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Skin Cancer Classification using Deep Learning

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ABSTRACT: This paper addresses the critical need for early and accurate diagnosis of skin cancer, a prevalent global health concern. Recognizing the challenges posed by prolonged waiting times and subjective evaluations in clinical settings, the study focuses on leveraging deep learning techniques to enhance skin cancer classification and detection. The research confronts the inherent class imbalance issue, where the affected class is significantly smaller than the healthy class, and aims to unravel the decision-making mechanisms of the models. The authors propose an end-to-end smart healthcare system through an Android application. Evaluating the effectiveness of the proposed deep learning technique, the study utilizes ResNet50, DenseNet169, VGG16, Xception, and DenseNet201 for classification, with Xception achieving a notable 96% accuracy.

KEYWORDS*:* Skin cancer, ResNet50, DenseNet169, VGG16, Xception, DenseNet201.

I. INTRODUCTION

Skin cancer poses a significant global health concern, emphasizing the critical need for advanced and efficient diagnostic tools. Harnessing the power of deep learning, this research focuses on developing a comprehensive skin cancer detection and classification system. The integration of state-of-the-art convolutional neural network architectures, including ResNet50, DenseNet169, VGG16, Xception, and DenseNet201, aims to enhance the model's ability to discern intricate patterns and features within dermatoscopic images.

In the realm of classification, these models are meticulously trained on diverse datasets to accurately identify and categorize skin lesions, contributing to improved diagnostic precision.The amalgamation of these powerful architectures lays the foundation for an advanced, automated system capable of effectively identifying and categorizing skin abnormalities, propelling strides towards early intervention and enhanced patient outcomes.

This research aims to address challenges in skin cancer diagnosis, including prolonged waiting times and subjective interpretations in clinical evaluations. By leveraging deep learning techniques, the study focuses on mitigating class imbalance issues and improving the efficiency of skin cancer classification and detection for enhanced patient outcomes.

II.LITERATURE SURVEY

Skin cancer is a significant health concern worldwide, with varying prevalence rates and patterns across different regions. Understanding the current state of research and advancements in the field is crucial for effective diagnosis and treatment strategies. This literature survey aims to provide insights into recent studies and approaches concerning skin cancer, encompassing both melanoma and nonmelanoma types.

AlSalman et al. [1] conducted a single-center study in Saudi Arabia, providing insights into nonmelanoma skin cancer (NMSC) cases. Their findings shed light on the prevalence and characteristics of NMSC within the Saudi Arabian population, contributing valuable data to the global understanding of skin cancer epidemiology.
Nehal and Bichakjian [2] presented an update on keratinocyte carcinomas, emphasizing recent developments in diagnosis and management. Keratinocyte carcinomas, including basal cell carcinoma (BCC) and squamous cell carcinoma (SCC), represent the most common forms of skin cancer, necessitating continuous research efforts to refine treatment protocols and improve patient outcomes.

The American Cancer Society [3] provided key statistics on melanoma skin cancer, offering insights into its prevalence, incidence rates, and survival outcomes. Such epidemiological data play a crucial role in informing public health policies and guiding research initiatives aimed at reducing the burden of melanoma.

Albahar [4] proposed a novel approach for skin lesion classification using convolutional neural networks (CNNs), leveraging advanced machine learning techniques to enhance diagnostic accuracy. This study underscores the growing interest in leveraging artificial intelligence (AI) for automated skin cancer detection, offering promising avenues for improving diagnostic efficiency.

Hasan et al. [5] conducted a comparative analysis of benign and malignant skin cancer detection using CNNs, highlighting the potential of deep learning algorithms in discriminating between different lesion types. Their findings contribute to the ongoing discourse on leveraging AI for precision medicine applications in dermatology.

Siegeland [6] provided comprehensive statistics on colorectal cancer, highlighting the importance of cancer research across different organ systems. While not directly related to skin cancer, such epidemiological insights underscore the broader context of cancer research and its implications for healthcare systems worldwide.

Ajagbe et al. [7] explored the application of deep CNN approaches for the multi-classification of Alzheimer's disease using magnetic resonance images (MRI). Although focusing on a different medical condition, this study exemplifies the versatility of deep learning techniques in medical image analysis and disease diagnosis.

Barata et al. [8] proposed a deep attention model for the hierarchical diagnosis of skin lesions, aiming to improve diagnostic accuracy through attentive feature selection. Their approach represents an innovative contribution to the field of computer-aided diagnosis in dermatology, potentially enhancing the capabilities of automated lesion recognition systems.

Soyer et al. [9] discussed dermoscopy as a diagnostic tool for pigmented skin lesions, emphasizing the importance of visual examination techniques in dermatological practice. Dermoscopy enables clinicians to assess skin lesions with enhanced magnification and illumination, facilitating the early detection of melanoma and other malignant lesions.

Ankad et al. [10] conducted a descriptive study on dermoscopy findings in non-melanocytic and pink tumors in individuals with Brown skin. By characterizing dermoscopic features specific to diverse skin types, their study contributes to a more comprehensive understanding of dermatological manifestations across different ethnicities.

In summary, recent research efforts have focused on elucidating the epidemiology, diagnostic modalities, and treatment approaches for various types of skin cancer. From epidemiological studies to advanced machine learning algorithms and diagnostic techniques, the interdisciplinary nature of skin cancer research underscores the collaborative efforts needed to combat this global health challenge. By integrating insights from diverse disciplines, including oncology, dermatology, and artificial intelligence, researchers strive to improve early detection rates, refine treatment protocols, and ultimately enhance patient outcomes in the fight against skin cancer.

III. METHODOLOGY

PROPOSED WORK:

The proposed system pioneers a comprehensive approach to skin cancer diagnosis by integrating advanced deep learning techniques into an end-to-end smart healthcare system. Targeting the limitations of lengthy waiting times and subjective interpretations in clinical assessments, the system employs ResNet50, DenseNet161, VGG16, Xception, and DenseNet201 for skin cancer classification. Emphasis is placed on mitigating the class imbalance problem inherent in skin-related datasets.. By providing an integrated solution, this proposed system not only enhances the accuracy of skin cancer diagnosis but also offers clinicians a deeper understanding of the decision-making mechanisms employed by the models. The integration of diverse models and the end-to-end nature of the system mark a significant stride toward efficient, accessible, and accurate skin cancer diagnostics in clinical practice.

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ALGORITHMS:

ResNet50: ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pretrained version of the neural network trained on more than a million images from the ImageNet database [1].

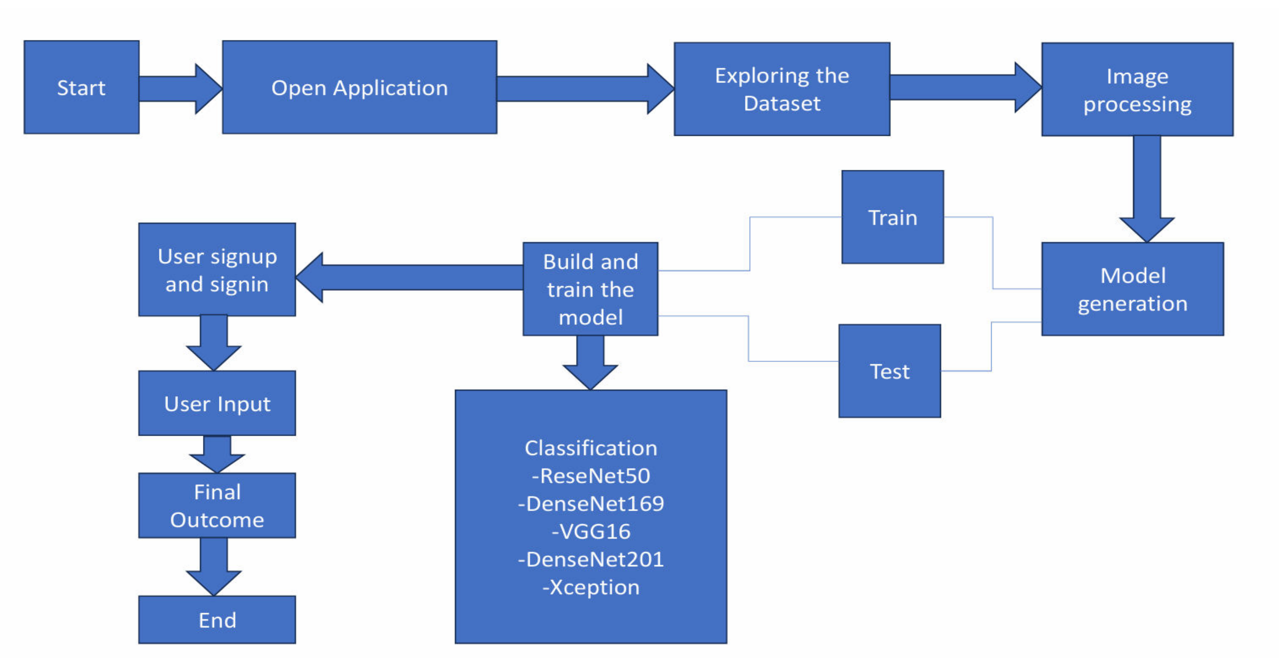
DenseNet169: DenseNet is a type of convolutional neural network that utilises dense connections between layers, through Dense Blocks, where we connect all layers (with matching feature-map sizes) directly with each other. The densenet-169 model is one of the DenseNet group of models designed to perform image classification.

VGG16: VGG-16 is a convolutional neural network that is 16 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

Xception: Xception is a convolutional neural network that is 71 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals .

DenseNet201: DenseNet-201 is a convolutional neural network that is 201 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

WORK FLOW:



V. RESULT AND DISCUSSION

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

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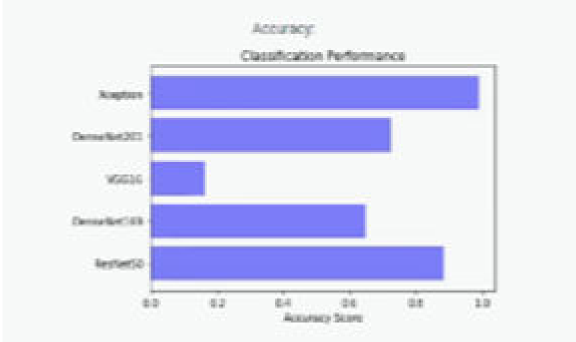

Fig 2 Accuracy Comparison graph for classification

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

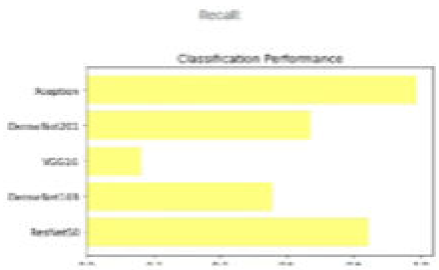

Fig 3 Recall Comparison graph for classification

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:
Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

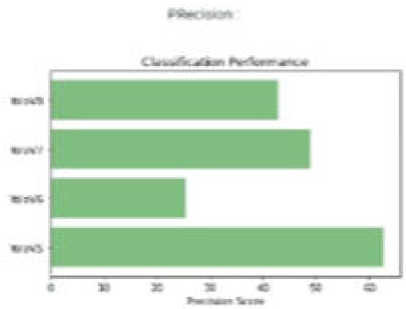

Fig 4 Precision comparison graph for detection

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mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

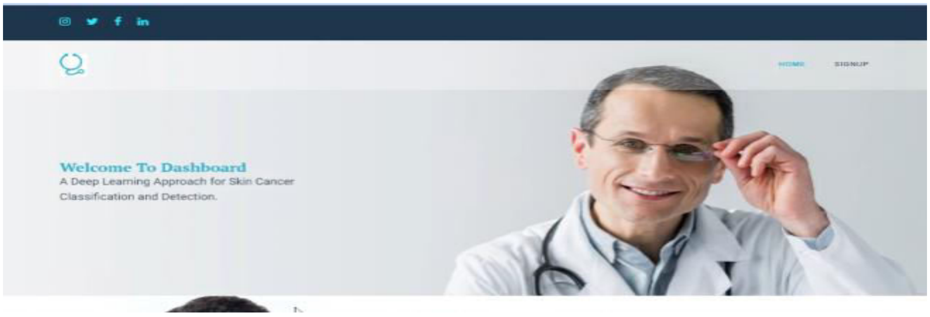

Fig 1Home page

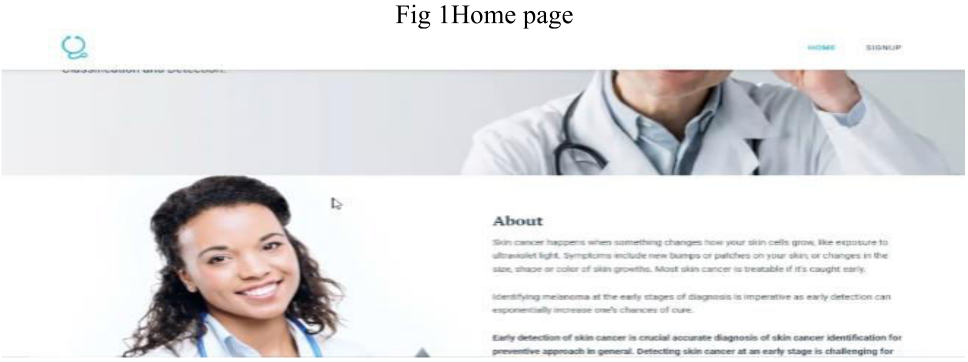

Fig 2 About page

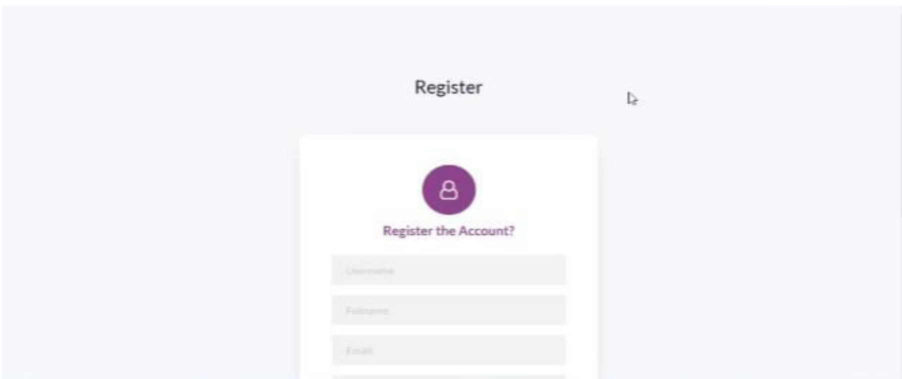

Fig 3 Registration page

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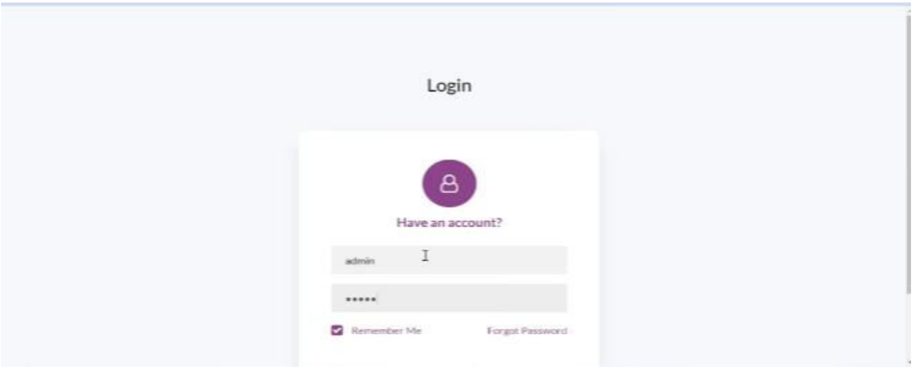

Fig 4 Login page

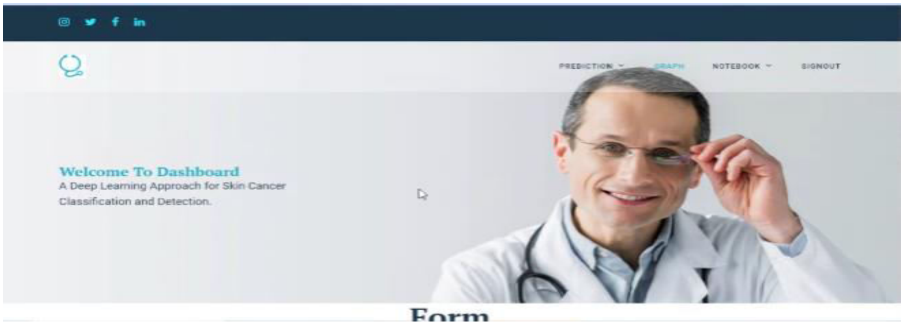

Fig 5Main page

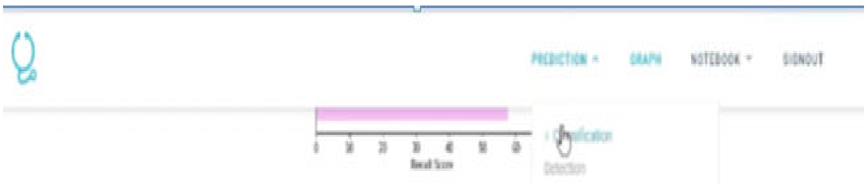

Fig 6 Prediction for classification

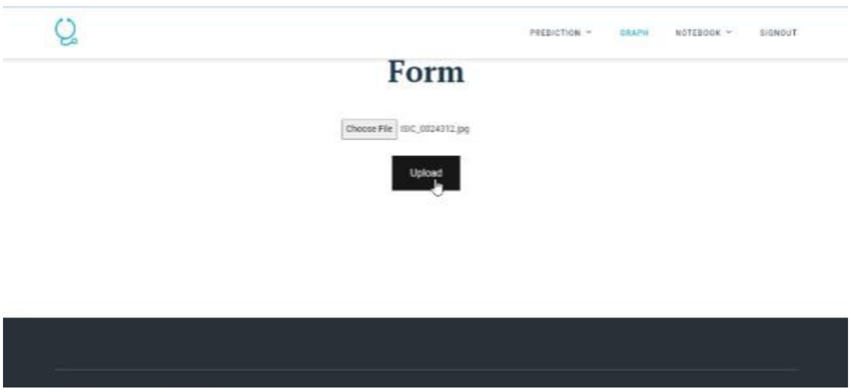

Fig7 Upload input image

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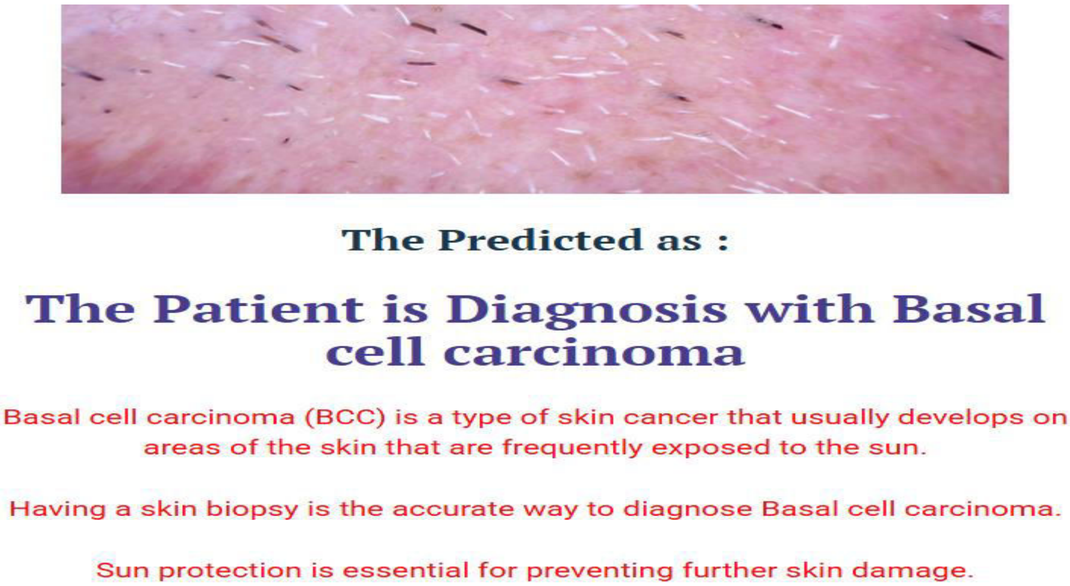

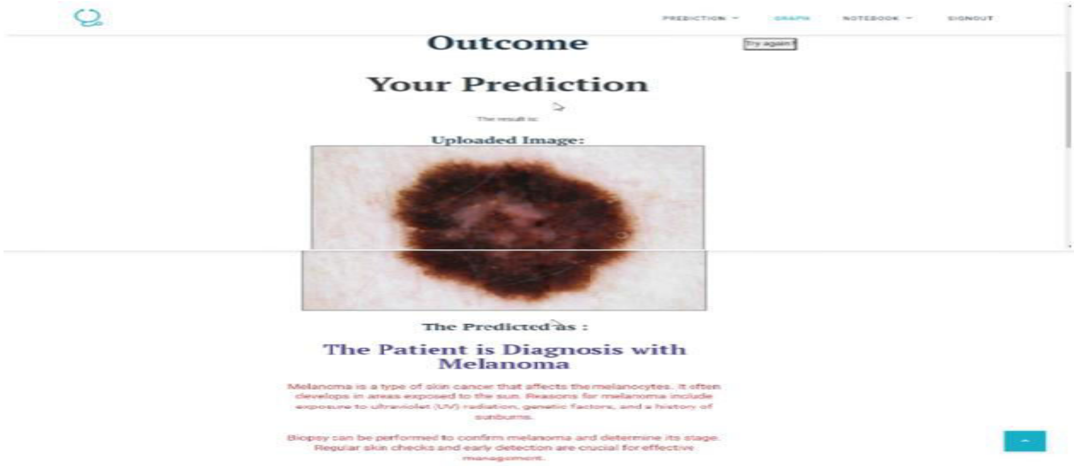

IV.CONCLUSION

In conclusion, this research underscores the pivotal role of deep learning in advancing skin cancer diagnosis, addressing critical challenges in clinical evaluations. The integration of diverse models, including ResNet50, DenseNet161, VGG16, Xception, and DenseNet201 for classification.The achievement of 96% accuracy with Xception and 90% with ResNet50 signifies the potential for enhanced diagnostic capabilities. Moreover, the system successfully tackles the class imbalance issue inherent in skin-related datasets, contributing to more robust and reliable outcomes.

V. FUTURE SCOPE

The future scope of this research involves exploring scalability for widespread adoption in diverse healthcare settings. Further enhancements could focus on real-time implementation and continuous model refinement to adapt to evolving skin cancer patterns. Integration with emerging technologies, such as telemedicine platforms, could extend the reach of the proposed system, offering remote diagnostic capabilities. Additionally, collaboration with dermatologists and continuous data augmentation could refine the models, ensuring their adaptability to a broader spectrum of skin conditions for improved diagnostic precision.

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