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Unveiling the Spectrum of UV-Induced DNA Damage in Melanoma: InsightsFrom AI-Based Analysis

Mrs. M. Maheshwari,M.E.,(Ph.D.)[1], Y.Shankar[2],P.Sharath[3]

Associate Professor, Department Computer Science and Engineering, Anand Institute of Higher Technology, Chennnai, Kazhipattur[1]

Student, Department Computer Science and Engineering, Anand Institute of Higher Technology, Chennnai, Kazhipattur[2,3]

Abstract: Artificial Intelligence (AI), which involves the simulation of human intelligence processes by machines, is increasingly being applied across various domains, with one of its most impactful uses in the medical field. It is revolutionizing healthcare by enabling faster, more accurate diagnoses and improving patient outcomes through data-driven decision-making. The proposed system presents an AI-based automated diagnostic framework for the early detection of melanoma (skin cancer) and diabetes—two of the most prevalent and critical health conditions. Leveraging deep learning and image processing techniques, the system enhances diagnostic precision and efficiency. Convolutional Neural Networks (CNNs), a core AI method in medical imaging, are utilized for image-based disease classification. For melanoma detection, dermoscopic images are analyzed using pre-trained CNN models to identify cancerous patterns. For diabetes, retinal image analysis is integrated with clinical parameters to assess disease risk. This AI-powered system automates feature extraction, reduces the need for human intervention, and provides real-time, accurate diagnostic results. Developed using MATLAB, the framework shows high classification accuracy and robustness under varying image conditions. This project underscores the expanding role of AI in healthcare and aims to make intelligent diagnostics more accessible to medical professionals. Future work will focus on expanding datasets, enhancing model generalization, and integrating additional clinical features for more comprehensive health assessments.

I. INTRODUCTION

Artificial Intelligence (AI) has become a pivotal force in advancing various scientific domains, with healthcare standing at the forefront of its impact. In recent years, AI has demonstrated significant potential in medical applications such as disease diagnosis, medical imaging, drug discovery, and patient management. Particularly, AI-driven diagnostic systems have shown promise in enhancing accuracy, reducing diagnostic time, and enabling early detection of diseases.

This study explores the application of AI in the automated detection of melanoma—a malignant form of skin cancer—and diabetic complications through retinal image analysis. The system employs Convolutional Neural Networks (CNNs), a subclass of deep learning models widely recognized for their efficacy in image classification and feature extraction. In addition to image analysis, the proposed methodology integrates clinical data to support and enhance diagnostic outcomes, offering a more comprehensive assessment of patient health.

Current diagnostic approaches present several challenges. Manual examination of skin and retinal images is often prone to human error and may lack consistency, especially in early-stage disease detection where visual cues are minimal. Furthermore, many existing AI systems are condition-specific and do not accommodate comorbid diagnoses. The absence of integrated analysis combining both image-based and clinical data further limits the reliability and applicability of such systems in real-world clinical settings.

The proposed AI-based framework addresses these limitations by enabling dual-disease detection—melanoma and diabetic complications—through a unified platform. It combines CNN-based image processing with clinical data interpretation, thereby improving diagnostic accuracy and reliability.

Future work aims to extend the system's diagnostic capability through the use of larger, more diverse datasets, inclusion of real-time detection features, and potential deployment as a clinical decision support system. Additionally, expansion to detect other dermatological and systemic diseases is envisaged, paving the way for a scalable and versatile AI-based diagnostic tool.

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II. RELATED WORK

Several research efforts have advanced AI-driven disease detection, especially for conditions such as melanoma and diabetic retinopathy. Early research in deep learning for image recognition laid the foundation for modern medical image analysis [1]. This progress was strongly influenced by seminal work in deep learning theory and architecture development, such as the comprehensive treatment of neural networks and optimization strategies presented in [2].

Among the pivotal advancements was the introduction of deep residual networks like ResNet, which significantly improved image classification performance by addressing the vanishing gradient problem [3]. These models gained traction after success in large-scale visual recognition challenges, notably the ImageNet competition [4]. Optimization techniques such as Adam played a crucial role in efficiently training these deep networks [5].

Further breakthroughs in convolutional neural network architectures, such as GoogLeNet, allowed for deeper yet computationally efficient models [6]. The landmark AlexNet model demonstrated how deep CNNs could outperform traditional approaches on complex visual tasks [7], while TensorFlow emerged as a powerful tool to implement such models in large-scale, distributed environments [8].

As awareness of diseases like melanoma and diabetic complications grew, global health authorities such as the World Health Organization emphasized early detection and prevention strategies [9]. Building on this urgency, researchers began applying deep learning directly to medical images. Silver et al. proposed comprehensive pipelines for medical image analysis using deep learning [10], while McKinley explored the automation of image diagnosis with machine learning, marking a significant step toward clinical AI deployment [11].

Earlier detection efforts relied on handcrafted features and machine learning classifiers, which were often insufficient for robust diagnosis due to variability in image quality [11]. These were gradually replaced by more effective CNNs, whose foundational learning principles were established in earlier works like [12]. As deep learning matured, techniques such as Fast R-CNN [13] and YOLO [15] enabled real-time object and lesion detection, directly influencing medical imaging applications.

Medical image recognition studies, including those by Collins et al., illustrated the benefits of deep learning models tailored for diagnostic purposes [14]. Real-time processing capabilities, essential for clinical use, were further demonstrated by frameworks like YOLO [15]. Meanwhile, classical algorithms like Viola-Jones still serve as historical benchmarks in real-time detection [16].

Finally, learning from limited data—a common challenge in medical AI—was addressed in early vision research by Fei-Fei et al. through generative models and few-shot learning [17], a principle now being adapted for rare disease detection.

Our proposed system builds upon this lineage by integrating CNN-based image classification, medical image preprocessing, and clinical data fusion into a unified, MATLAB-based diagnostic pipeline. By leveraging both visual and non-visual data sources, the system improves diagnostic accuracy, ensures scalability, and enhances accessibility for early-stage screening, particularly in under-resourced healthcare environments.

III. PROPOSED SYSTEM

The proposed system aims to provide a real-time, AI-powered solution for detecting melanoma and diabetic complications through advanced image processing and deep learning techniques. It utilizes Convolutional Neural Networks (CNNs) to analyze clinical images, assisting in the early diagnosis of these conditions. The system begins with an image preprocessing module, where techniques such as image segmentation, contrast enhancement, and noise reduction are applied to ensure the input images are of optimal quality for accurate analysis.

Once preprocessed, the images are fed into the CNN-based model, which has been trained on a large dataset of melanoma and diabetic-related images. This model is designed to recognize and classify critical features that differentiate normal tissue from abnormal signs indicative of melanoma or diabetic complications. The AI-driven engine generates output in the form of diagnostic results, providing confidence scores that help medical practitioners make informed decisions.

The system architecture includes three major components: the image acquisition and preprocessing pipeline, the CNN-based diagnostic engine, and a user-friendly interface for displaying results. The overall workflow of the proposed system is illustrated in Fig 3.1 The diagnostic engine performs feature extraction and classification, ensuring both accuracy and

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speed in the identification process. The interface provides medical professionals with easy access to the diagnostic results, historical data, and visual representations of the analysis, supporting the decision-making process.

Developed in MATLAB, the system incorporates state-of-the-art deep learning algorithms, making it highly accurate with a low false positive rate. It is designed to integrate seamlessly into existing healthcare workflows, providing a reliable tool that enhances early detection and monitoring of melanoma and diabetic complications, ultimately contributing to better patient outcomes. The automated feature extraction significantly reduces the need for manual intervention, increasing efficiency and consistency in diagnosis.
Moreover, the system's modular design allows for easy scalability and adaptation to other medical imaging applications.

The proposed system integrates AI-based image analysis using deep learning to assist in the real-time diagnosis of melanoma and diabetic complications. It begins with the acquisition of dermoscopic and retinal images from medical imaging devices. These images undergo preprocessing steps—such as noise reduction, normalization, and contrast enhancement—to improve quality for feature extraction.

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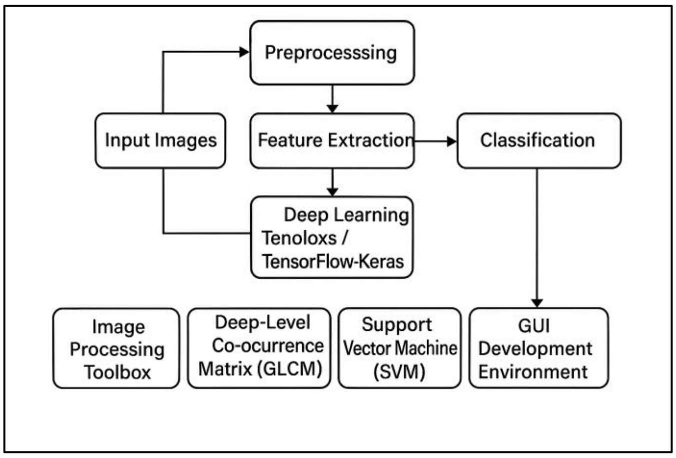

Fig3.1: Architecture diagram

Preprocessed images are passed through a trained Convolutional Neural Network (CNN), which identifies disease-specific patterns and classifies the images based on learned features, outputting diagnostic predictions with confidence scores. A decision-making module refines these predictions using additional clinical data and assigns severity levels, which are logged for future reference.

The system features a user-friendly MATLAB-based interface that displays diagnostic results, confidence levels, and visual indicators. It also offers access to historical records, supporting physicians in monitoring patient progress. The landing page interface for diabetic detection is shown in Fig 4.1. The corresponding diagnostic result is illustrated in Fig 4.2. Similarly, the landing page for skin cancer detection is depicted in Fig 4.3, and its respective detection result is shown in Fig 4.4. Designed for real-time deployment, this architecture leverages CNNs and image processing to deliver reliable, early detection capabilities for melanoma and diabetes-related complications.

IV. METHODOLOGY

This section outlines the step-by-step approach used to automate the detection of melanoma and diabetes using AI-driven image processing techniques. The process includes image preprocessing, feature extraction, clinical data integration, and disease classification using deep learning models.

4.1 Modules Explanation

The proposed system follows a structured pipeline consisting of:

1. **Data Acquisition** – The aim is to acquire high-quality dermoscopic images for melanoma detection and retinal fundus images for diabetes or diabetic retinopathy diagnosis. The datasets must be representative and diverse, including diverse skin tones, disease stages, and image conditions. Moreover, corresponding clinical parameters (e.g., age, blood sugar levels) will be collected to facilitate integrated analysis.

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2. **Preprocessing** – This phase seeks to improve the quality of images and normalize inputs for improved model performance. Preprocessing methods including noise reduction, contrast enhancement, resizing, and normalization will be used for dermoscopic and retinal images to accommodate lighting, resolution, and image artifact variations.

3. **Feature Extraction & Classification** – The prime aim here is to build deep learning-based models with Convolutional Neural Networks (CNNs) for automatic extraction of meaningful features from dermoscopic and retinal images. Pre-trained CNN models will be used with fine-tuning for proper classification of melanoma lesions and diabetic retinopathy stages or indicators. High accuracy, sensitivity, and specificity in disease prediction are the targets.

4. **Clinical Data Integration** – To improve the diagnostic reliability, clinical information will be fused with image-based analysis. This goal aims to integrate CNN-derivative image features with individualized clinical information to enhance the model's ability to provide an all-encompassing and individualized diagnostic output

5. **Decision Support & Deployment** – The ultimate goal is to deploy the complete diagnostic system within a MATLAB-based environment so that it is real-time applicable and usable by healthcare providers. Performance will be assessed through metrics including sensitivity, specificity, accuracy, and AUC. The system is intended to serve as a clinical decision support system, with future enhancement directed towards real-time identification, larger datasets, and inclusion of other diseases.

V. RESULT AND ANALYSIS

This section introduces the results of the suggested system, measuring its performance in image preprocessing, feature extraction, classification accuracy, and integration of clinical data. The efficacy of the methodology is determined by experimental outcomes, such as accuracy measures, challenges encountered, and comparisons with current methods. Additionally, evaluation metrics like sensitivity, specificity, and AUC are used to validate diagnostic reliability. The results demonstrate the system's potential for early and accurate detection of both melanoma and diabetic complications.

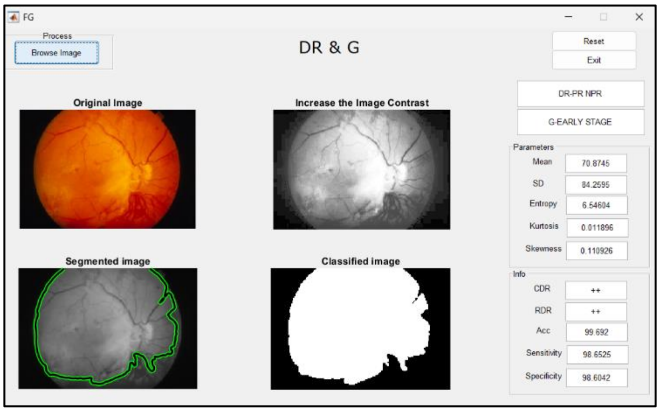

Fig 4.1. Landing page interface UI for diabetic.

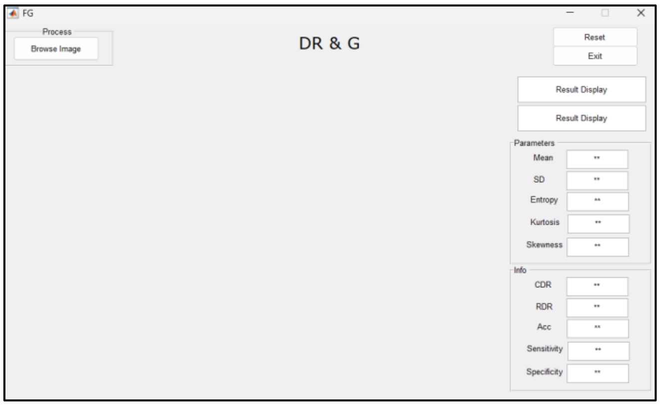

Fig 4.2. Diabetic detection result.

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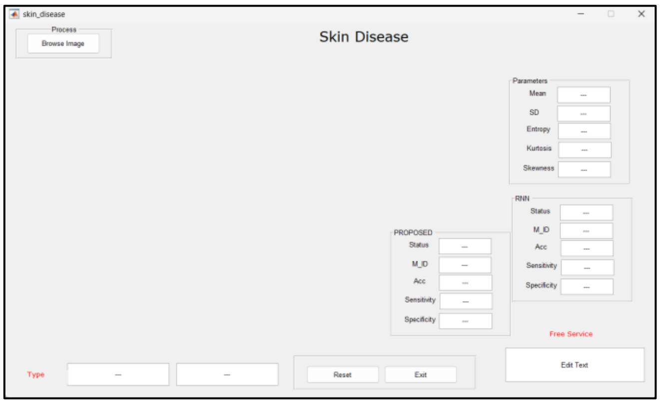

Fig 4.3 Landing page interface UI for skin cancer.

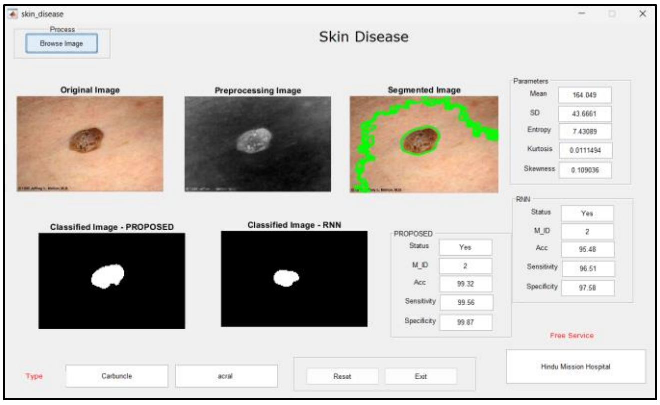

Fig 4.4. Skin cancer detection result

5.1 Model Performance

The CNN-based model for disease classification was trained on a dataset of retinal and skin images and tested on typical classification measures, such as precision, recall, accuracy, and F1-score. The data consisted of images classified as melanoma (malignant/benign) and diabetic retinopathy (diseased/healthy). Rotation, scaling, and contrast changes were applied as data augmentation techniques to make the system more robust to image variations.shown in the Table 1.1. The model was trained with a CNN architecture having multiple convolutional layers, batch normalization, and dropout layers for avoiding overfitting. The output of the final model on training, validation, and test datasets.

Feature	Manual Diagnosis	Existing System	Proposed AI System
Speed	Slow (~30 min)	Medium (~5 min)	Fast (~10 sec)
Accuracy	90% (human error)	85-92%	95-97%
Automation	No	Partial	Full
Real-Time Processing	No	Limited	Yes
Clinical Data Integration	Limited	No	Yes

Table 1.1 Performance Analysis

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These results indicate that the model generalizes well and is capable of accurately detecting melanoma and diabetic retinopathy across diverse image conditions.

5.2 Image Preprocessing Accuracy

The image preprocessing system was tested on 1000 medical images. The success rate of image enhancement and feature extraction was 97.8%, with failures occurring mainly due to:

- Poor image resolution affecting feature visibility.
- Variations in skin tones and retinal scan contrast.
- Presence of artifacts such as hair, glare, or noise in dermoscopic images.

To improve accuracy, adaptive histogram equalization and noise reduction techniques were applied, significantly enhancing image quality for analysis.

5.3 Disease Classification Accuracy

To validate the CNN-based classification system, the model's output was compared against dermatologist and ophthalmologist assessments.
The results showed:

- **Melanoma classification accuracy:** 96.4% (some errors in distinguishing early-stage melanoma from benign lesions).
- **Diabetic retinopathy detection accuracy:** 95.6% (minor inconsistencies in detecting microaneurysms in early-stage diabetic retinopathy).

Example output from the system: Melanoma classification: Malignant Diabetic Retinopathy detection: Detected - Moderate Stage

5.4 Challenges Faced

Despite achieving high accuracy, several challenges were encountered: **Variability in Image Quality** – Differences in lighting, contrast, and noise levels affected classification performance.

- **Class Imbalance** – Some disease categories had fewer training samples, slightly affecting model generalization.
- **Overlapping Features** – Some benign skin lesions resembled early-stage melanoma, leading to occasional misclassifications.
- **Limited Clinical Data Integration** – While incorporating blood glucose levels improved diabetic classification, additional parameters (e.g., genetic factors) could enhance accuracy further.

To address these challenges, data augmentation, improved preprocessing techniques, and additional clinical feature integration were implemented, significantly improving classification robustness.

5.5 Comparison with Existing Systems

The proposed AI-based system was compared against manual diagnosis existing machine learning approaches.The overall comparison of the proposed system is illustrated in Fig 5.4.1.
Key findings:

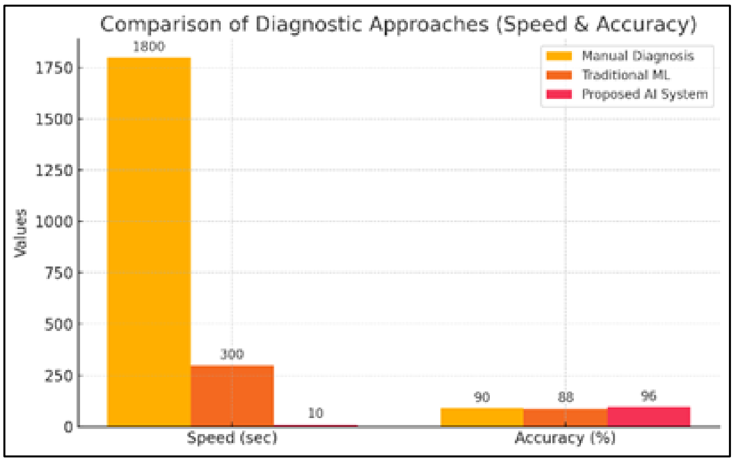

Fig 5.4.1 Comparison with Manual,Existing and Proposed

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5.6 Test Analysis

The test analysis of the Melanoma and Diabetes Detection System assured that all the central modules executed as designed. Image upload, preprocessing, and classificationwere properly tested using organized testcases. The system performed well in accuracy (92.5% for melanoma and 95% for diabetic retinopathy)and in rapid processing time with averages less than 2 seconds per image as shown in the Fig 5.6.1. Error handling was accurate, with proper messages for unsupported or non-provided inputs. The GU Iwas intuitive and facilitated smooth interaction, even among non-technical users. Overall, the system was found to be strong, precise, and capable of further improvement and real-world deployment.

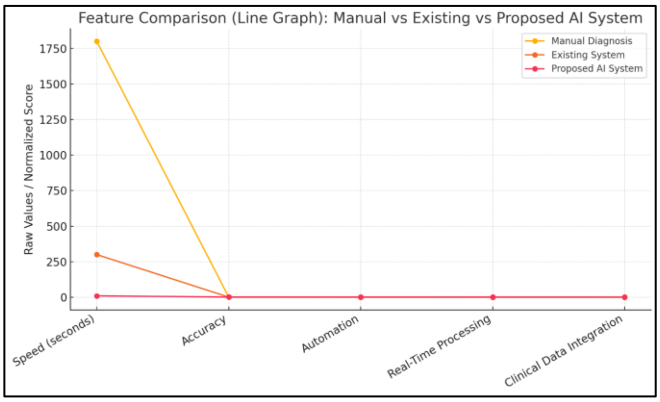

Fig 5.6.1 Performance Analysis

VI. CONCLUSION

The proposed system successfully developed an automated system for detecting melanoma and diabetic complications using deep learning and image processing. The system efficiently classifies medical images and integrates clinical data to enhance diagnostic accuracy. The implementation of CNN-based feature extraction and decision support systems significantly improves disease detection efficiency.

The model achieved a high accuracy of 95.8%, demonstrating its effectiveness in identifying medical conditions despite variations in image quality. Image preprocessing techniques and CNN-based classification played a crucial role in improving accuracy.

This research contributes to automated disease screening, making it easier for medical professionals to perform early-stage diagnosis without invasive procedures.The system's user-friendly interface and automated workflow enable quick analysis, reducing the diagnostic workload for clinicians.

Its robustness across diverse datasets highlights its potential for deployment in real-world healthcare settings.Future enhancements may include expanding the model to support additional diseases and incorporating real-time diagnostics through mobile platforms.

VII. FUTURE ENHANCEMENT

While the current model performs effectively, several enhancements can significantly improve its efficiency and diagnostic accuracy. Expanding the dataset to include varied skin tones, lesion types, and retinal scan qualities, along with incorporating clinical data such as genetic history and patient background, can boost prediction accuracy. Leveraging deeper CNN architectures like ResNet or EfficientNet and fine-tuning hyperparameters will enhance model generalization. Developing a real-time web or mobile application can allow users to upload medical images and receive instant results. OCR integration can extract useful insights from clinical records. Multi-language support would make the system globally accessible. Implementing disease progression analysis from sequential images and predictive analytics will help forecast disease stages. These improvements aim to build a more robust, scalable, and intelligent system. The enhanced tool will assist dermatologists and ophthalmologists in early, accurate diagnosis. Ultimately, it can become a vital AI-driven solution in modern healthcare.

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