Identification Of Melanoma from Hyperspectral Pathological Image

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Abstract Melanoma is responsible for 75% of skin cancer-related deaths, but early detection and treatment offer a 99% survival rate. Traditional diagnostic methods include dermoscopic and histopathological analysis. However, existing systems rely on 2D dermoscopic images, which lose crucial features due to their limited dimensionality, reducing diagnostic accuracy. Additionally, 2D images fail to provide early-stage melanoma detection. To overcome these limitations, we propose using 3D hyperspectral pathology images, which preserve all essential features during extraction, ensuring more accurate results. Our system employs a deep convolutional network for melanoma segmentation with enhanced precision. A three-dimensional convolutional network further analyzes hyperspectral images, leveraging spectral features to improve melanoma detection. By utilizing 3D hyperspectral imaging and deep learning techniques, our approach enhances early detection and diagnostic accuracy, ultimately increasing survival rates. This advanced method significantly improves upon conventional 2D imaging systems in melanoma diagnosis and treatment planning.

***Key Words*:** Melanoma, Dermoscopic images, Segmentation, Hyper spectral images,convolution network.

1. INTRODUCTION

Image segmentation's objective of detecting unhealthy or malignant tissue in the epidermal area is crucial. Hyperspectral imaging techniques can be used to handle these tasks. In this technology, two-dimensional spatial imaging is combined with several spectral bands to get three-dimensional data. In recent years, development in HSI have led to the expansion of telemetry into a broad range of life sciences. It is possible to identify the position of melanoma and differentiate it from healthy skin epidermis using hyperspectral pathology images. An optimization of spatial information along the third dimension could be achieved by employing a 3D convolutional layer on 3D images.

A method of categorizing pixels based on their surrounding pixels is used in most studies. U-net-based architectures can be used for hyperspectral imaging segmentation. In our system, we

have used these models in the 3D medical imaging technique. In hyperspectral pathology images, skin tissue contains distinct structures. It is a big challenge to the different network architectures. At the last encoder-decoder module, we establish a twofold path for multiple feature extraction. For low-resolution applications, one of the paths uses dilated convolution. We used a 3D convolutional network for melanoma identification from hyperspectral pathology images.

2. LITERATURE REVIEW

[1] In 2018, a study conducted by T. J. Alhindi, S. Kalra, K. H. Ng, A. Afrin, and H. R. Tizhoosh compared three classification models using the KIMIA Path960 dataset. These models utilized different feature extraction methods, including the histogram of gradients (HOG), local binary pattern (LBP), and deep features extracted from the pre-trained VGG 19 network. Various classifiers, such as support vector machines (SVM), decision trees (DTs), and artificial neural networks, were trained using these feature vectors. The LBP feature extractor is commonly used in face recognition and text identification, following specific procedures outlined in Figure 2.1. HOG captures characteristics by tracking gradient orientation frequencies. In traditional HOG, the image is divided into separate cells, and a histogram of gradient orientations is computed for each cell, making it widely applicable in object and facial recognition, as detailed in Figure 2.2. VGG 16 and VGG 19 are deep convolutional network (ConvNet) architectures. Evaluating very deep networks for large-scale image classification involved five max-pooling layers that performed spatial pooling over a 2×2 pixel window with a stride of two. The network's generic architecture consisted of small 3×3 convolution filters with a fixed stride of one pixel.

[2] In 2019, Hesamian, M.H., Jia, and He X presented a comprehensive assessment of deep-learning techniques applied to segment pharmaceutical images. They provided an analysis of prominent network architectures used for image segmentation, highlighting their advantages and limitations.

The authors introduced several network architectures, such as convolutional neural networks (CNN), fully convolutional networks (FCN), U-Net, cascaded refinement networks (CRNs), and recurrent neural networks (RNNs). They also discussed advanced training methods employed in deep neural network model training, including transfer learning, deeply supervised learning, and weakly supervised learning.

The paper addressed various challenges associated with deep learning-based medical image segmentation, primarily arising from data, training, and network architecture. Difficulties encountered during training deep models include overfitting, prolonged training duration, gradient vanishing, and organ appearance. Furthermore, the study provided potential solutions from the existing literature for each problem related to network design, data, and training.

[3] In 2020, Y. Xie, J. Zhang, Y. Xia, and C. Shen addressed the simultaneous segmentation and classification of skin lesions by proposing the Mutual Bootstrap Deep Convolutional Neural Networks (MB-CNN) model. This model consists of an improved segmentation network (improved-SN), a mask-guided classification network (mask-CN), and a rough segmentation network (rough-SN).

The rough-SN generates preliminary lesion masks to assist the mask-CN in accurately locating and classifying skin lesions. Conversely, the lesion localization maps produced by the mask-CN are fed into the improved-SN to transfer localization knowledge for precise lesion segmentation. Through this iterative process, both segmentation and classification networks mutually support and exchange knowledge, following a bootstrapping approach.

[4] 2020, L. Ichim and D. Popescu proposed a novel intelligent system that combines multiple neural networks at two levels of classification.The initial level consists of five subjective classifiers: ResNet, AlexNet, a generative adversarial network (GAN) coupled with the ABCD rule for segmentation, and a perceptron connected with color local binary patterns, color histograms, and directed gradients. These classifiers were selected through an experimental process, considering various characteristics of melanomas, such as texture, shape, color, size, and pixel connections.Leveraging learning-adjusted weights and the judgments from the first level, a single perceptron-type classifier determines whether the lesion is a melanoma at the second level (objective level). The final decision—melanoma or non-melanoma—is made at this stage using a back-propagation perceptron. Separate training phases were conducted to optimize the system's performance.

[5] In 2020, C. Yu, R. Han, M. Song, C. Liu, and C.-I. Chang developed HSIC, a framework combining 2D and 3D CNNs for spatial-spectral fusion. The 2D CNN extracts spatial features, while the 3D CNN captures inter-band correlations. A deconvolution layer enhances feature reconstruction. The model achieved 97.98% accuracy, outperforming MFAST (97.49%), 2D+D (97.49%), and 2D+3D (97.10%). The best accuracy (98.33%) was obtained with the 2D-3D-D framework. Depth-wise separable convolution improved performance across four hyperspectral datasets. The study demonstrated the effectiveness of 3D convolutions and deconvolution layers in refining deep features for medical image analysis.

[6]n 2020, Kadampur and Al Riyaee applied deep learning to enhance dermatologists' ability to detect skin cancer. Their approach trained a computer system to analyze skin cancer images and identify abnormalities. They utilized Deep Learning Studio (DLS), an advanced tool with drag-and-drop components for neural network modeling. The research involved data preparation, model construction, fine-tuning, and validation. The models built with DLS demonstrated outstanding performance, achieving a high AUC of 99.77% in cancer cell detection. This study highlighted the effectiveness of deep learning in improving diagnostic accuracy for skin cancer detection.

[7] In 2020, Adegun and Viriri introduced a deep learning-based approach for automatic melanoma detection and segmentation. They proposed an enhanced encoder-decoder network with skip connections, improving feature extraction and aligning encoder and decoder feature maps. Their method employed a multi-stage, multi-scale strategy and a softmax classifier for pixel-wise melanoma classification. Based on these results, they introduced a novel technique, the Lesion-classifier, to distinguish melanoma from non-melanoma skin lesions. This approach demonstrated improved accuracy and efficiency in melanoma detection, highlighting the potential of deep learning for precise skin cancer diagnosis.

[8] In 2020, M. Goyal, A. Oakley, P. Bansal, D. Dancey, and M. H. Yap trained ensemble models based on Mask R-CNN and DeeplabV3+ using the ISIC-2017 segmentation dataset. Their performance was evaluated on the ISIC 2017 and PH2 testing datasets. The methodology began with preprocessing, including color normalization and illumination adjustment using a color constancy algorithm. DeeplabV3+, a powerful semantic segmentation network, utilized an Xception-65 encoder-decoder to generate a coarse score map, refined with a conditional random field. A pre-trained PASCAL VOC 2012 model was fine-tuned, converting 21-class outputs to a single-class for precise skin lesion segmentation

3. PROBLEM STATEMENT

As the global population ages, many elderly individuals fact Melanoma is responsible for 75% of skin cancer-related deaths, yet early detection significantly improves survival rates, with a 99% chance of recovery. Existing diagnostic methods rely on 2D dermoscopic images, which lose essential spatial and spectral features, reducing accuracy, especially in early-stage detection. To address this limitation, a 3D imaging approach is proposed, utilizing hyperspectral pathology images analyzed by a deep convolutional network. By leveraging a 3D convolutional network, the system effectively captures both spatial and spectral features, improving melanoma segmentation accuracy and enabling early detection, which is critical for timely and effective treatment

4. PROPOSED SYSTEM

After reviewing various research papers on skin cancer detection models, it became clear that existing approaches primarily rely on 2D image datasets. However, 2D images fail to capture deeper tissue structures, leading to information loss. To overcome this limitation, we propose a system utilizing 3D hyperspectral pathology images, which provide detailed spectral and spatial data across multiple layers. This enhances feature extraction and classification accuracy, aiding in early melanoma detection. Since early-stage melanoma has a 99% survival rate, using 3D images significantly improves diagnostic precision, ensuring better clinical outcomes and reducing false negatives compared to conventional 2D imaging methods.

This section presents a detailed overview of IDENTIFICATION OF MELANOMA FROM HYPERSPECTRAL PATHOLOGICAL IMAGE 6 key modules. They are given below:

1. Hyperspectral Pathological Image Acquisition:The system utilizes a Multispectral Hyperspectral Imaging MHSI system, which employs an Acousto-Optic Tunable Filter AOTF and a grayscale Charge-Coupled Device CCD camera to obtain hyperspectral images. This process allows for the collection of detailed spatial and spectral data, enabling more accurate feature extraction and early-stage melanoma detection.

2. Pre-processing :Pre-processing plays a vital role in improving image quality by reducing noise, enhancing contrast, and correcting variations in illumination. Since hyperspectral images contain multiple spectral bands, different environmental and acquisition conditions can introduce distortions. The system applies advanced color constancy techniques, including the Retinex algorithm, to normalize colors and correct lighting inconsistencies. Additionally, the images are resized to a uniform resolution to ensure compatibility with deep learning models. Principal Component Analysis (PCA) is also employed to identify and retain the most significant spectral bands, removing redundant or less informative data for efficient processing.

3. Segmentation: Segmentation is a critical step in isolating melanoma lesions from the surrounding skin tissue. The system utilizes deep learning-based segmentation models, with U-Net as the primary architecture due to its efficiency in medical image segmentation. The encoder-decoder structure of U-Net helps extract low-level and high-level features from the hyperspectral images. This segmentation process involves:

4. Feature Extraction :After segmentation, the next step is extracting spatial and spectral features that contribute to melanoma detection. Feature extraction is performed using convolutional neural networks (CNNs) such as ResNet-50 and VGG-16, which are pre-trained on large datasets. These models help in capturing:

6 Classification: Once features are extracted, the system classifies the segmented lesion as either melanoma or non-melanoma. To achieve this, multiple CNN architectures, including ResNet-50, VGG-16, and Inception V3, are implemented and compared to determine the most accurate model. These deep learning models analyze the extracted features and learn patterns associated with melanoma, ensuring precise classification. The classification process consists of

7. Performance Metrics Calculation : The evaluation module measures the accuracy and efficiency of the melanoma detection system by comparing predicted results with ground truth labels. It uses statistical and mathematical methods to quantify the effectiveness of segmentation and classification. The performance is assessed using four key metrics

RESULTS AND DISCUSSION

The proposed melanoma detection system using 3D hyperspectral pathology images was evaluated based on segmentation and classification accuracy. U-Net was employed for segmentation, effectively isolating melanoma regions, while classification was performed using ResNet-50, VGG-16, and Inception V3 models. Among these, ResNet-50 demonstrated the highest accuracy, leveraging deep residual learning.

The system was assessed using performance metrics such as Dice Similarity Coefficient, Sensitivity, Specificity, and Matthews Correlation Coefficient. The Dice score indicated high segmentation precision, while sensitivity and specificity values confirmed minimal false positives and false negatives. Compared to traditional 2D dermoscopic imaging, the 3D hyperspectral approach significantly improved melanoma detection, particularly in early-stage cases.

These findings highlight the superiority of 3D imaging in medical diagnostics, offering enhanced feature extraction and deeper tissue analysis. The results validate the system's potential for clinical integration, enabling early and accurate melanoma detection to improve patient outcomes.

The Home Page of Identification Of Melanoma From Hyperspectral Pathological Image where the participants can Register and Admins can log in.

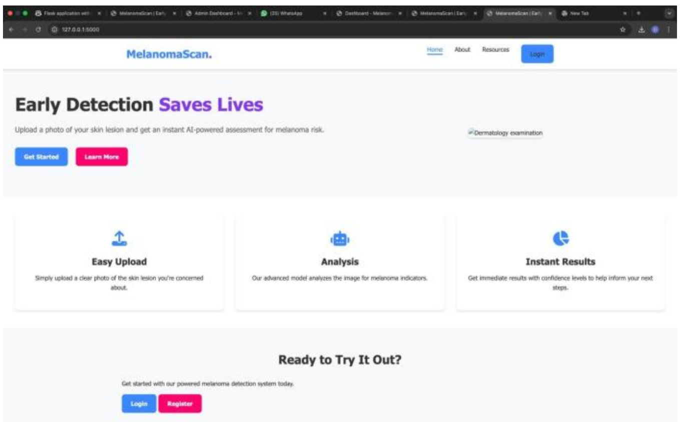


Fig 2: Home Page

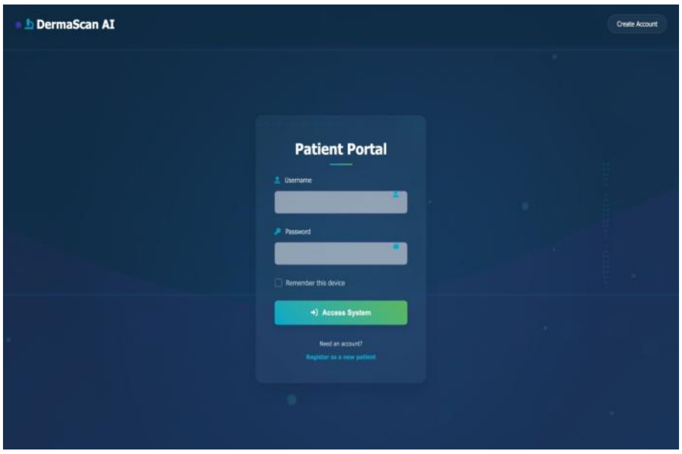


Fig 3: Login Page

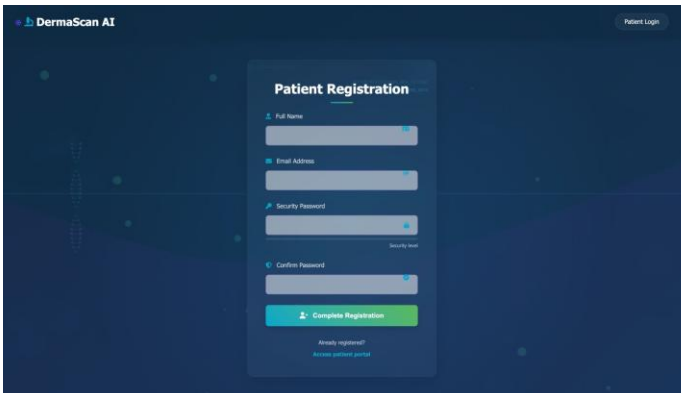
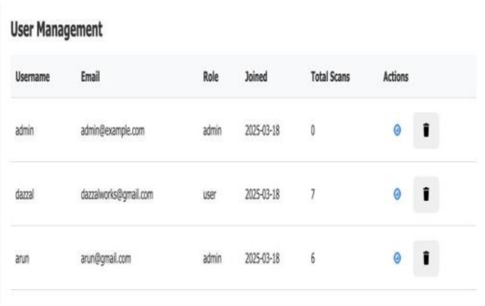


Fig 3: Registration Page



User Management

Username	Email	Role	Joined	Total Scans	Actions
admin	admin@example.com	admin	2025-03-18	0	
dazzal	dazzalworks@gmail.com	user	2025-03-18	7	
arun	arun@gmail.com	admin	2025-03-18	6	

Fig 4: user management Page

In the dashboard section, users will be to see their registered events. They will be able to see the Team wise participation, the venue and time details.

Fig 5: Dashboard Page

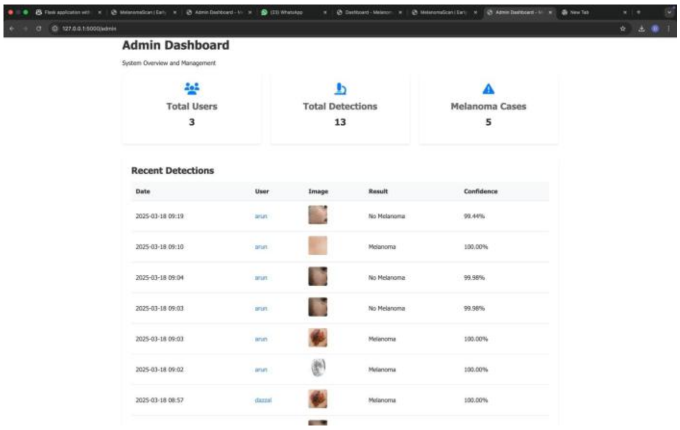


Fig 6: Admin Page

In the Admin Dashboard Page, the admins can view the total participants, total events live, total registrations.

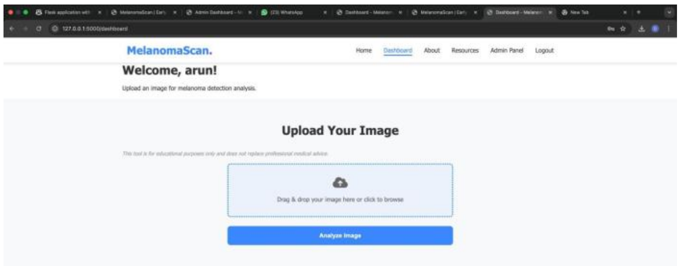


Fig 7: Analysis Page

6. CONCLUSION

Our project demonstrated that a 3D convolutional neural network (CNN) can effectively differentiate melanoma from other pathological tissues in hyperspectral images, aiding pathologists in diagnosis. Under 10X and 20X magnification, melanoma was distinguished with over 92% accuracy. By modifying the loss function, we enhanced diagnostic sensitivity, reducing false positives and false negatives. Comparisons with 2D CNN models confirmed that hyperspectral images offer superior tissue-specific features, improving segmentation. Future work involves refining the MHSI system by expanding spectral range and improving channel quality. Further research and validation are needed before clinical implementation, ensuring accuracy and reliability.

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