SKIN CANCER DETECTION THROUGH IMAGE ANALYSIS AND MACHINE LEARNING TECHNIQUE

[1]Vikrant Pawar, [2]Jay Rupareliya, [3]Shrikant Bhise, [4]Prof. Sunita Naik
[1]Department Of Computer Engineering, Mumbai University, Mumbai, India
[2]Department Of Computer Engineering, Mumbai University, Mumbai, India
[3]Department Of Computer Engineering, Mumbai University, Mumbai, India
[4]Assistant Professor, Department Of Computer Engineering, Mumbai University, Mumbai, India
[1]21301062vikrant@viva-technology.org, [2]21312015jay@viva-technology.org
[3]21312008shrikant@viva-technology.org, [4]sunitanaik@viva-technology.org

Abstract : Skin cancer, including melanoma, basal cell carcinoma, and squamous cell carcinoma, is a growing global health concern primarily caused by prolonged exposure to ultraviolet (UV) radiation. It often manifests as abnormal moles, new growths, or changes in existing lesions. With factors such as ozone depletion and evolving lifestyle habits contributing to its increasing prevalence, early detection remains critical for improving treatment outcomes. However, late-stage diagnoses pose significant challenges, often requiring aggressive interventions with lower success rates. To address this, we developed a Flask-based Skin Cancer Detection Website, an AI-powered platform designed to assist individuals in identifying potential signs of skin cancer. The platform enables users to upload images of skin lesions, which are analyzed using advanced machine learning algorithms to assess the risk of malignancy. In addition to providing real-time risk assessments, the system offers personalized recommendations, including guidance on whether medical consultation is necessary. Furthermore, the platform serves as an educational resource, offering information on skin cancer symptoms, risk factors, and preventive measures. This web application is designed to be accessible on both desktop and mobile devices, ensuring ease of use for a wide range of users. By integrating cutting-edge AI technology with healthcare awareness, the system empowers individuals to take a proactive approach to skin health. Early detection through such digital solutions can significantly reduce the severity and incidence of skin cancer, ultimately improving patient outcomes and alleviating the burden on healthcare systems.

***Index Terms*: AI in dermatology, Deep learning, Medical image analysis, Skin cancer detection, VGG16**

I. INTRODUCTION

Skin cancer arises from the abnormal and uncontrolled growth of skin cells, primarily due to damage caused by ultraviolet (UV) radiation from the sun or tanning beds. This damage can lead to genetic mutations, disrupting normal cell growth and resulting in various forms of skin cancer, including basal cell carcinoma, squamous cell carcinoma, and melanoma the most dangerous type. To detect skin cancer, machine learning models can be developed to analyze images of skin lesions. The process begins with acquiring an image of the suspected area, which is then preprocessed to enhance quality and facilitate analysis. Feature extraction is performed using VGG16, a deep Convolutional Neural Network (CNN) that identifies crucial patterns indicative of cancerous cells. The extracted features are then classified using a CNN-based model, which predicts the likelihood of the lesion being cancerous. The results are displayed through a user-friendly interface for easy interpretation. Developing such a model requires a comprehensive dataset of labeled skin images to train the CNN, enabling it to learn distinguishing features between cancerous and non-cancerous lesions. The model's performance is evaluated using metrics like accuracy, sensitivity, and specificity. Continuous refinement and validation are essential to ensure reliability and effectiveness in real-world applications. By leveraging deep learning, the proposed system provides an accessible and effective tool for early skin cancer detection. The CNN model processes user-uploaded images, assessing them for abnormalities like asymmetry, irregular borders, or color variations common indicators of malignant growths. The integration of this technology enhances the accuracy and speed of preliminary risk assessments, providing valuable insights that can prompt early medical intervention and improve treatment outcomes.

II. REVIEW OF LITERATURE SURVEY

2.1. Literature Survey

A survey was conducted on existing literature and skin cancer detection methodologies to identify their limitations and the gaps present in their designs. This survey involved an evaluation of 15 key research papers, and the most relevant among them are discussed below.

Pedro M. M. Pereira et al. [1] explored the potential of 3D imaging techniques in melanoma detection, highlighting how traditional AI-based diagnostic systems relied solely on 2D images, which could sometimes lead to misclassification due to a lack of depth-related features. Their study demonstrated that integrating 3D surface imaging with machine learning models could significantly enhance classification accuracy, particularly in detecting melanoma-specific surface texture, elevation changes, and border irregularities. The authors highlighted that 3D imaging could provide dermatologists with a more detailed visual representation of lesions, potentially reducing false positives and false negatives. However, the study also identified challenges, particularly regarding hardware requirements and computational costs, as 3D imaging required specialized sensors and higher processing power. They suggested that future research should focus on developing cost-effective, mobile-compatible 3D imaging solutions, making the technology more accessible for widespread clinical use.

Lubna Riaz et al. [2] addressed the challenges of early skin cancer detection, emphasizing the importance of advanced image analysis in improving diagnostic accuracy. While significant advancements in dermoscopic imaging had facilitated early diagnosis of skin abnormalities, their study primarily focused on utilizing the HAM10000 dataset to identify multiple skin conditions. Their approach integrated advanced preprocessing techniques, such as noise reduction and contrast enhancement, to minimize distortions in lesion images and improve classification precision. Furthermore, they combined Convolutional Neural Networks (CNNs) and Local Binary Patterns (LBP) for feature extraction, which demonstrated improved generalization and practical applicability across different lesion types. However, their findings indicated that the model's effectiveness was limited by dataset diversity, and they recommended expanding future research to include more comprehensive datasets covering a broader range of skin types and lesion variations.

Raissa Schiavoni et al. [3] introduced a microwave reflectometry-based system for non-invasive skin cancer detection, offering a promising alternative to traditional dermoscopic imaging techniques. Their study demonstrated that microwave technology could effectively differentiate between malignant and benign lesions, making it a valuable tool for early-stage skin cancer detection and monitoring. The system was experimentally validated, proving its potential for rapid and objective diagnostic support. It was also portable, user-friendly, and capable of providing quick responses, making it an appealing option for low-cost, large-scale cancer screenings. However, the study acknowledged that microwave reflectometry had lower resolution than dermoscopic imaging, limiting its effectiveness in detecting small or subtle lesion abnormalities. The authors suggested that combining microwave reflectometry with high-resolution optical imaging techniques could create a hybrid diagnostic system, leveraging the strengths of both modalities to improve the accuracy and reliability of AI-assisted skin cancer detection.

Muhammad Imran Faizi et al. [4] proposed an efficient region-of-interest (ROI) detection method, aiming to improve computational efficiency while maintaining classification accuracy. Their study introduced template matching techniques in combination with grayscale conversion and Haralick feature extraction, which significantly reduced processing overhead. Unlike traditional CNN models that required extensive training on large datasets, their method achieved high accuracy while minimizing computational complexity, making it particularly suitable for real-time applications in mobile health technologies. Their research further highlighted that lightweight AI models could be instrumental in resource-constrained medical environments, such as rural healthcare centers and telemedicine-based skin cancer screening platforms. They suggested that future improvements could involve adaptive template matching, where AI dynamically adjusts feature extraction based on lesion characteristics, thus further enhancing the robustness of mobile AI-driven skin cancer diagnostics.

H. L. Gururaj et al. [5] analyzed the growing prevalence of UV-induced skin cancer and explored the potential of deep learning-based classification techniques in improving diagnostic efficiency. Their study revealed that CNNs, particularly those fine-tuned through transfer learning, significantly enhanced classification accuracy. However, they pointed out that hyperparameter optimization played a crucial role in determining model performance, as improperly tuned networks tended to overfit smaller datasets.

Stephanie S. Noronha et al. [6] conducted an in-depth review of deep learning techniques in dermatological disease detection, focusing on their applicability in real-world medical practice. Their findings confirmed that CNN-based architectures achieved significantly higher classification accuracy compared to traditional machine learning models. However, their study identified several challenges, including high computational costs, dataset limitations, and domain-specific variations in lesion appearance. They suggested that integrating hybrid AI models, which combined deep learning with expert-driven dermatological knowledge, could lead to more reliable and interpretable diagnostic systems.

Khalid M. Honsy et al. [7] examined the role of segmentation in melanoma detection, emphasizing its impact on overall classification accuracy. Their research demonstrated that poor segmentation techniques could lead to substantial misclassifications, as they might exclude critical lesion features or introduce unnecessary background noise. The study reviewed various segmentation strategies, including thresholding, contour detection, and deep learning-based segmentation, concluding that hybrid approaches combining traditional and AI-driven segmentation performed best. The authors highlighted the need for more robust segmentation techniques that adapted dynamically to different image conditions, ensuring precise lesion isolation. They also suggested that integrating unsupervised segmentation with self-learning AI models could provide more generalizable solutions applicable across different imaging datasets.

Azhar Imran et al. [8] developed an ensemble model that combined VGG, Caps-Net, and ResNet architectures, demonstrating that multi-model fusion significantly improved classification robustness. Their study showed that combining different feature extraction techniques enhanced model performance, reducing false positives and false negatives in melanoma detection. By leveraging the strengths of different architectures, their ensemble model achieved higher classification accuracy compared to single-model approaches. However, they acknowledged that ensemble models increased computational requirements, making them less suitable for mobile-based implementations. They suggested that future research should focus on optimizing ensemble learning algorithms, allowing them to run efficiently on lightweight hardware while maintaining high accuracy.

Saban Ozturk et al. [9] focused on resolving class imbalance issues in skin cancer datasets, particularly those related to melanoma detection. Traditional deep learning models tended to favor majority classes, leading to biased predictions and high false negative rates for rare lesion types. To address this challenge, they proposed a deep clustering method utilizing COM-Triplet loss, which enabled the model to learn more representative feature embeddings for underrepresented lesion classes. Their approach outperformed standard data augmentation and transfer learning methods, which often failed to resolve bias effectively. However, they suggested that integrating domain-specific augmentation techniques and multi-modal imaging approaches could further enhance classification accuracy, especially when dealing with complex and rare lesion cases.

Rehan Ashraf et al. [10] examined the role of transfer learning in melanoma detection, utilizing the AlexNet model to optimize classification accuracy. Their study demonstrated that pretrained deep learning models significantly outperformed traditional CNNs, especially when applied to small and specialized dermatology datasets. By using transfer learning, they reduced the need for large-scale annotated datasets, which often pose a challenge in medical AI research. However, they also noted that fine-tuning pretrained models was essential to prevent overfitting and to ensure adaptability to specific lesion types. The study suggested that combining transfer learning with real-time clinical feedback could improve model reliability, allowing AI-based systems to continuously learn from dermatologist evaluations and improve over time. They also recommended that future research should explore hybrid models, integrating multiple pretrained architectures to enhance robustness in skin lesion classification.

Krishna Mridha et al. [11] developed a Clinical Decision Support System (CDSS) aimed at assisting dermatologists in classifying skin lesion images with higher confidence. Their research emphasized the need for Explainable Artificial Intelligence (XAI), which allowed AI-based diagnostic models to provide human-readable justifications for their predictions. By implementing perturbation-based explanation techniques, their system enabled users, particularly dermatologists, to gain insight into why a lesion was classified as malignant or benign. This aspect significantly improved trust in AI-powered medical applications, as clinicians could verify and validate AI-driven decisions before making critical medical recommendations. Despite the promising results, the authors suggested that more extensive real-world validation was required to refine the system and ensure reliable clinical deployment across different dermatological conditions.

Guang Yang et al. [12] reviewed multiple AI-based classification approaches, including supervised, semi-supervised, self-supervised, and ensemble learning techniques. Their study found that self-supervised learning showed particular promise, as it allowed AI models to learn from unlabeled medical images, reducing dependency on manually annotated datasets. They emphasized that AI-based skin cancer detection still faced major challenges, particularly in real-world dataset generalization and interpretability of model decisions. They recommended that future research should focus on developing more explainable AI models, ensuring that dermatologists can understand the reasoning behind AI predictions. Additionally, their review highlighted the potential of ensemble learning methods, which combine multiple machine learning models to create a more robust and accurate classification system.

Peng Chen et al. [13] analyzed the effectiveness of AI-driven self-diagnosis platforms for early skin cancer detection, finding that real-time AI-based assessment tools helped users identify suspicious lesions early. Their study showed that AI-driven mobile applications and websites empowered individuals to take proactive steps in managing their skin health. However, they warned that these tools should only act as preliminary screening aids, not as replacements for professional dermatological consultations. They emphasized the need for clinical validation of AI-powered self-diagnosis systems to ensure their accuracy and reliability across different demographics and skin types.

Anwesha Mohanty et al. [14] examined the impact of dataset limitations on AI-driven skin disease analysis, emphasizing that smaller datasets often led to overfitting and poor model generalization. Their study highlighted that GANs (Generative Adversarial Networks) could be used to generate synthetic training data, helping AI models learn from a more diverse range of skin lesion images. They argued that dataset expansion through synthetic data generation could improve classification accuracy, particularly in detecting rare skin conditions. However, they also noted that GAN-generated images needed careful validation to ensure they accurately represented real-world lesions. They recommended that future studies should explore combining synthetic and real-world data to improve AI model performance while maintaining clinical reliability.

Ahmed Magdy et al. [15] analyzed the impact of AI-powered computer-assisted diagnostic (CAD) systems in enhancing medical decision-making. Their study demonstrated that AI-driven tools significantly improved dermatologist confidence, particularly in cases where visual diagnosis alone was insufficient. By integrating machine learning algorithms with expert medical knowledge, their model provided a secondary level of analysis, reducing the likelihood of human error in diagnosis. However, they also stressed that AI systems should not replace clinical expertise but rather function as a supportive tool. They advocated for a human-in-the-loop framework, where AI-generated predictions are verified by trained dermatologists before making final diagnostic decisions. Their findings further highlighted the need for real-world validation of CAD systems in hospitals and clinics to ensure their long-term feasibility and acceptance in medical practice.

2.2 Analysis Table

Table 1. Analysis Table

Sr. No.	Technology Used	Advantages	Disadvantages
[1]	Deep Clustering, Margin Free-Triplet Loss	1.Improved Rare Lesion Detection 2.Effective for Imbalanced Datasets	1. Difficult Training 2.Resource Intensive
[2]	Convolutional Neural Networks (CNNs)	1.Accurate Skin Cancer Detection	1.Large and Diverse Dataset Requirement

		2.Efficient Transfer Learning	2.Generalization Challenges
[3]	Deep Learning	1.High-Precision Detection 2. Enhanced Disease Classification	1.High Computational Power Requirement
[4]	Computer Vision Algorithms	1. Automated Image Analysis	1.Complex Training 2.Resource Intensive
[5]	Data Augmentation, Deep (CNNs)	1.Improved Generalization with Data Augmentation	1. Dependence on Large Annotated Datasets
[6]	Deep Learning Segmentation Networks	1.Detailed Skin Lesion Boundaries	1. Resource Heavy Models
[7]	K-Means Clustering	1. Simple & Efficient Implementation 2.Real-Time Application Suitability	1. Limitations on Irregular Shapes
[8]	Data Augmentation.	1.Efficient use of limited data.	1. Relying on augmented data
[9]	Microwave Reflectometry, Low-Cost Sensors	1. Cost-Effective Skin Cancer Detection 2.Accessible Diagnostic Tool	1.Lower Resolution than Other Techniques
[10]	Convolutional Neural Networks, Optimization	1.Reduced Dermatologist Workload 2.High-Accuracy Classification	1. Detailed Skin Lesion Information
[11]	Transfer Learning	1.High Precision Detection 2.Early Diagnosis Improvement	1.Requires Specialized Expertise
[12]	Machine Learning Techniques, Clinical Image Analysis	1.Comprehensive Review of Techniques	1.Limited Specificity to Skin Cancer Detection
[13]	Recurrent Attentional Convolutional Networks	1.Enhanced Segmentation of Lesions	1. Computationally Intensive
[14]	Skin Disease Analysis	1. Limited Data with Framework for Skin Disease Analysis	1. Limited Scope for Large-Scale Application
[15]	Region-of-Interest (ROI) Detection, Transfer Learning	1. ROI Detection for Accuracy	1.Transfer Learning Limitations

Our project utilizing VGG16 for skin cancer detection effectively bridges gaps identified in previous research. Studies have highlighted several challenges, including the high computational demands of advanced models, limitations in dataset diversity, and difficulties in lesion segmentation. Some works propose 3D imaging and ensemble models to enhance accuracy, but these approaches often require expensive hardware, making them less practical for widespread clinical use. Others emphasize the importance of hybrid AI models, combining deep learning with traditional techniques to improve reliability, yet they often lack real-world validation. Dataset imbalance remains a major issue, as models tend to favor majority classes, leading to biased predictions. Additionally, the need for lightweight AI solutions is evident, especially for mobile and telemedicine applications in resource-limited settings. While various feature extraction techniques, such as Local Binary Patterns and microwave reflectometry, have been explored, deep learning remains the most promising approach for accurate classification.

Transfer learning, as demonstrated in several studies, enhances model efficiency, but careful fine-tuning is necessary to avoid overfitting. Our approach using VGG16 strikes a balance between accuracy and efficiency, making it suitable for real-time applications without excessive computational requirements. Moreover, by refining lesion segmentation techniques, we ensure that critical features are not lost, improving classification precision. Explainability is another crucial factor, as clinicians require AI-generated results that are interpretable and trustworthy. To enhance trust, our model incorporates methods that allow dermatologists to verify AI decisions, reducing diagnostic errors. Our project also considers the potential of dataset limitations, ensuring better generalization. By integrating these advancements, we create a practical and effective AI-driven skin cancer detection system, making it more accessible and reliable for medical professionals and patients alike.

III. METHODOLOGY

The proposed AI-driven skin cancer detection system follows a structured methodology comprising data preparation, feature extraction using VGG16, model training, classification, and preprocessing, all implemented through a Flask-based web and mobile application for enhanced accessibility. The process begins with dataset collection, where skin lesion images from publicly available medical sources like ISIC are labeled with ground truth annotations. To improve model generalization and mitigate overfitting, data augmentation techniques such as rotation, scaling, and flipping introduce variations in lighting, angles, and lesion shapes. The augmented dataset is then divided into training, validation, and testing sets. Feature extraction is performed using the VGG16 model, a pretrained convolutional neural network (CNN) known for its strong feature representation. The model captures essential patterns through convolutional, pooling, and fully connected layers, generating deep spatial feature maps for classification. The extracted features are then passed to a CNN-based classifier, which is optimized using Adamax to ensure faster convergence and improved classification accuracy. When a user uploads a dermoscopic image via the Flask application, it undergoes feature extraction through VGG16 before being classified by the trained CNN model as either cancerous or non-cancerous, accompanied by a confidence score for reliability. To ensure optimal input quality, preprocessing techniques such as noise reduction and image resizing are applied. Finally, the classification result is displayed on the user-friendly interface, enabling easy interpretation and accessibility for users.

3.1 Block Diagram

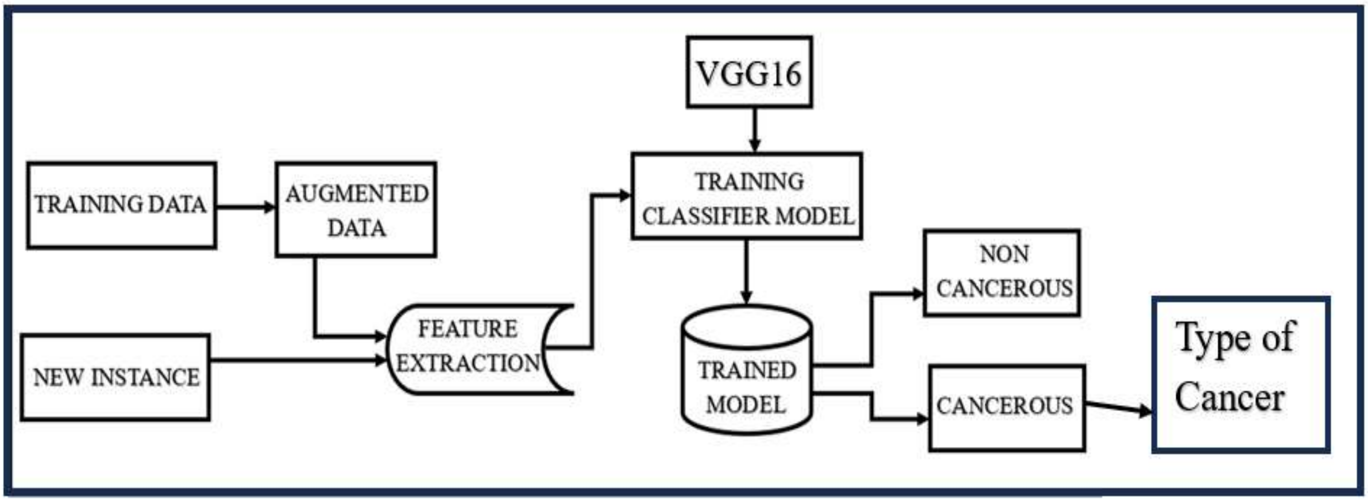

Fig 3.1 Block Diagram For Proposed System

Fig 3.1 illustrates the workflow of the proposed skin cancer detection system utilizing the VGG16 model for classification. The process begins with the acquisition of training data, which undergoes data augmentation to enhance the model's ability to generalize across diverse skin lesion types. Additionally, when a new instance (user-uploaded image) is introduced, it is processed alongside the augmented dataset. The feature extraction step is crucial, where key visual patterns from the images are identified and refined before being fed into the classifier. The VGG16 model, a deep learning-based Convolutional Neural Network (CNN), is employed for feature extraction and training the classifier model. The extracted features are utilized to develop a trained model, which is then used for classification. The system distinguishes between cancerous and non-cancerous lesions, ultimately predicting the type of cancer present in the image. By leveraging deep learning, the proposed framework enhances early detection and diagnostic support, enabling more accurate and efficient assessments of skin cancer risks.

3.2 System Flow Diagram

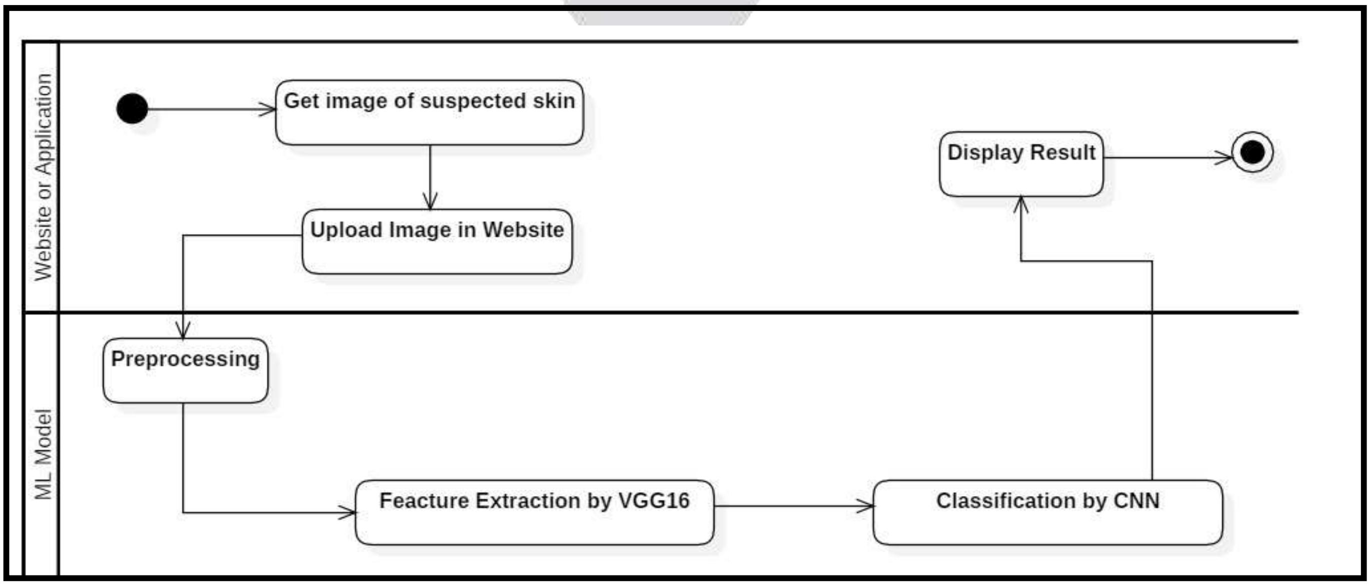

Fig 3.2 Activity Diagram

Fig 3.2 illustrates the system flow diagram for the proposed AI-driven skin cancer detection model. In the first stage, users capture an image of a suspected skin lesion using a mobile device or camera. This image is then uploaded to the system via a website or application interface, initiating the automated analysis process. In the second stage, the ML model processes the image. The first step is preprocessing, where the image undergoes enhancement techniques such as noise reduction and normalization to improve clarity and contrast. Once preprocessed, the system extracts important visual patterns from the image using VGG16, a deep learning-based feature extraction model. These extracted features are then classified using a Convolutional Neural Network (CNN) to determine whether the lesion is cancerous or non-cancerous. Finally, the classification result is displayed back to the user through the website or application interface, providing an intuitive and easy-to-understand diagnosis. This streamlined approach ensures accurate and efficient skin lesion detection, leveraging deep learning for enhanced diagnostic precision.

IV. Results

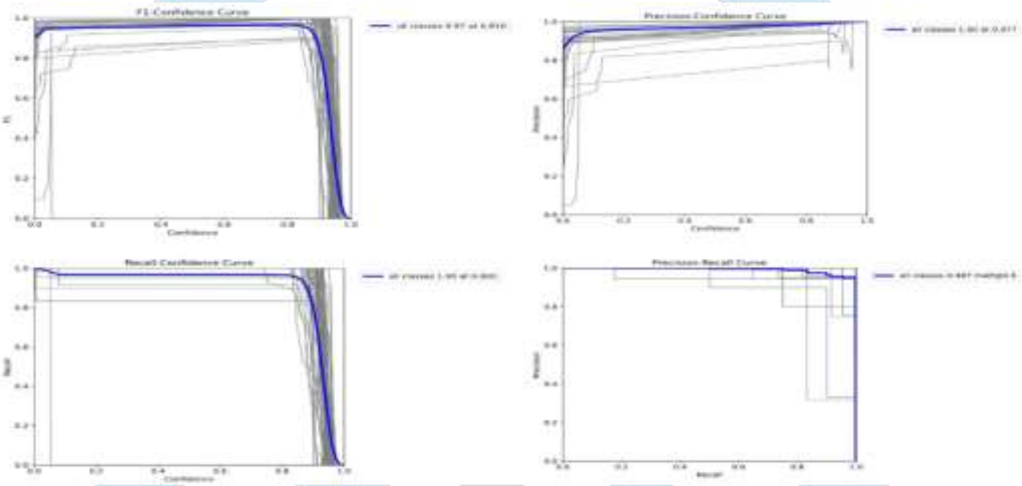

Fig 4.1 Performance Evaluation Metrics for Skin Lesion Classification Model

Fig 4.1 illustrates the performance evaluation metrics of the deep learning-based skin lesion classification model using four key curves. The F1-Confidence Curve (top-left) shows that the model achieves a peak F1-score of 0.97 at a confidence level of 0.810, indicating a strong balance between precision and recall. The Precision-Confidence Curve (top-right) demonstrates that the model attains 100% precision at 0.977 confidence, highlighting its ability to make highly accurate predictions at high confidence levels. Similarly, the Recall-Confidence Curve (bottom-left) indicates that the model maintains 100% recall at 0.000 confidence, suggesting it detects all true positives when no confidence threshold is applied. However, recall decreases as confidence increases, filtering out less certain predictions. Lastly, the Precision-Recall Curve (bottom-right) presents the trade-off between precision and recall, with the model achieving a mean Average Precision (mAP) of 0.987 at IoU 0.5, signifying strong predictive performance. These curves collectively validate the model's robustness in accurately classifying skin lesions.

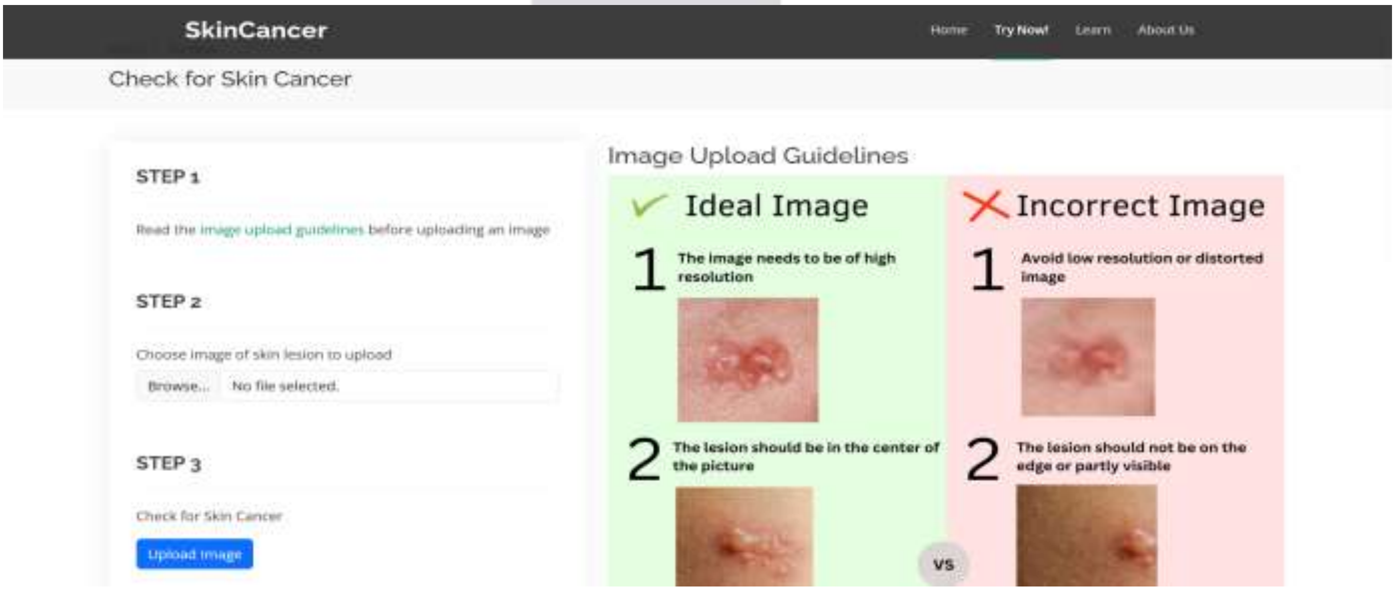

Fig 4.2 Image Upload Interface and Guidelines

Fig 4.2. illustrates the user interface of the skin cancer detection system, focusing on the image upload process and essential guidelines for submitting high-quality images. The interface is structured to guide users through three key steps: first, reading the image upload guidelines to understand the requirements; second, selecting an image of the skin lesion from their device; and third, uploading the chosen image for analysis. On the right side of the interface, the image upload guidelines provide a clear distinction between ideal and incorrect images to ensure optimal input quality for the AI model. Ideal images must be of high resolution and have the lesion centered within the frame, as this ensures better feature extraction and accurate classification. In contrast, incorrect images include low-resolution, blurry, or distorted images, which may compromise detection accuracy. Additionally, images where the lesion is partly visible or positioned at the edges are discouraged, as they hinder proper analysis. By adhering to these guidelines, users can enhance the accuracy of the system, which utilizes deep learning techniques such as VGG16 and Adamax optimization for precise skin cancer classification.

Fig 4.3 Diagnosis of Melanocytic Nevus

Fig 4.3 illustrates the diagnosis of a skin lesion classified as Melanocytic Nevus with 100% confidence. Melanocytic nevi, commonly known as moles, are typically benign but require monitoring due to their potential for transformation into melanoma. The lesion in the image exhibits a well-defined border and a relatively uniform pigmentation. The AI-based classification model successfully identifies this lesion as non-malignant, providing crucial diagnostic support to dermatologists.

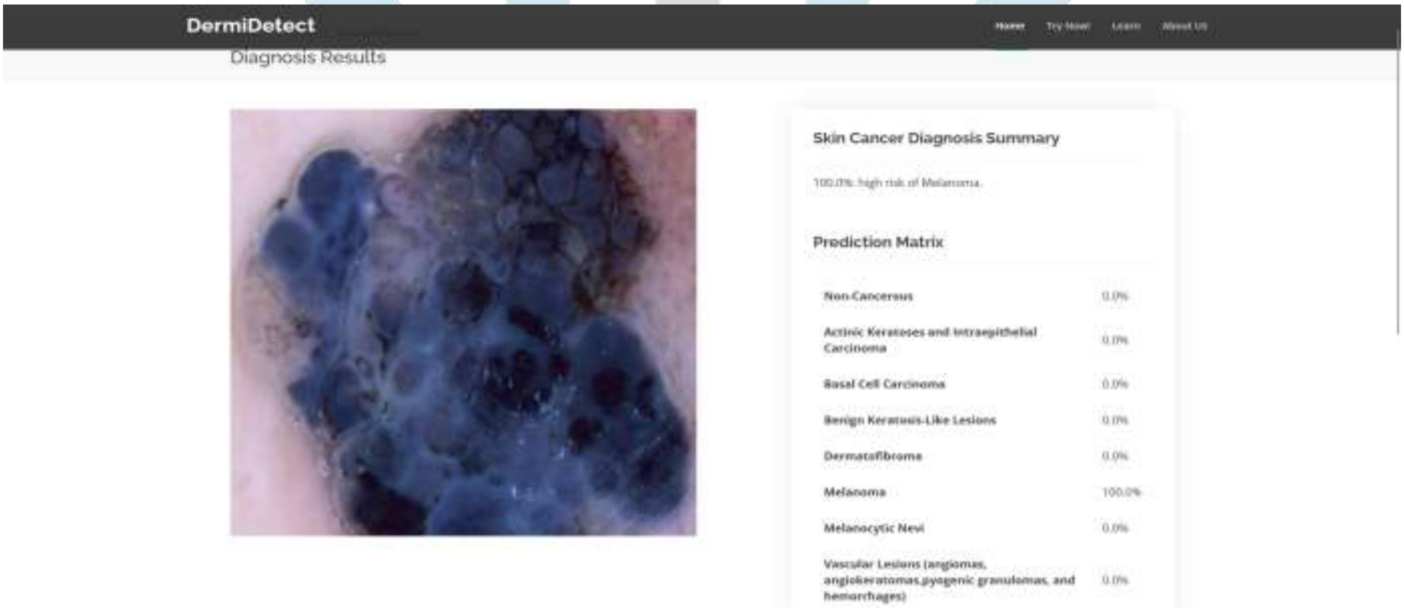

Fig 4.4 Diagnosis of Malignant Melanoma

Fig 4.4 presents a skin lesion diagnosed as Malignant Melanoma, with the model predicting 100% risk for this condition. Melanoma is the most dangerous form of skin cancer, characterized by irregular borders, uneven pigmentation, and rapid growth. The image showcases a lesion with a dark, heterogeneous color pattern, indicating the presence of malignant cells. Early detection of melanoma is critical for successful treatment, and AI-powered diagnostic tools help in timely identification and intervention.

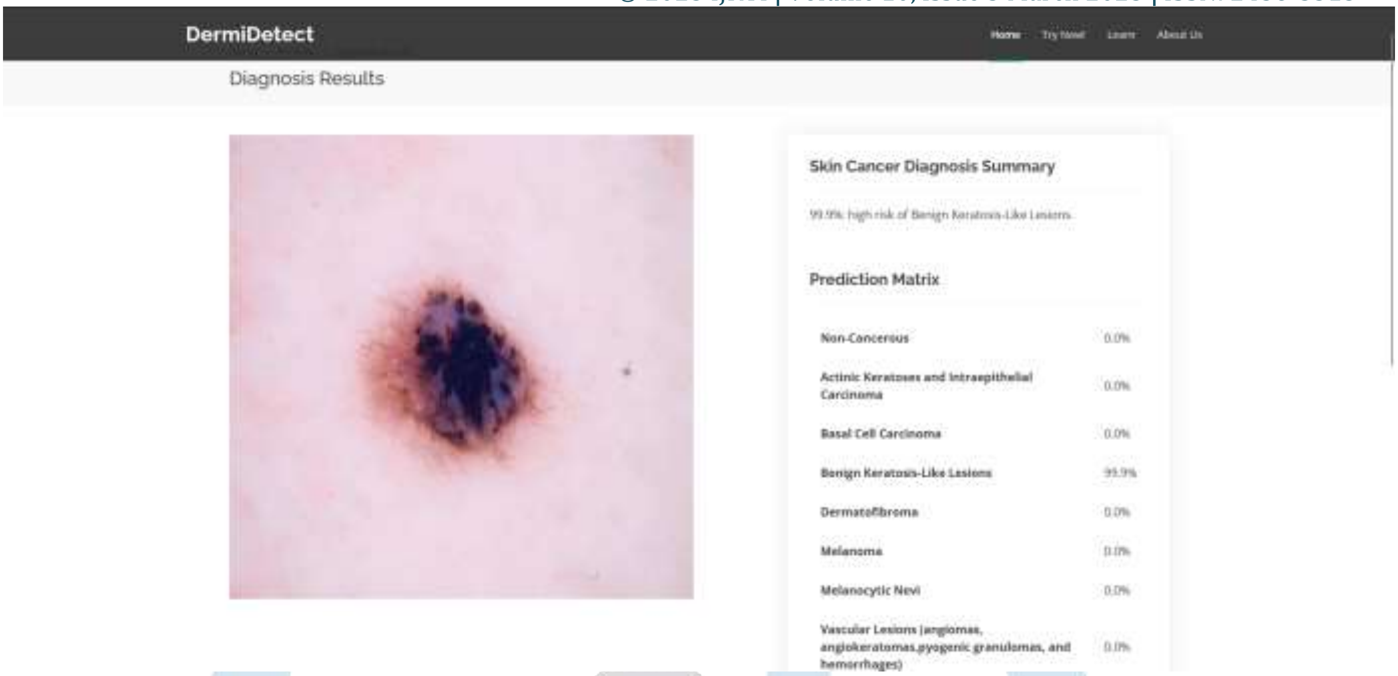

Fig 4.5 Diagnosis of Benign Keratosis-Like Lesion

Fig 4.5 demonstrates the classification of a skin lesion as a Benign Keratosis-Like Lesion, with a 99.9% confidence level. Benign keratoses are non-cancerous skin growths that often appear as rough, scaly patches. The lesion in the image has a darkened center with some irregular features, which might lead to misinterpretation as a malignant condition. However, the AI model accurately differentiates it from melanoma, showcasing the effectiveness of deep learning models in precise dermatological diagnostics.

V. Conclusion

In conclusion, the proposed skin cancer detection system integrates advanced AI techniques, including VGG16 for feature extraction and an optimized Adamax for accuracy, to provide accurate and efficient classification of skin lesions. By leveraging deep learning and optimization techniques the system enhances diagnostic reliability while maintaining accessibility through user-friendly web and mobile interfaces. This tool empowers individuals by enabling early risk assessment, facilitating timely medical consultation, and raising awareness about skin health. While not a replacement for professional diagnosis, it serves as a valuable supplement to traditional healthcare, promoting early intervention and potentially reducing the impact of skin cancer through proactive monitoring and education.

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