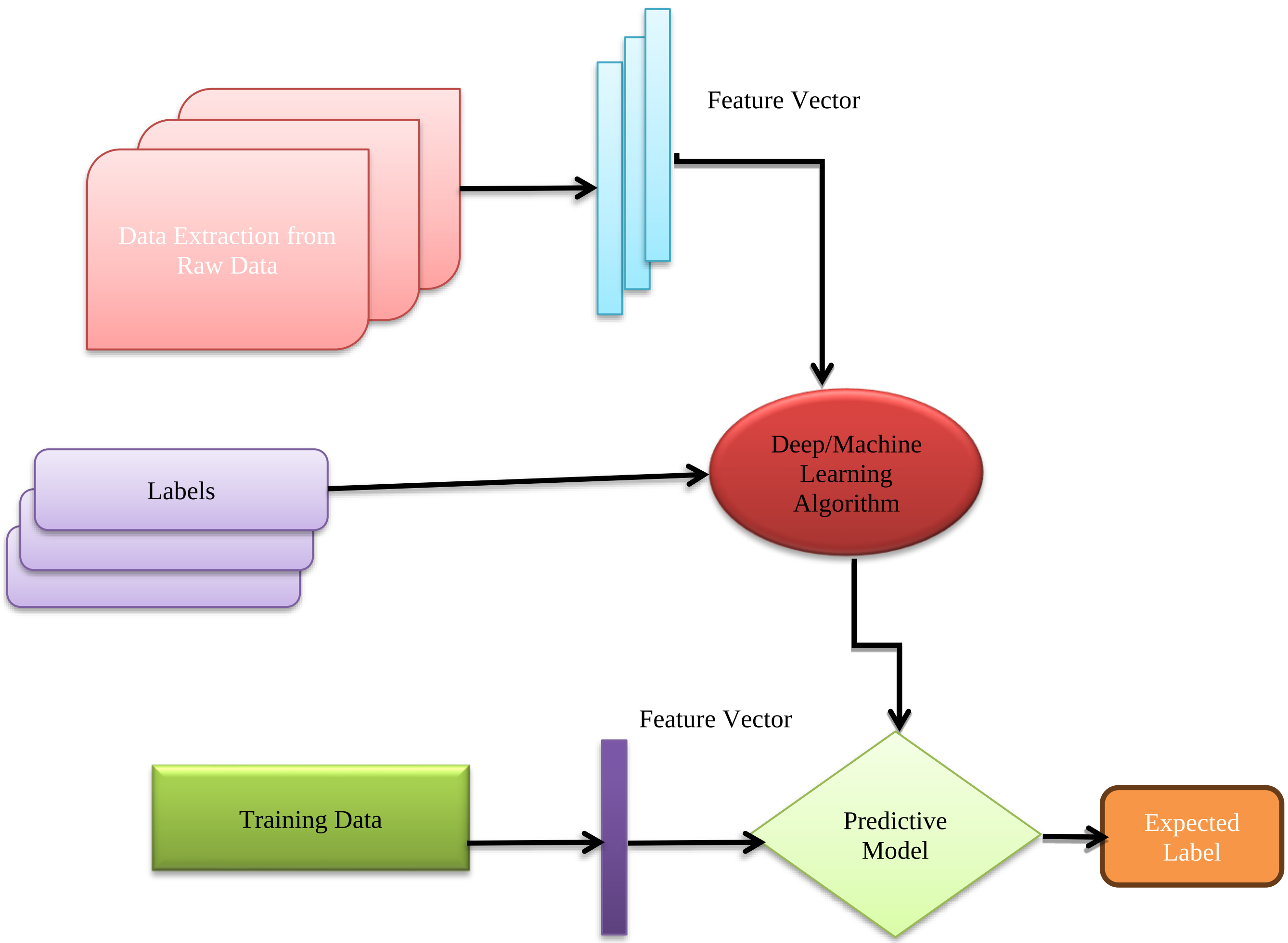


Fig. 6 ML based classification process

DL models are built upon the principles of traditional machine learning but with additional layers of non-linear transformations and sophisticated architectures. These models can capture and represent high-level abstractions by progressively extracting features at different levels of abstraction. Each layer of the neural network learns increasingly more abstract and meaningful representations. DL has shown remarkable performance improvements in various tasks, particularly image classification, compared to traditional machine learning approaches. DL models excel in learning representations directly from raw data, such as images, by leveraging large-scale labelled and unlabeled datasets. The representations learned by DL models are optimized to capture intricate patterns and structures within the data. The advancements in DL are inspired by insights from neuroscience, particularly the understanding of how the nervous system processes and communicates information. Neural coding, which relates to how the brain represents and encodes different stimuli and their corresponding neuronal responses, has influenced the development of DL models. DL aims to mimic the hierarchical processing and representation learning observed in the brain, leading to more powerful and effective learning algorithms.

6. IoT-driven Image Processing Framework for Diagnosis

Integrating Internet of Things (IoT) technologies with image-processing techniques to facilitate the diagnosis of various medical disorders is referred to as an IoT-driven image-processing framework for diagnostics. This system collects and transmits medical images utilizing IoT devices and connectivity, which are then processed and evaluated using image processing algorithms and machine learning approaches. The following are the main components and advantages of an IoT-driven image processing framework for diagnosis: Connectivity with IoT Devices: The framework uses IoT devices such as smartphones, wearable cameras, and specialist medical imaging devices equipped with sensors and connections. These gadgets take medical images and send them via the internet, allowing healthcare practitioners to examine and analyze them remotely. These processes are depicted in Figure 7 and can be described as follows:

Preprocessing: In this step, the input data could be medical images or other data types. Preprocessing techniques include image normalization, noise reduction, contrast adjustment, and resizing.

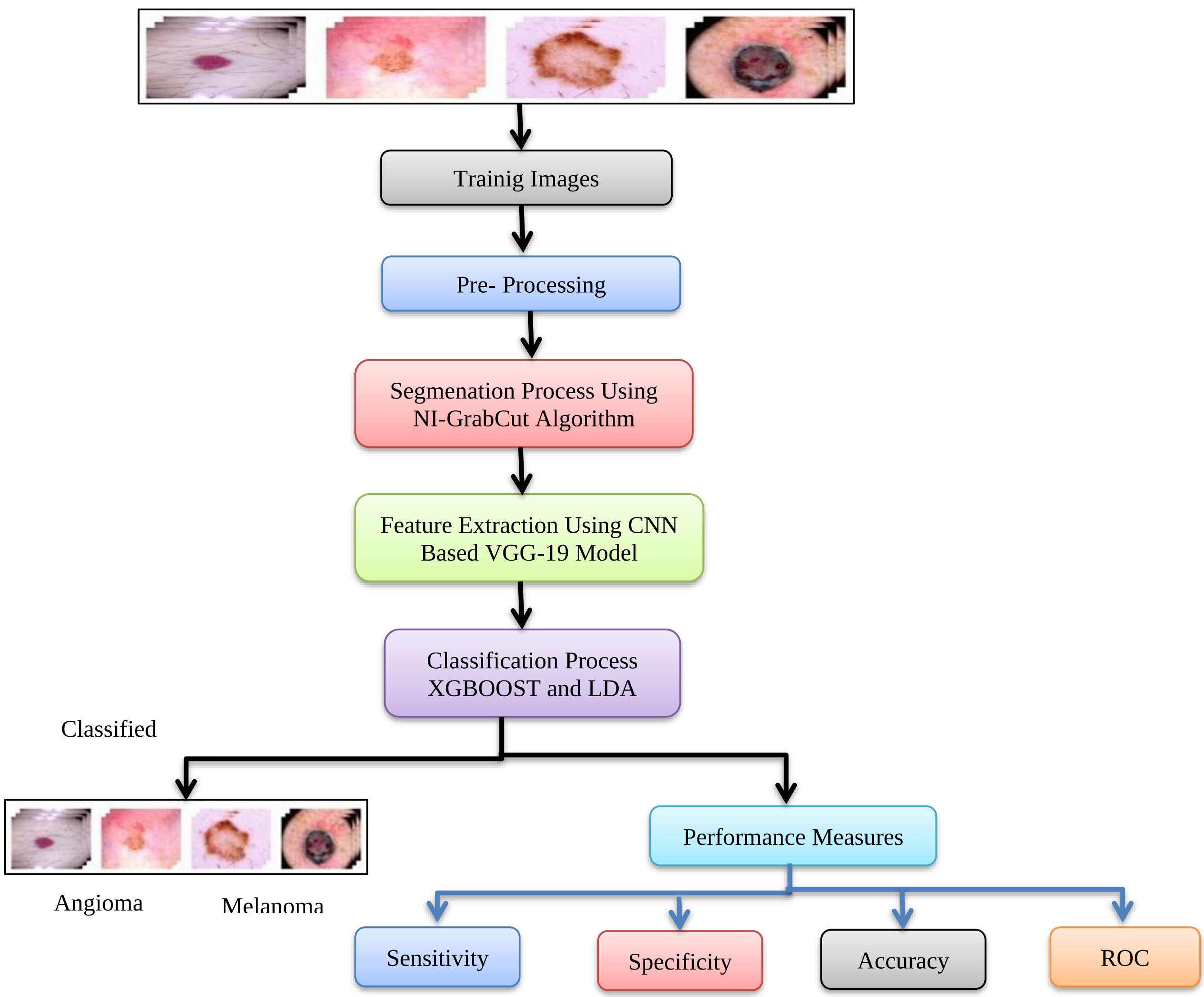


Fig. 7 IoT-Driven image processing framework

Segmentation delineates and extracts specific structures or regions of interest (ROIs) from the images. This can be achieved through thresholding, region growing, or advanced algorithms like active contours or deep learning-based segmentation networks.

Feature Extraction: Once the ROIs or segmented regions are obtained, relevant features are extracted to represent the characteristics of these regions. Feature extraction involves selecting or computing a set of informative attributes that capture the discriminative information necessary for classification. These features include shape descriptors, texture features, statistical measures, and deep learning-based feature representations from convolutional neural networks (CNNs) or other architectures.

Classification: In the classification step, the extracted features are input to a classification algorithm or model that assigns a label or class to the input data. Various classification algorithms can be applied. The DTL model integrates these processes to enable automated diagnosis or decision-making based on the input data. The model can learn complex patterns and representations from the data by leveraging deep learning techniques, leading to more accurate and robust diagnosis or classification outcomes.

The Gaussian filter (GF) is commonly used as a weighting calculation scheme in the bilateral filter (BF) space domain. The distance between two pixels is calculated using the following function: The parameter sigma_s determines the spread or width of the Gaussian distribution and influences the strength of the spatial filtering effect. Smaller values of sigma_s result in a narrower distribution and more vital spatial filtering. In the bilateral filter, the spatial weight w_s is combined with the range weight wr, which measures the similarity of pixel intensities, to determine the overall weight for each pixel. This combined weight is used to compute the weighted average of the pixel intensities in the filtering process, considering both the spatial and range domains—the bilateral filter, with its spatial and range weights, balances edge-preserving smoothing and noise reduction. The energy function represents the cost of assigning pixels to the foreground or background. The goal is to find the optimal assignment of pixels that minimizes the energy function. By minimizing the energy function, the graph cut algorithm finds the optimal assignment of pixels to foreground and background segments. The graph cut algorithm then finds a cut in the graph that separates the foreground and background regions while minimizing the energy function.

Feature extraction involves passing the segmented image through the VGGNet-19 model and extracting high-level features from the image. The model has been trained on a large dataset of images and has learned to recognize various image patterns and structures. By extracting features from the segmented image using this pre-trained model, the model can capture important discriminative information that can be used for further analysis. The features extracted from the VGGNet-19 model can include abstract representations of the image, such as shapes, textures, and patterns relevant to the classification task. These features are typically represented as a vector of values that encode the presence or absence of specific visual characteristics in the image. Once the features are extracted, they can be used as input to a classification algorithm to predict the diagnosis or classification of the skin lesion. The proposed diagnosis model aims to capture meaningful and discriminative information from the segmented image, enabling accurate classification and diagnosis of skin lesions.

The VGGNet-19 is shown in Figure.8. It has demonstrated strong performance When doing various computer vision tasks, such as picture categorization. Using the pre-trained network as a feature extractor, the VGGNet-19 can extract discriminative features from photos. The VGGNet-19-based feature extraction procedure is described in the following manner: Architecture of the VGGNet-19: 16 convolutional layers and three fully connected layers make up the 19 layers of the VGGNet-19. Each block in which the convolutional layers are arranged has several convolutional layers followed by a max-pooling layer. The input size for the network is set at 224x224 pixels. Pre-trained Model: VGGNet-19 is frequently pre-trained using big image classification datasets, including ImageNet, which has millions of annotated photos from various categories. The network gains the ability to identify different low-level and high-level elements from the input images during pre-training.

The pre-trained model is used as a feature extractor while using VGGNet-19 to extract features. The pre-trained weights are injected into the network, and the input picture is routed through the layers of the network until it reaches the appropriate layer of interest. The output of this layer is then regarded as the representation of the extracted feature. Dimensionality reduction: The VGGNet-19 features that were retrieved had a high dimensionality. Transfer Learning: Subsequent classification models or machine learning techniques can be applied with the extracted features as input. Transfer learning can be used by fine-tuning the pre-trained VGGNet-19 model on a particular dataset related to skin lesion diagnosis. The final few layers of the network's weights are updated, while the earlier ones are frozen during fine-tuning. As a result, the model can modify itself to the particular task at hand.

The retrieved features are matched with the associated ground truth labels, and the classifier is trained on labeled data. The classifier gains the ability to map the retrieved features to the correct classes during the training phase. The advantage of using a pre-trained deep learning model that has acquired rich representations from an extensive dataset is VGGNet-19-based feature extraction. This strategy is quite helpful when a small amount of data is available for skin lesion diagnosis. The succeeding classification models can take advantage of the discriminative capability of the learnt features by utilizing the features retrieved from VGGNet-19, potentially improving accuracy and performance in skin lesion diagnosis tasks.

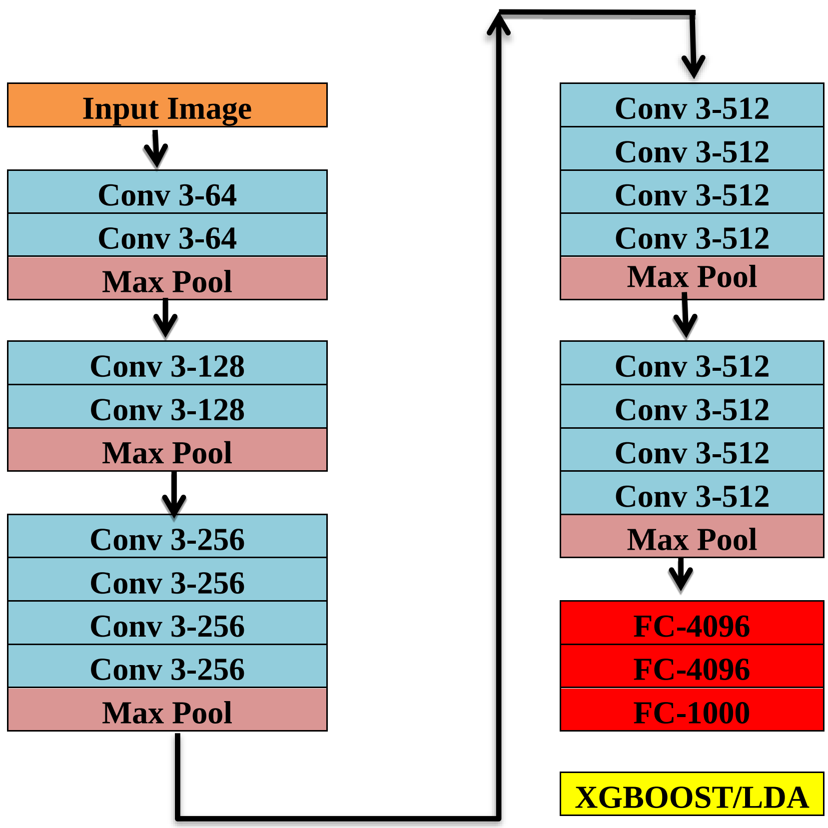


Fig. 8 Structure of VGG-19

$$f(x) = \max(0, x) \tag{1}$$

The VGG-19 network utilizes smaller 3x3 convolution kernels instead of larger 5x5 kernels to reduce the number of parameters and computation time without sacrificing accuracy. It has been observed that stacking multiple layers with 3x3 kernels has the same impact on feature extraction as using a single layer with a larger kernel, such as 5x5. Using multiple 3x3 layers, the model can capture complex patterns and relationships within the input data while maintaining a more efficient parameter count. In the pooling layers of VGG-19, the primary goal of maximum pooling is to downsample the feature maps and reduce the spatial dimensions. It helps preserve the essential texture features while reducing the influence of precise positional information. By applying maximum pooling, the network can focus on the most prominent features and discard less important details, leading to more efficient and robust input data representation. The VGG-19 network comprises three fully connected (FC) layers with 512, 256, and 6 units, respectively. These FC layers are responsible for the final classification task, where the network predicts the probabilities for the different classes. In previous works, the output of the FC layers is typically normalized using the softmax function. The softmax function transforms the output scores from the FC layers, which range from negative to positive infinity, into a probability distribution ranging from 0 to 1. The sum of the probabilities for all

Classes are equal to 1, allowing the network to assign a probability score to each class based on the input data. By employing the softmax function, the output of the FC layers in VGG-19 is converted into a probability score, indicating the likelihood of the input image belonging to each class. This probability score can be used to make predictions and classify the input image into one of the predefined classes.

$$S_i = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_i}}, i\epsilon(1, n) \tag{2}$$

The DTL (Deep Transfer Learning) approach is a technique used to train a deep learning model when limited training data is available. In the DTL framework, the pre-trained network's parameters are utilized in the initialization stage to leverage the features learned from many images.

These pre-trained parameters can aid feature extraction and facilitate training, even with limited data.

7. Results and Discussion

The BF (preprocessing) technique for dermoscopic images functions by putting them through several processes to improve their quality and eliminate extra noise. Figure 9 illustrates the steps with the original dermoscopic images in (a) and the masked and preprocessed images in (b) to (c). The original dermoscopic pictures are displayed in Figure 9(a). Dermoscopes are used to take these pictures, which help learn more about skin lesions but may also contain noise, artefacts, or other undesirable aspects. The BF technique is used to enhance the images' quality and get them ready for more analysis. Figures 9(b) through 9(c) show the masked and preprocessed pictures obtained after employing the approach. The technique seeks to remove the noise from the photos and improve the critical information.

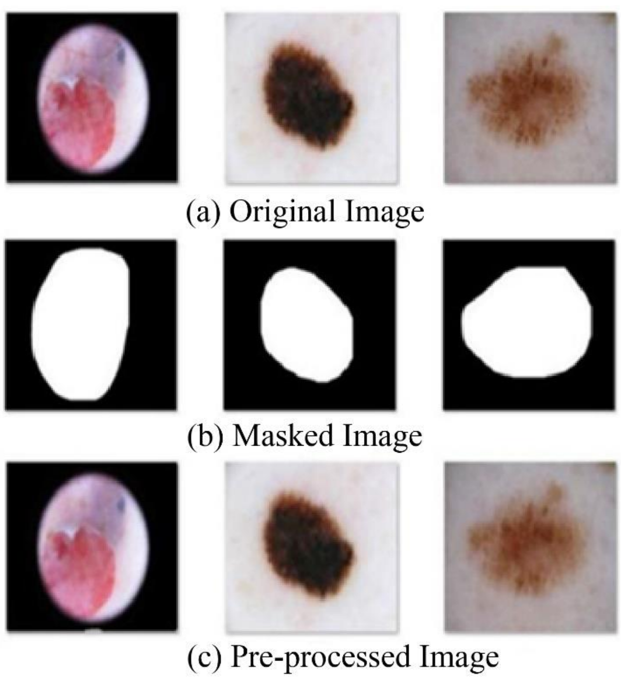


Fig. 9 BF preprocessing method

The specifics of the BF method are as follows: Noise reduction: To reduce noise in dermoscopic images, the approach may use filters or algorithms. Random pixel-level noise can be eliminated, textures and imperfections can be smoothed out, and undesired artefacts can be suppressed. Image masking: The method could use masking to highlight the dermoscopic images' region of interest (ROI). Segmenting and isolating the skin lesion region, usually the analysis's primary emphasis, may be necessary. Preprocessing: Additional preprocessing techniques increase the photos' quality and analysis. These procedures may involve adjusting the contrast, normalizing the image, sharpening the image, or using other image-enhancing methods unique to the study of skin lesions. The dermoscopic images are efficiently preprocessed using the BF approach, improving image quality and reducing noise. This improves the validity and precision of subsequent dermoscopic image analysis and classification tasks. Figure 9 illustrates how the BF technique for dermoscopic image preprocessing works. Three sub-figures comprise the primary figure: (a) The Original Photo The original dermoscopic image can be seen in this sub-figure. It represents the dermoscope's raw input image, including the skin lesion and surrounding area. The original image could have undesired objects, noise, or artefacts. (b) Masked picture: The masked picture is displayed in this sub-figure. The dermoscopic image's region of interest (ROI), which often correlates to the location of the Skin lesion, is highlighted during the masking procedure. The masking technique is used to isolate and draw attention to the precise area of the image that needs investigation. (c)

Preprocessed Image: This sub-figure shows the preprocessed image. It results from applying preprocessing methods to improve the quality and prepare the image for additional analysis.

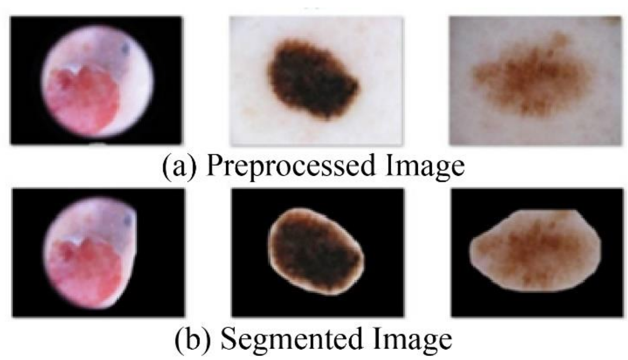


Fig. 10 Illustrate the effectiveness of the presented segmentation technique

The preprocessing process may include noise reduction, contrast correction, normalization, and other image-enhancing techniques specifically targeted to the needs of skin lesion analysis. Figure 9 shows the progression of the dermoscopic image from its initial state to the masked state, which highlights the area of interest, and then to the preprocessed state, where a variety of preprocessing techniques have been used to enhance the image quality and get it ready for upcoming analysis and classification tasks.

Figure. 10. displays a sample result that was obtained using the segmentation technique that was provided. The graphic shows how well the segmentation technique works to define the limits of the skin lesions precisely. The figure probably consists of several sub-figures, each showing a skin lesion image that has already been processed along with the results of its segmentation. Various image improvement techniques would have been used for the preprocessed images to boost their quality and prepare them for segmentation. The preprocessed skin lesion image is shown in each sub-figure, displaying the skin lesion's specifics. The segmentation result is next to the original image to show how precisely the lesion boundaries were delineated using the provided segmentation technique. The segmentation method used in Figure 10 is anticipated to distinguish the skin lesion from the backdrop or surrounding healthy skin, enabling further classification and analysis. To obtain the desired result, the described technique may use other segmentation algorithms or approaches, such as thresholding, region-based segmentation, or edge-based segmentation. The visual depiction in Figure 10 demonstrates how well the segmentation technique worked to precisely segment the images of skin lesions after preprocessing.

The preprocessed image and the segmented image are each represented by two separate sub-figures in Figure 10.

Predicted Class \ Actual Class	Angioma	Nevus	Lentigo NOS	Solar Lentigo	Melanoma	Seborrheic Keratosis	BCC
Angioma	21	0	0	0	0	0	0
Nevus	0	42	4	0	0	0	0
Lentigo NOS	0	5	36	0	0	0	0
Solar Lentigo	0	0	3	65	0	0	0
Melanoma	0	5	0	0	46	0	0
Seborrheic Keratosis	0	0	3	0	2	49	0
BCC	1	0	0	0	2	0	34

Actual Class

(a) VGG19-LDA

Predicted Class \ Actual Class	Angioma	Nevus	Lentigo NOS	Solar Lentigo	Melanoma	Seborrheic Keratosis	BCC
Angioma	21	0	0	0	0	0	1
Nevus	0	45	0	1	0	0	0
Lentigo NOS	0	0	40	1	0	0	0
Solar Lentigo	0	0	0	68	0	0	0
Melanoma	0	0	0	2	48	1	0
Seborrheic Keratosis	0	0	0	4	1	49	1
BCC	0	0	0	2	0	1	34

Actual Class

(b) VGG19-XGBoost

Fig. 11 Presents the confusion matrix of the proposed models

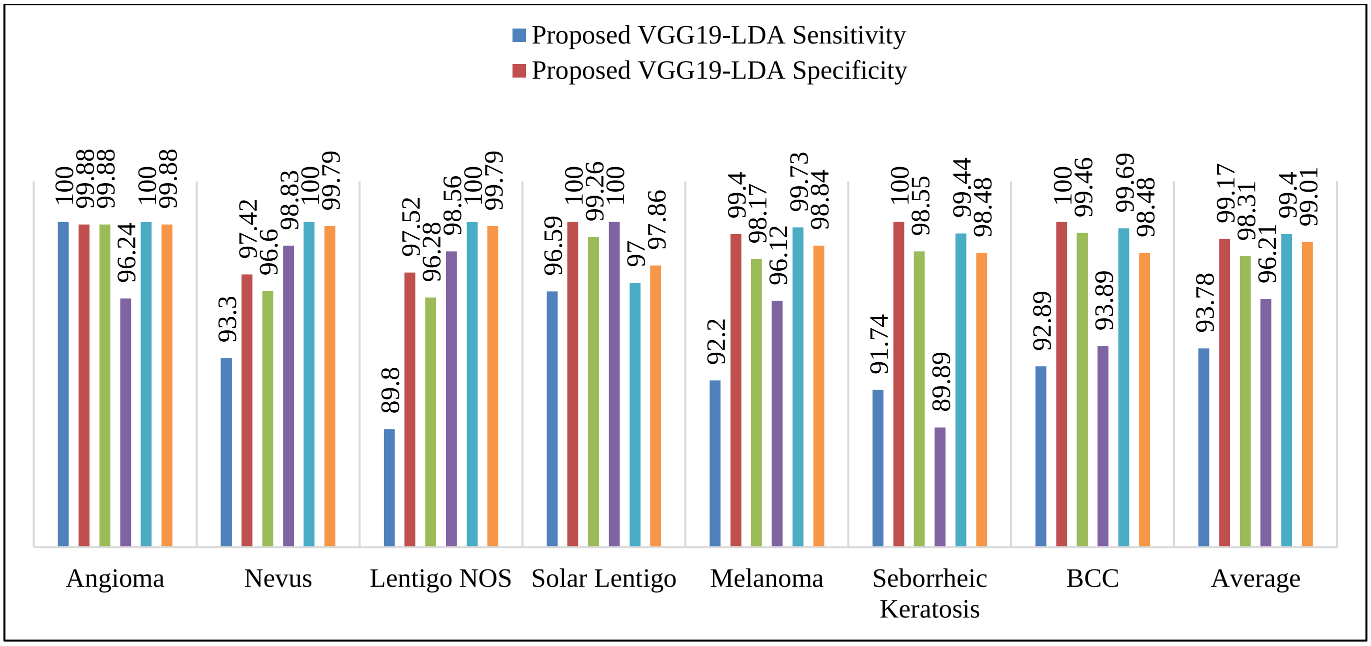


Fig. 12 Performance Analysis

The explanation for each sub-figure is as follows: (a) Preprocessed Image: The preprocessed image of a skin lesion is shown in this sub-figure. The image has undergone several image improvement procedures to boost its quality and get it ready for more investigation. These image improvement approaches tailored to skin lesion analysis may include noise reduction, contrast modification, normalization, and other image enhancement techniques. The preprocessed image shows the skin lesion in an improved and crystal-clear manner. (b) Segmented Image: The segmented image obtained using the described segmentation technique is shown in this sub-figure. The segmentation approach aims to define the limits of the skin lesion precisely. It highlights the particular area of interest by separating the lesion from the backdrop or healthy skin around it. The segmented image shows how the segmentation technique successfully detected and isolated the skin lesion. These sub-figures in Figure 10 work together to graphically demonstrate how well the segmentation technique described works on the skin lesion photos that have already been processed. The preprocessed image displays the skin lesion's improved quality, while the segmented image illustrates how precisely the approach could segment the area. In order to accurately extract features from the segmented skin lesion for classification or further diagnostic analysis, this result is crucial for future analysis.

The categorization of various dermoscopic images is shown in Figure 11. The classification outcomes for each model for the various classes of skin lesions are shown in the confusion matrix. Applied to the VGG19-LDA model: 21 pictures were identified by the model as angiomas. The model identified forty-two photos as Nevus. Thirty-six photos were labelled as Lentigo NOS by the model. Sixty-five photos were labelled as Solar Lentigo by the model. The model identified melanoma in 46 of the pictures. Forty-nine photos were labelled as having seborrheic keratosis by the model. The model identified thirty-four photos as BCC.

According to the VGG19-XGBoost model, 20 pictures were identified as angiomas. The model identified forty-five photos as Nevus. Forty photos were labelled as Lentigo NOS by the model. The model identified Solar Lentigo in 68 photos. The model identified forty-eight photos as melanoma. The model identified Seborrheic Keratosis in 48 of the pictures. The model identified thirty-four photos as BCC.

The confusion matrix breaks down the classification outcomes, showing the proportion of cases for each class successfully classified (true positives) and wrongly classified (false positives). The values in the confusion matrix represent the counts of images placed in each category by the corresponding models. The confusion matrix sheds light on the effectiveness and precision with which the models classified the dermoscopic pictures—specifically the VGG19-LDA model in sub-figure (a) and the VGG19-XGBoost model in sub-figure (b). The confusion matrix provides a comprehensive overview of the classification results for the distinct dermoscopic images.

Figure 12 evaluates the VGG19-LDA model's ability to classify dermoscopic pictures of skin lesions. The model's sensitivity, specificity, and accuracy for several kinds of skin lesions are shown in the image. These metrics reveal how well the model can distinguish between various skin lesions. The sensitivity measures how well the model can detect positive situations, while the specificity measures how well it can rule out false positives. The model's ability to accurately categorize photos of skin lesions across all classes is represented by the overall accuracy measure. High sensitivity, specificity, and accuracy levels for most skin lesions indicate the VGG19-LDA model's efficacy in this task. It has a high sensitivity for identifying positive instances and a high specificity for identifying negative ones. Overall, the model's success in correctly labelling dermoscopic pictures of skin lesions is further validated by its high level of accuracy.

Figure 13 comprehensively evaluates the VGG19-XGBoost approach to dermoscopy image classification of skin lesions. Positive sensitivity, specificity, and accuracy are shown for categorising skin lesion types. The findings show that the VGG19-XGBoost model correctly categorizes various skin lesions. It has a high sensitivity for detecting true positives and specificity for ruling out false positives. Overall, the model performs exceptionally well in classifying skin lesions, as seen by its excellent accuracy over a wide range of categories. The skin lesion classifications Nevus, Lentigo NOS, and Solar Lentigo all benefit from the VGG19-XGBoost model's high levels of sensitivity and specificity. The model's dependability in identification and classification is further validated by its excellent accuracy when identifying various skin lesion kinds. These results highlight the potential value of the VGG19-XGBoost model in dermatology and skin disease diagnostics, providing helpful support for the precise categorization of different skin lesions.

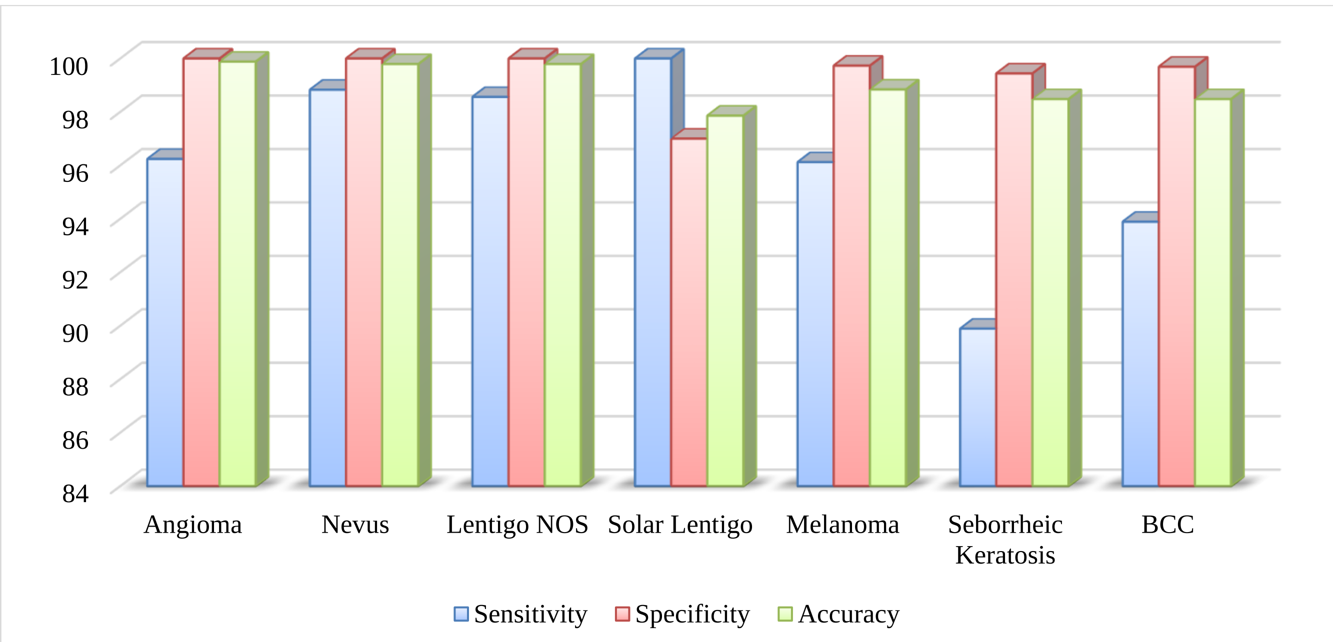
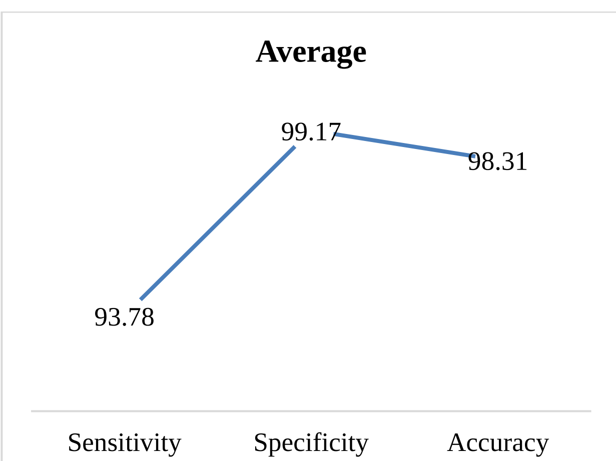
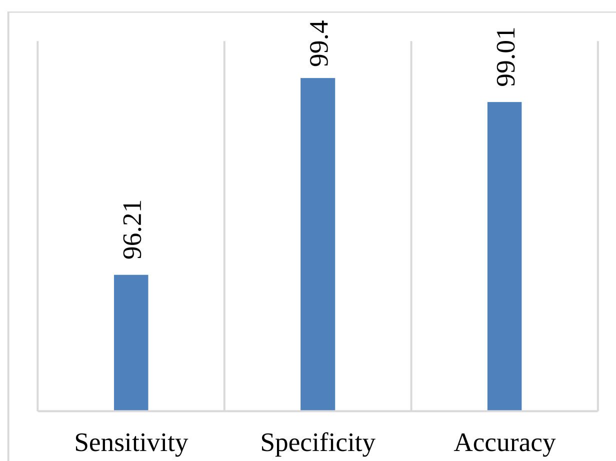


Fig. 13 An examination of the proposed method outcomes with various classes



(a) VGG19-LDA



(b) VGG19-XGBoost

Fig. 14 Presents the Average Analysis of the proposed model

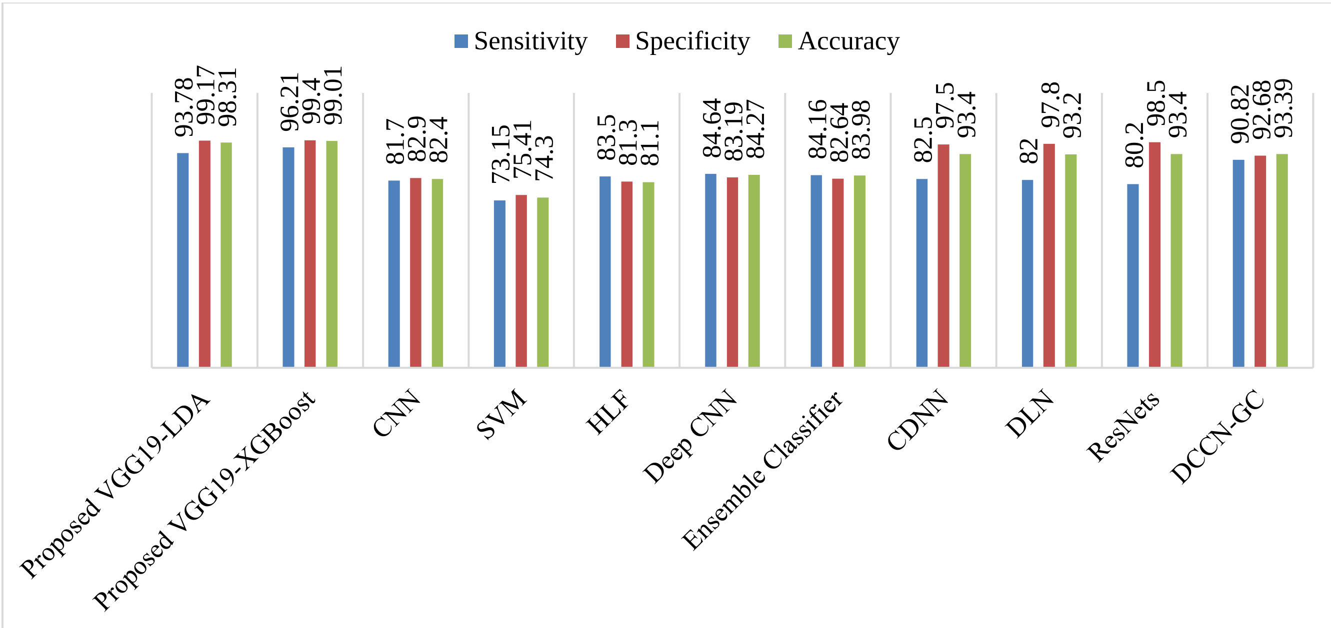


Fig. 15 Evaluate and compare the performance of different approaches

Figure 14 and Figure.15 show the results of a comparison study used to assess the sensitivity and specificity of several models for classifying skin lesions. Here is a rundown of what we learned: The CDNN model showed increased performance compared to earlier models, with a sensitivity of 82.5%. The HLF model's sensitivity results were in the middle of the pack. The Ensemble Classifier and the Deep CNN had higher sensitivity values than all except the DCCN-GC. DCCN-GC: The sensitivity of this model was 90.82%, which is very close to perfect. Maximum sensitivities of 93.78% and 96.21% were achieved with the suggested VGG19-LDA and VGG19-XGBoost models, respectively, compared to all other approaches. Promising methodologies for skin lesion categorization showed significant effectiveness in detecting positive instances. Analyzing for Precision: The SVM model had the lowest specificity compared to the other approaches. The Deep CNN model achieved a respectable specificity value of 83.19%, indicating improved performance compared to earlier methods such as HLF, CNN, and the Ensemble Classifier. DCCN-GC: The DCCN-GC model outperformed the other methods by a wide margin in specificity. The specificity values for the HLF, CNN, and Ensemble Classifier techniques were all higher than those for the SVM model, which suggests that the HLF, CNN, and Ensemble Classifier methods are more accurate. Regarding specificity, the Deep CNN model performed even better than the DCCN-GC model, which showed significant gains.

After analyzing accuracy values for skin lesion classification, the following results were found: SVM model was the least accurate of the three. HLF, CNN, and the Ensemble Classifier all performed better than SVM, achieving somewhat high levels of accuracy. The Deep CNN model obtained a respectable level of accuracy (84.27 percent). Compared to other methodologies already in use, the DLN framework performed well. With almost similar accuracy levels, DCCN-GC and ResNets outperformed every other technique except CDNN, VGG19-LDA, and VGG19-XGBoost. CDNN: With an accuracy of 93.4%, the CDNN model achieved similar outcomes. The disclosed VGG19-LDA and VGG19-XGBoost approaches achieved optimum accuracies of 98.31% and 99.01%, respectively, surpassing the performance of the other techniques by a wide margin. Based on these results, the SVM model seemed less accurate than the alternatives. Superior accuracy was achieved by using the HLF, CNN, and Ensemble Classifier approaches. While the DCCN-GC and ResNets methods were more successful, the Deep CNN and DLN models performed well. ON THE OTHER HAND, the CDNN, VGG19-LDA, and VGG19-XGBoost models outperformed every other approach by a wide margin. Overall, the results of the comparison showed that the SVM model was less accurate than the HLF, CNN, Ensemble Classifier, Deep CNN, DLN, DCCN-GC, ResNets, CDNN, VGG19-LDA, and VGG19-XGBoost approaches.

The VGG19-LDA model achieved an AUC of 0.9560, while the VGG19-XGBoost model attained an AUC of 0.9711. These results indicate that both models have effectively classified skin lesions, with the VGG19-XGBoost model demonstrating slightly higher performance. Considering the overall experimental results, the VGG19-XGBoost model exhibited excellent diagnostic performance for skin lesions. These findings highlight the effectiveness of the VGG19-XGBoost model in accurately classifying and diagnosing different types of skin lesions.

8. Conclusion

In conclusion, this paper suggested an Internet-of-Things-driven image processing system for reliable diagnosis and categorization of skin conditions. The framework uses IoT devices and image-processing algorithms to improve skin lesion recognition and classification efficiency. The current methodologies and categorization systems for skin diseases were investigated through a thorough literature review. Hair artefacts, low contrast, irregular boundaries, and other difficulties in skin lesion detection were discovered. Data gathering utilizing IoT devices, picture segmentation, feature extraction, feature selection, and image classification are all part of the proposed system's pipeline to overcome these obstacles. Two models, VGG19-LDA and VGG19-XGBoost, were used for image classification; both used the VGGNet-19 architecture for feature extraction. The efficiency of the suggested framework was experimentally demonstrated using the ISIC dataset. The proposed models outperformed other sensitivity, specificity, and accuracy techniques when categorizing different skin lesions. The outcome shows that the proposed framework shows potential for accurate skin disease diagnosis and categorization by combining IoT devices with modern image processing techniques. It might make dermatological evaluations quicker and more precise, leading to earlier diagnoses and more effective treatments for skin ailments.

This study enhances skin lesion identification and classification accuracy and reliability by introducing an IoT-driven image processing framework incorporating state-of-the-art approaches. The success and impact of the framework in real-world healthcare settings can be validated by progressively developing and expanding the dataset and conducting real-world clinical validations.

References

[1] Marcos A M Almeida, and Iury A X Santos, “Classification Models for Skin Tumor Detection using Texture Analysis in Medical Images,” *Journal of Imaging*, vol. 6, no. 6, pp. 51, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] Jainesh Rathod et al., “Diagnosis of Skin Diseases using Convolutional Neural Networks,” *Second International Conference on Electronics Communication and Aerospace Technology*, pp. 1048-1051, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[3] Muhammad Ridaffa Purnomo, and Irma Palupi, “Classification of Skin Diseases to Detect their Causes using Convolutional Neural Networks,” *International Conference on Data Science and Its Applications*, Bandung, Indonesia, pp. 187-193, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] Zhen Ma, and João Manuel R S Tavares, “A Novel Approach to Segment Skin Lesions in Dermoscopic Images Based on a Deformable Model,” *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 2, pp. 615-623, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[5] Zhe Wu et al., “Studies on Different CNN Algorithms for Face Skin Disease Classification Based on Clinical Images,” *IEEE Access*, vol. 7, pp. 66505-66511, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[6] Piotr Dollár, and C. Lawrence Zitnick, “Fast Edge Detection using Structured Forests,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 37, no. 8, pp. 1558-1570, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[7] Rajvi Parikh, and Hitesh Shah, “A Survey on Computer Vision Based Diagnosis for Skin Lesion Detection,” *International Journal of Engineering Science and Innovative Technology*, vol. 2, no. 2, pp. 431-437, 2013. [Google Scholar] [Publisher Link]

[8] Md. Anwar Hussen Wadud, M. F. Mridha, and Mohammad Motiur Rahman, “Word Embedding Methods for Word Representation in Deep Learning for Natural Language Processing,” *Iraqi Journal of Science*, vol. 63, no. 3, pp. 1349-1361, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Sheetalrani R Kawale et al., “An Intelligent System for Remote Monitoring of Patients Health and the Early Detection of Coronary Artery Disease,” *International Conference on Smart Generation Computing, Communication and Networking*, Bangalore, India, pp. 1-6, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] K. Veera Swamy, and B. Divya, “Skin Disease Classification using Machine Learning Algorithms,” *2nd International Conference on Communication, Computing and Industry 4.0*, Bangalore, India, pp. 1-5, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[11] Jihan Alam, “An Efficient Approach for Skin Disease Detection using Deep Learning,” *IEEE Asia-Pacific Conference on Computer Science and Data Engineering*, Brisbane, Australia, pp. 1-8, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[12] Igielska - Kalwat Joanna, and Kilian - Pięta Ewa, “The Use of Dalmatian Tansy and Auxiliary Substances as Natural Substitutes in the Treatment of Dermatosis,” *SSRG International Journal of Applied Chemistry*, vol. 8, no. 3, pp. 1-9, 2021. [CrossRef] [Publisher Link]

[13] Zhixiang Zhao et al., “A Novel Convolutional Neural Network for the Diagnosis and Classification of Rosacea: Usability Study,” *JMIR Medical Informatics*, vol. 9, no. 3, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[14] N. Vikranth Kumar et al., “Classification of Skin Diseases using Image Processing and SVM,” *International Conference on Vision towards Emerging Trends in Communication and Networking*, pp. 1-5, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[15] M Ramesha et al., “An Integrated IoT Technology for Health and Traffic Monitoring System with Smart Ambulance,” *IEEE North Karnataka Subsection Flagship International Conference*, Vijaypur, India, pp. 1-6, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[16] K. Neetu Chikyal, and Veera Swamy, "Performance Assessment of Various Thyroid Image Segmentation Techniques with Consistency Verification," *Journal of Advance Research in Dynamical & Control Systems*, vol. 11, no. 2, pp. 1299-1309, 2019. [Publisher Link]

[17] Muhammad Attique Khan et al., "Multi-Class Skin Lesion Detection and Classification via Teledermatology," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 12, pp. 4267-4275, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] V. Dankan Gowda et al., "Implementation of a Machine Learning-Based Model for Cardiovascular Disease Post Exposure prophylaxis," *International Conference for Advancement in Technology*, Goa, India, pp. 1-5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Archana Ajith et al., "Digital Dermatology: Skin Disease Detection Model using Image Processing," *International Conference on Intelligent Computing and Control Systems*, pp. 168-173, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[20] Md. Anwar Hussen Wadud, Mohammed Alatiyyah, and M. F. Mridha, "Non-Autoregressive End-to-End Neural Modeling for Automatic Pronunciation Error Detection," *Applied Sciences*, vol. 13, no. 1, p. 109, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] K. Manivannan, and S. Sathiamoorthy, "Bird Mating Optimizer with Deep Learning-based Tuberculosis Detection using Chest Radiographs," *International Journal of Engineering Trends and Technology*, vol. 71, no. 2, pp. 341-348, 2023. [CrossRef] [Publisher Link]

[22] Vinayshekhar Bannihatti Kumar, Sujay S Kumar, and Varun Saboo, "Dermatological Disease Detection using Image Processing and Machine Learning," *Third International Conference on Artificial Intelligence and Pattern Recognition*, pp. 1-6, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[23] Avinash Sharma et al., "Extraction of Fetal ECG using ANFIS and the Undecimated-Wavelet Transform," *IEEE 3rd Global Conference for Advancement in Technology*, pp. 1-5, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] K. C. Shahana sherin, and R. Shayini, "Classification of Skin Lesions in Digital Images for the Diagnosis of Skin Cancer," *International Conference on Smart Electronics and Communication*, Trichy, India, pp. 162-166, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[25] Avinash Sharma et al., "Computer Vision Based Healthcare System for Identification of Diabetes & Its Types using AI," *Measurement: Sensors*, vol. 27, p. 10075, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[26] Adheena Santy, and Robin Joseph, "Segmentation Methods for Computer Aided Melanoma Detection," *Global Conference on Communication Technologies*, pp. 490-493, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[27] C. Saraswathi, and B. Pushpa, "Computer Imaging of Alopecia Areata and Scalp Detection: A Survey," *International Journal of Engineering Trends and Technology*, vol. 70, no. 8, pp. 347-358, 2022. [CrossRef] [Publisher Link]

[28] Ranjeet Suryawanshi et al., "Enhanced Diagnostic Methods for Identifying Anomalies in Imaging of Skin Lesions," *International Journal of Electrical and Electronics Research*, vol. 10, no. 4, pp. 1077-1085, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[29] Habeba Mahmoud, Mohamed Abdel-Nasser, and Osama A Omer, "Computer Aided Diagnosis System for Skin Lesions Detection using Texture Analysis Methods," *International Conference on Innovative Trends in Computer Engineering*, pp. *140-144, 2018.* [CrossRef] [Google Scholar] [Publisher Link]

[30] P. Ajay et al., "Intelligent Breast Abnormality Framework for Detection and Evaluation of Breast Abnormal Parameters," *International Conference on Edge Computing and Applications*, pp. 1503-1508, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[31] Parameshwar R. Hegde, Manjunath M. Shenoy, and B H Shekar, "Comparison of Machine Learning Algorithms for Skin Disease Classification using Color and Texture Features," *International Conference on Advances in Computing Communications and Informatics*, pp. 1825-1828, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[32] M Ramesha et al., "Implementation of IoT Based Wireless Electronic Stethoscope," *Third International Conference on Multimedia Processing, Communication & Information Technology*, pp. 103-106, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[33] M. Chandrahasa, Varun Vadigeri, and Dixit Salecha, "Detection of Skin Cancer using Image Processing Techniques," *International Journal of Modern Trends in Engineering and Research*, vol. 3, no. 5, pp. 111-114, 2016. [Google Scholar]

[34] Aya Abu Ali, and Hasan Al-Marzouqi, "Melanoma Detection using Regular Convolutional Neural Networks," *International Conference on Electrical and Computing Technologies and Applications*, pp. 1-5, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[35] M. Koteswara Rao, K. Veera Swamy, and K. Anitha Sheela, "Advanced Machine Learning Discriminant Analysis Models for Face Retrieval System," *2nd International Conference on I-SMAC (IoT in Social Mobile Analytics and Cloud) (I-SMAC)*, pp. 609-613, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[36] Seema Kolkur, and D. R. Kalbande, "Survey of Texture based Feature Extraction for Skin Disease Detection," *International Conference on ICT in Business Industry & Government*, pp. 1-6, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[37] Sakil Ahammed et al., "An IoT-based Real-Time Remote Health Monitoring System," *International Journal of Recent Engineering Science*, vol. 8, no. 3, pp. 23-29, 2021. [Google Scholar] [Publisher Link]

[38] Lincy Vincent, and J Roopa Jayasingh, "Comparison of Psoriasis Disease De-Tection and Classification through Various Image Processing Techniques-A Review," *6th International Conference on Devices Circuits and Systems*, pp. 122-124, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[39] Alaa Haddad, and Shihab A. Hameed, “Image Analysis Model for Skin Disease Detection: Framework,” *7th International Conference on Computer and Communication Engineering*, pp. 1-4, 2018. [CrossRef] [Google Scholar] [Publisher Link]
[40] R. Kavitha et al., “Cardiovascular Disease Prediction using LSTM Algorithm Based on Cytokines,” *4th International Conference for Emerging Technology*, Belgaum, India, pp. 1-5, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[41] Yujun Yang, Jianping Li, and Yimei Yang, “The Research of the Fast SVM Classifier Method,” *12th International Computer Conference on Wavelet Active Media Technology and Information Processing*, pp. 121-124, 2015. [CrossRef] [Google Scholar] [Publisher Link]
[42] Shamim Ahmed et al., “Human Skin Diseases Detection and Classification using CNN,” *International Conference on Electrical, Computer and Communication Engineering*, Chittagong, Bangladesh, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]