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A Comprehensive Review on Different Types of Skin Cancer and Effective Detection Methods

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Abstract**:** In the fast moving global scenario and the increasing burden almost in every part of life due to various circumstances, the inhibition of cancer is inevitable to lead the furthermost substantial health encounters of the 21st century. Therefore, creating specialized healthcare systems and though high standard education is absolutely required in these days, it is highly instrumental to provide self-awareness to the every human being even from the very beginning where we start providing the formal education. Based on the cancer statistics come out in these days, wherein we can drastically focus on early diagnosis and whereby we can reduce the mortality rate of our precious human kind, from the research and developments.

Keywords**:** Melanoma skin cancer, classification, image analysis, effective, detection, multispectral.

1. Introduction

Skin cancer is the uncharacteristic growth of abnormal cells in the epidermis, the outermost skin layer, caused by unrepaired DNA damage that triggers mutations. These mutations lead the skin cells to multiply rapidly and form malignant tumors. The main types of skin cancer are Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and melanoma and Merkel Cell Carcinoma (MCC). Other Types includes Kaposi sarcoma, cutaneous lymphoma, and Skin adnexal tumors.

2. Survey Reports

Skin cancers are the most shared clusters of cancers detected worldwide, with approximately more than 1.50 million new cases estimated in the year 2022. In 2022, an estimated 330000 new cases of melanoma skin cancer were identified all-inclusive and almost 60000 people deceased from this fatal one. There are large geographical differences in melanoma occurrence rates across countries and world provinces. In most of the countries, melanoma occurs more frequently in men than in women.

A new study in the year 2022 forecasts that the number of new cases of cutaneous melanoma per year will surge further by more than 50% from 2020 to 2040. Although many cases are preventable, cutaneous melanoma remains the most serious type of skin cancer and accounts for approximately 1 in 5 skin cancers. Skin cancers are the most common groups of cancers diagnosed worldwide. In 2020, an estimated 325000 new cases of melanoma were diagnosed worldwide and 57000 people died from the disease. The maximum

Occurrence rates per 100000 cases were detected in Australia and New Zealand (42 in men and 31 in women), followed by Western Europe (19 in both men and women), Northern America (18 in men and 14 in women), and Northern Europe (17 in men and 18 in women). On the basis of global population changes, the scientists estimated that more than 500000 new cases of melanoma per year and almost 100000 deaths from melanoma should be expected worldwide by 2040.

2.1 The Encumbrance of Skin Cancer Worldwide

Skin cancer poses a significant encumbrance on individuals and healthcare systems worldwide. Here are some key points about the burden of skin cancer.

Skin cancer is the most commonly diagnosed cancer, with over 5.6 million cases annually in the United States alone. This places a substantial burden on healthcare resources. Non-melanoma skin cancers like basal cell and squamous cell carcinomas are the most prevalent, but melanoma is the most deadly, causing the majority of skin cancer deaths. Incidence rates for both melanoma and non-melanoma skin cancers have been rising significantly over the past several decades, likely due to increased UV exposure from the sun and tanning beds. This trend is expected to continue. Skin cancers often occur on sun-exposed areas like the head and neck, which can lead to significant morbidity and disfigurement during diagnosis and treatment. This impacts quality of life. Skin cancer disproportionately affects fair-skinned populations. Individuals with light skin, poor immune function, and a history of sunburns are at higher risk.

In summary, the encumbrance of skin cancer is multifaceted it is the most common cancer, has rising incidence, can be disfiguring, and imposes a major economic burden on healthcare systems. Continued research into prevention, early detection and treatment is crucial to mitigate this growing public health challenge.

An estimated number of new skin cancer cases in India for 2022 was 1,413,316. This includes both melanoma and non-melanoma skin cancers. The age-standardized incidence rate

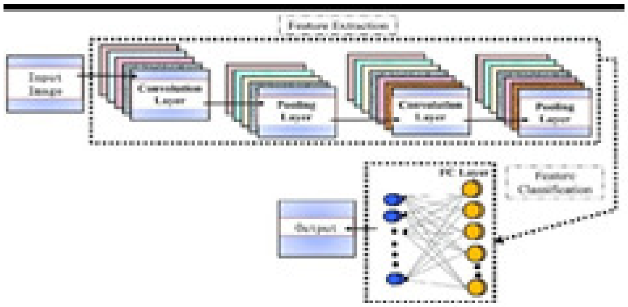

Figure 1. CNN working structure

was 98.5 per 100000 population. Non-melanoma skin cancers like squamous cell carcinoma and basal cell carcinoma are more common than melanoma. Incidence rates appear to be increasing in India. Skin cancers are more common in males compared to females. The overall cancer incidence in India was projected to rise from 1.46 million cases in 2022 to 1.57 million in 2025, an increase of 12.8%. This trend is likely to impact skin cancer rates as well.

In nutshell, skin cancer remains a significant public health concern in India, with rising incidence rates and a substantial disease burden. Improved surveillance and preventive measures are needed to curb this growing setback.

3. Testing and Diagnosing Technologies for Early Detection of Skin Cancer

The emerging technologies for early detection of skin cancer include non-invasive tools like total body photography, Reflectance Confocal Microscopy (RCF), Deep Learning Techniques and Artificial Intelligence (AI) algorithms. These technologies aim to improve diagnostic accuracy, reduce unnecessary biopsies, and enhance monitoring of skin lesions over time. RCF, for instance, offers high-resolution images aiding in diagnosing melanocytic lesions more effectively than dermoscopy. AI and machine learning algorithms show promise in enhancing early skin cancer diagnosis, with reasonable diagnostic accuracy for melanoma, squamous cell carcinoma, and basal cell carcinoma.

Deep learning techniques play a crucial role in detecting skin cancer by enhancing accuracy and efficiency. These methods, particularly Convolutional Neural Networks (CNNs), excel in analyzing healthcare images like skin lesions, aiding in precise classification of cancerous and non-cancerous lesions. By automating feature extraction and classification, deep learning models improve diagnostic accuracy, reduce subjectivity, and offer a promising avenue for advancing skin cancer detection methodologies.

There were so many results via various tactics presented and conversed with regard to several segmentation process, different algorithms and architectures were used to achieve those stated.

Ronneberger et al. [1], applied u-net to a cell segmentation task in light microscopic images as part of the ISBI cell tracking challenge and achieved an average "intersection over union" of 92%. It follows a architecture of a 3x3 convolutional network, each followed by a ReLU. Here the CNN proves a supremacy.

Abbadi et al. [2], the diagnosis of cancer was measured based on total dermoscopy score (TDS) under the ABCD Rule, and for calculating the final score the formula TDS=[(A score x 1.3) + (B score x 01) + (C score x 0.5) + (d score x 0.5)] there were 220 images were used, 113 images are cancer and 107 images are non-cancer, ultimately, if the TDS score is less than 4.75, it is interpreted 'benign melanocytic lesion' and if the TDS is greater than 5.45, the conclusion is 'lesion highly suspicious melanoma'. Accuracy reached to 95.45%. A=Asymmetry=border, C=colour, D=diameter. The pathway to the multilayer spectrum way for detecting skin cancer diagnosis.

Haenssle et al. [3] Google's inception v4 Convolutional Neural Networks architecture was trained and validated using dermoscopic images and corresponding diagnoses are used and the CNN's performance was compared with the top-five algorithms of the 2016 International Symposium on Biomedical Imaging (ISBI) challenge. The main outcome measures are sensitivity, specificity and Area Under the Curve (AUC) of Receiver Operating Characteristics (ROC). For diagnostic classification of lesions by the CNN. In the II level diagnostic performance, the CNN sensitivity is 88.9% and specificity curve is 82.5%, which are significantly higher than the dermatologist's findings. The study reveals that the results of this study demonstrate the adequately trained deep learning CNN is highly capable of accurate diagnostic classification of dermoscopic images of melanocytic origin. Here CNN was focused.

Perez et al. [4] all data comes from the ISIC Challenge 2017 dataset. They evaluate the factors that affect the choice of CNN architecture for skin lesion analysis. They evaluate 13 factors over 9 architectures on 5 sets of splits created on the ISIC 2017 classification Challenge dataset. The performance of simple ensemble schemes, contrast them to single-model performance are also evaluated.

Mou et al. [5] presented distributed deep learning approaches on the ISIC 2019 dataset. They use the mean accuracy for the internal evaluation during the training process and the mean accuracy 2 and the mean recall 1(as known as mean sensitivity) for the final evaluation on the test dataset. To deal with the problem of various image resolutions, center cropping strategy are used. The cropping images are then resized in the resolution of 256x256 as the fixed size fed into CNNs. ResNet that have been pre-trained on the ImageNet.

Chandy et al. [6], after obtaining the region of interest of the image the processed images are ready to go through classification to predict the output, they use CNN, RNN and LSTM, after preprocessing and segmentation, They obtain 96.06% accuracy when they use CNN. CNN stressed.

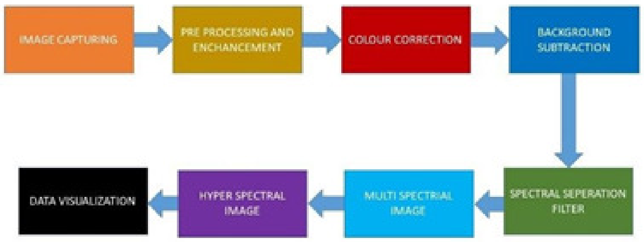

Figure 2. Building block diagram of the proposed methodology

Vega-Huerta et al. [7] use SIIM-ISIC dataset for their proposed study, where, a model was built consisting of a 3-dimensional input layer, a base architecture, a Pooling layer, and Dense layer. It is proposed to train on 7 different convolutional neural network architectures via EfficientNet B4, EfficientNet B5, EfficientNet B6, InceptionV3, ResNet50, ResNet110, VGG19. Seven. Height, width are measured with the 7 input layers. It is also proposed to validate in 3 scenarios the performance of the application of the "Data Augmentation" and "K-Fold" techniques with five folds.

Salma et al. [8] have classified skin lesions whether beningn or malignant, different by using pretrained CNNs networks such as VGG-16, ResNet50, ResNetX, InceptionV3 and MobileNet. Here a new approach based on morphological filtering is investigated to remove the hair from the skin images by using two steps, first, the colour images are converted into grayscale versions using the weighted process, wherein the grayscale image is obtained from the RGB colour space by the relation: grayscale=0.3R+0.59G + 0.11B. Morphological black-hat transformation is used to recognize contour of the grayscale images, and at last, inpainting function is used to generate façade centered on Fast-Marching Method (FMM). Segmentation is automatically done by using Grab-cut-segmentation technique, wherein boundary region is identified. Using Gaussian Mixture Model (GMM) is used to extract the fore ground region. Jaccard Coefficient (JC) is used for valuation metrics. For skin lesion identification the ABCD rule is used. Here the pretrained CNN architecture is in the picture to receive the ABCD dermoscopy image. To enhance the system it is further combined with the kernel SVM classifier. This ResNet50 CNN architecture with SVM for skin lesion classification is compared with other similar 16 recent systems. CNN architectures proved better.

Krishnan et al. [9] state that CNN architecture is unique to the effect that it makes them highly effective in tasks for image classification and recognition, based on the this study where both SVM and Deep Neural Networks are utilized for classification techniques using ISIC skin image dataset.

Rahman et al. [10] again uses the CNN's architecture such as NASNet using images included in ImageNet dataset, for design and neural architecture search method. The lightweight network NASNetMobile, where it searches approach to look through tiny picture datasets for most effective convolutional layers or cells.

Singh et al [11] precisely focused on a comprehensive study on Convolutional Neural Networks at the beginning of the study. Also it is stated that advanced deep learning architectures such as DNN, CNN, LSTM, and RNN, have demonstrated notable success in the detection and classification of cancer cells including those associated with skin cancer. A comprehensive Analysis of Employing K- Nearest Neighbour in the Detection of Skin Cancer also well explained. Those the above mentioned architectures work well, and shows superior performance with the standard datasets including PH2, med-node, DermIS, DermQuest, and various retrieved from repositories such as ISIC, ISBI, among additional sources. It emphasizes the working methodology on CNNs, emerging to the promising alternatives to traditional machine learning methods, taking into consideration its effective image recognition tasks, capturing spatial hierarchies and patterns and automatically learn the relevant features.

4. Conventional Methods for Detecting Skin Cancer

Conventional methods for detecting skin cancer traditionally involved invasive techniques like biopsies. In these methods require the removal of skin for testing its malignancy. The decision is arrived on seeing the skin image primarily and its biological know-how based on laboratory experiments. Supplementary tests influence imaging tests to examine the nearby lymph nodes for signs of cancer or a procedure to remove a nearby lymph node and test it for signs of cancer (sentinel lymph node biopsy).

5. Limitations of Conventional Methods

The Conventional methods for detecting skin cancer have several limitations as given below:

a They are invasive, often requiring the removal of skin samples for biopsy testing to determine malignancy. This can be painful and leave scars.

b Accuracy depends heavily on the experience of the clinician. Differentiating between benign and malignant lesions can be challenging, leading to misinterpretation in some cases.

c Conventional techniques like photography and dermoscopy alone are not sufficient screening tools. A combination of methods is needed to resolve the limitations of each individual technique.

d There is no clear consensus on the age of onset and frequency at which screening should be performed, leading to limited data for diagnosis.

e Conventional methods have not been shown to increase melanoma survival rates, likely due to the subjective nature of the results.

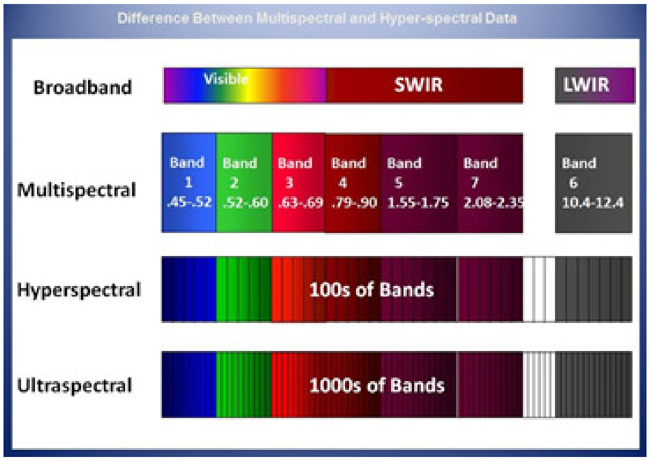

Figure 3. An illustration of multispectral image

Put a nutshell, while conventional techniques like biopsy, photography and dermoscopy are still widely used, they have significant drawbacks in terms of invasiveness, accuracy and standardization. More advanced non-invasive techniques are being developed to address these limitations.

6. Proposed Methodology

The proposed method use multi spectral image to enhance the detection threshold and improve the accuracy of the overall results.

6.1 Image Capturing

The initial step involves capturing images of the skin lesion using high-resolution cameras. This may include standard photographic images as well as multi-spectral and hyper-spectral images to capture a wide range of wavelengths and detailed information about the lesion.

6.1.1 Image Capturing Algorithm

Utilize automated image capture protocols to ensure consistent imaging conditions. Implement image stabilization algorithms to avoid blurring.

6.1.2 Tools

High-resolution cameras (e.g., DSLR, smartphone cameras with macro lenses). Multi-spectral and hyper-spectral imaging systems (e.g., SPECIM IQ). Image stabilization software (e.g., OpenCV).

6.2 Pre-Processing and Enhancement

The captured images often contain noise and imperfections that can affect the accuracy of the analysis. Pre-processing techniques, such as diagnosing, contrast enhancement, and sharpening, are applied to improve image quality and make key features more distinguishable

6.2.1 Pre-Processing and Enhancement Algorithm

Apply Gaussian blurring for noise reduction. Use histogram equalization to enhance contrast. Employ sharpening filters (e.g., Laplacian filter) to enhance edges.

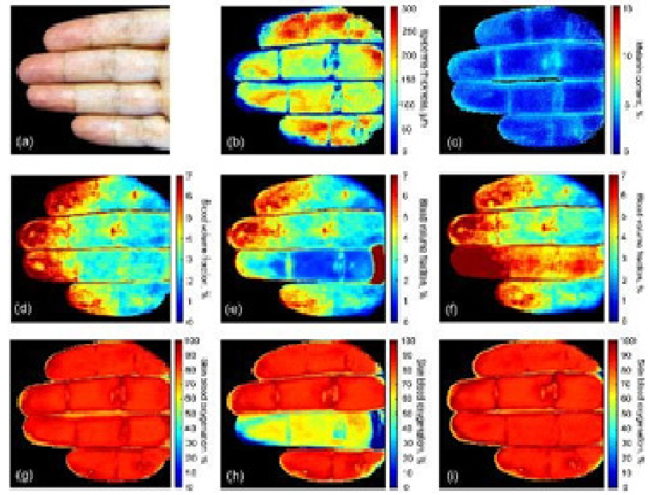

Figure 4. Multi-spectral image picture

6.2.2 Tools

Apply Gaussian blurring for noise reduction. Use histogram equalization to enhance contrast. Employ sharpening filters (e.g., Laplacian filter) to enhance edges.

- Open CV for image processing.
- MATLAB or Python (with libraries such as scikit-image, PIL).

6.3 Colour Correction

Consistent and accurate color representation is crucial for analyzing skin lesions. Colour correction techniques adjust the images to standardize the color properties, ensuring that variations in lighting and camera settings do not affect the diagnostic process.

6.3.1 Colour Correction Algorithm

- Implement White Balance adjustment.
- Use colour constancy algorithms (e.g., Gray World, Retinex).

6.3.2 Tools: Colour Correction Algorithm

OpenCV for colour correction functions. ImageJ with colour correction plugins.

6.4 Background Subtraction

To focus on the skin lesion, background subtraction is used to remove irrelevant parts of the image. This step isolates the lesion from the surrounding skin, enhancing the accuracy of subsequent analyses by eliminating distractions and reducing computational complexity.

6.4.1 Background Subtraction Algorithm

Use thresholding methods (e.g., Otsu's method) to distinguish between lesion and background. Apply morphological operations (e.g., erosion, dilation) to refine the mask.

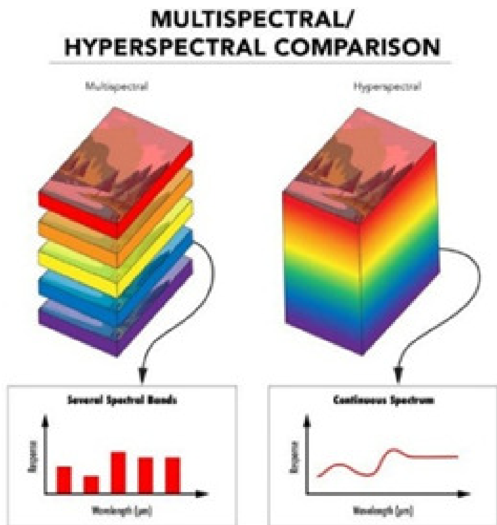

Figure 5. A comparative image of multispectral and hyperspectral images

6.4.2 Tools

Open CV for thresholding and morphological operations. MATLAB for image segmentation.

6.5 Spectral Separation Filter

This filter separates different spectral components of the image, allowing for the detailed examination of specific wavelengths. Spectral separation helps in identifying features that might not be visible in standard imaging, providing additional information about the lesion's properties.

6.5.1 Spectral Separation Filter Algorithm

Apply band-pass filters to separate different spectral bands. Use Principal Component Analysis (PCA) to reduce dimensionality while preserving spectral information.

6.5.2 Tools

ENVI software for spectral analysis. Python with scikit-learn for PCA implementation.

6.6 Multi-Spectral Image Analysis

Multispectral imaging (MSI) is a technique used to collect and analyse images from several spectral bands or wavelengths of light[12]. When applied to skin, MSI enables non-invasive, pixel-by-pixel surface measurements, making it a promising tool for in vivo skin study.

Key Aspects of Multispectral Skin Image Processing Include Acquiring spectral images of the skin at specific wavelengths, typically in the visible and near-infrared ranges[12]. Analyzing the spectral reflectance to estimate skin properties such as melanin and hemoglobin concentrations.

Using physics-based models or artificial intelligence to extract information from the spectral images [31][32]. Applying image processing techniques like spline

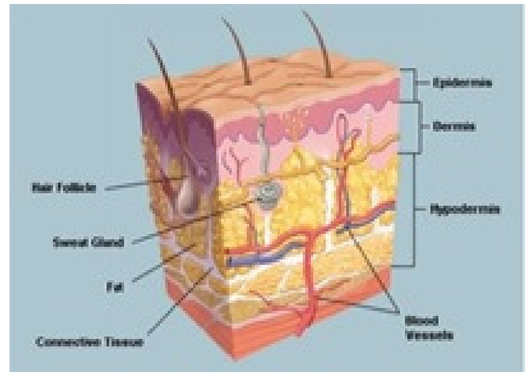

Figure 6. Multidimensional Image of a Skin Lesion

Interpolation, color feature extraction, and statistical descriptors to classify skin lesions [12]. Employing algorithms like spectral angle measure, support vector machines, and principal component analysis for automated classification of skin conditions[12]. MSI has shown potential for assessing various skin diseases, including acne, nevi, and skin cancers [12]. Recent studies have demonstrated that portable and cost-efficient MSI systems can extract characteristics useful for early melanoma diagnosis.

However, current MSI systems are still considered adjuvant tools for skin lesion assessment, and further efforts are needed to develop a fully-fledged diagnostic MSI device.

Multi-spectral imaging captures data at several specific wavelengths across the electromagnetic spectrum. Analyzing these images provides more detailed information about the skin lesion, including depth and pigment distribution.

6.6.1 Multi-Spectral Image Analysis Algorithm

Perform feature extraction on individual spectral bands. Use machine learning classifiers (e.g., SVM, Random Forest) to analyse spectral features.

6.6.2 Multi-spectral image analysis algorithm tools

ENVI or ERDAS IMAGINE for multi-spectral data processing. Python with libraries such as scikit-learn, TensorFlow.

6.7 Hyperspectral Image Analysis

Hyperspectral skin analysis is a non-invasive technique that captures detailed spatio-spectral information across a wide range of wavelengths, from visible to near-infrared, to study various aspects of human skin[12]. It combines the spectral information of diffuse reflectance spectroscopy with the spatial information of 2D imaging.

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Table 1. A Summative Statement of Different Works

S.No	Ref:	Year	Dataset Used	Algorithms Used	Results
1	[1]	2015	ISBI 2012 Cell Tracking Challenge	CNN, Application of U-Net tested	Accuracy of 77.5% achieved
2	[13]	2015	Dermoscopic Images in RGB & Grayscale	ABCD Rule	This tool is more useful for rural areas
3	[2]	2017	Dermoscopic Images	ABCD rules	95.45% accuracy achieved
4	[14]	2017	Dermis dataset of Medical images	K-means algorithm for efficient segmentation	Accuracy of 96% while combining GLCM and LBP features.
5	[15]	2017	Lloyd Dermatology and Laser Center	NN Classification	93% Accuracy for recognition of malignant type
6	[3]	2018	Dermoscopic Images	Google's inception CNN v4Architectur e.	Capable of high- accuracy detections
7	[16]	2019	ISIC Challenge on Skin Lesion Analysis	Lesion Segmentation, BACC	Better detection result
8	[4]	2019	ISIC Challenge 2017 dataset	CNN on ImageNet	Between 84 and 91%.
9	[5]	2020	BCN200 MSK HAM1000 dataset	Deep Learning Techniques. PHT Architecture	Exemplary image analysis use this case.
10	[17]	2021	ISIC-ISBI 2016 challenge with RGB Filter	OTSU thresholding	Random Forest Accuracy 93.89%
11	[6]	2022	Kaggle	CNN, RNN and LSTM tested	96.06% Accuracy in CNN
12	[10]	2023	ISIC and Kaggle	CNN-AlexNet,LeN et, and VGG-16 models	94% proved
13	[18]	2023	ISIC 2019 Dataset	CNN, ResNet50	91.70% Accuracy
14	[19]	2024	Dermoscopic images	CNN NASNet (DCNN)	Can improve Accuracy to 86.73%
15	[20]	2024	Dermoscopic images	LSVM, KNN and CNN	Three are consistently demonstrated superior performance

6.7.1 Hyper-Spectral Image Analysis Algorithm

Apply Spectral Angle Mapper (SAM) for material identification.
Use Constitutional Neural Networks (CNNs) tailored for hyper-spectral data.

6.7.2 Tools: Hyper-Spectral Image Analysis Algorithm

- ENVI for hyper-spectral image processing.
- Python with deep learning frameworks like Keras or TensorFlow.

6.8 Data Visualization

6.8.1 Data Visualization Algorithm

- Generate 2D/3D plots of spectral data.
- Create heat maps to visualize lesion characteristics.

6.8.2 Data Vistualization Algorithm Tools

MATLAB or Python (with Matplotlib, Seaborn for plotting). Visualization software like Para View or Tableau. **Summary:** Skin cancer is one of the most common malignancies worldwide, necessitating early and accurate detection methods to improve patient outcomes. Traditional diagnostic techniques, such as visual inspection and biopsy, are often limited by subjectivity and invasiveness. Multispectral and hyper-spectral imaging (MSI and HSI) offer promising non-invasive alternatives, leveraging the capability to capture a wide range of spectral information beyond the visible spectrum. This study explores the application of MSI and HSI in the detection and diagnosis of skin cancer, focusing on their potential to enhance diagnostic accuracy. Here some literature based on this technology is mentioned herewith help of comparison table When we understand from the references and the comparative statements of different studies stated here, it is obvious that different architectures, methods, algorithms were used to detect the presence of skin cancer cells/grow, using non-invasive techniques, and even then the convolutional neural networks dominate in the classification process in majority of the cases here and their accuracy level seems to be more or less as similar to that of other results. While even Biosensors [11] are used for diagnosis of skin cancer, in other cases like Neural Architectural Search [18] technique for skin cancer detection and classification are implemented.

Conclusion

Normally research focuses on non-invasive diagnostics rather than in the conventional methods due to very advancement in science and technology. Non-invasive methods for skin cancer detection can achieve comparable or even higher accuracy compared to invasive biopsies:

1) Dynamic thermal imaging (DTI) has demonstrated over 99% sensitivity and specificity for detecting skin cancer in a pilot study of 140 subjects [21]. DTI uses infrared imaging to analyse the thermal recovery of lesions after cooling.

2) Reflectance confocal microscopy (RCM) provides cellular-level resolution of skin lesions with high sensitivity (92%) and specificity (70%) for melanoma, reducing unnecessary excisions by 22- 53% [12]. RCM can also accurately detect basal cell carcinoma (sensitivity 97%, specificity 93%) and squamous cell carcinoma[12].

3) Optical coherence tomography (OCT) has 89-96% sensitivity and 60-98% specificity for basal cell carcinoma, reducing unnecessary biopsies by over 35% [14]. OCT provides high-resolution 3D imaging of lesions up to 2mm deep [12].

While we focus on skin images, various techniques for skin cancer detection have been analysed and compared in depth. From the observations, Multi-spectral and hyper-spectral imaging have emerged as promising tools for the detection and diagnosis of skin cancer. These imaging techniques offer several advantages over traditional methods by providing detailed spectral information that can differentiate between benign and malignant lesions with greater accuracy. It has majorly benefits such as wider detection range and improved detection accuracy. In conclusion, multispectral and hyper-spectral imaging represent a significant advancement in the field of dermatology, particularly for the detection and diagnosis of skin cancer. Continued research and development are essential to overcome current limitations and ensure these technologies can be effectively utilized in clinical practice, ultimately leading to better patient care and outcomes.

Declaration of Competing Interest

On behalf of my co-author, who is also the corresponding author of this study entitled “A Comprehensive Review on Different Types of Skin Cancer and Effective Detection Methods” submitted to the 13th International Hybrid Conference on Computer Engineering & Mathematical Sciences (ICCEMS 2024) scheduled from 11th and 12th July 2024 at Istanbul, Turkiye, declares that we have no conflict of interest. This work received no funding.

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