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Deep Dive into Skin Cancer Classification using Deep Learning

[1]Mrs. Y. Naga Lavanya,[2]K. Pravalika,[3]P.Gracia,[4]K. Urmila,[5]K. Thanvi,

[1]Assistant Professor, Dept. of IT, TKR College of Engineering and Technology, Meerpet, Hyderabad,

ynagalavanya85@gmail.com

[2,3,4,5]BTech Student, Dept. of IT, TKR College of Engineering and Technology, Meerpet, Hyderabad

pravalikakommula12@gmail.com,graciap14072002@gmail.com, kethavathurmila31@gmail.com, kommathanvi@gmail.com

Abstract: This study addresses the urgent global challenge of rapidly spreading skin cancer, emphasizing the critical role of accurate diagnosis for effective prevention. Dermatologists face difficulties in early detection, prompting the application of deep learning, particularly Convolutional Neural Networks (CNNs). Leveraging the MNIST: HAM10000 dataset featuring seven skin lesion types and 10,015 samples, the research employs data preprocessing techniques including sampling, dull razor, and autoencoder-based segmentation. Transfer learning with DenseNet169 and ResNet50 models is utilized, revealing that DenseNet169's undersampling yields high accuracy and F1-measure, while ResNet50's oversampling technique excels in both metrics. Building on the base paper's use of ResNet50, DenseNet161, and VGG16 (achieving 91% accuracy), this extension explores additional models like Xception, DenseNet201. Anticipating a 95% accuracy improvement, the study underscores the potential of diverse models and parameter tuning to advance skin cancer classification, offering a promising avenue for enhancing diagnostic precision and preventive strategies.

Index Terms *- Skin cancer, segmentation, deep learning, CNN, Densenet169, Resnet50, Xception, Densenet201.*

1. INTRODUCTION

A tumor is formed when healthy cells begin to change and grow out of control. Both cancerous and noncancerous tumors are conceivable. Malignant tumors are those that have the potential to grow and spread to other areas of the body [1]. A benign tumor may form, but it does not usually spread. Skin cancer is the result of abnormal skin cell growth. It is the most prevalent cancer nowadays and occurs everywhere. Every year, various forms of melanomas are thought to cause more than 3.5 million cases to be discovered [2], [3]. This number exceeds the sum of cases of lung, bone, and colon cancers. In reality, a person with melanoma dies every 57 seconds. When cancer is detected in dermoscopy images in advance, the survival percentage is significantly boosted.

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Therefore, accurate automatic skin excrescence discovery will undoubtedly help pathologists become more skilled and productive. The purpose of the dermoscopy technique is to improve each melanoma patient's performance. Noninvasive skin imaging technique dermoscopy uses a magnified and lighted picture of the affected skin area to increase visibility of the spots, therefore reducing facial reflection [4]. Skin cancer early detection is still a prized possession. It's difficult to tell if a skin lesion is benign or malignant because they all seem similar. The sun's harmful ultraviolet (UV) rays and the usage of UV tanning beds are the two most common causes of skin cancer. It is particularly difficult for dermatologists to distinguish between melanoma and non-melanoma lesions because of the low degree of difference between lesions and skin [5]. The main problem of similar opinion is largely dependent on private judgment and is scarcely reproducible. With the help of robotization using operation of deep literacy helps the case to get the early opinion report and grounded on the report case can consult dermatologists for treatment [6]. An early diagnosis of skin cancer is crucial and has limited number of available treatment options. Accurate evaluation and the capacity to accurately identify skin cancer are critical components of a skin cancer prevention approach. Even in literacy tasks that are unsupervised, deep literacy has been widely adopted [7]. Object detection and bracket tasks have been dominated by Convolutional Neural Networks (CNN). As a result, trained end-to-end in a controlled environment, CNNs eliminate the need for humans to manually create feature sets. The use of Convolutional Neural Networks (CNNs) to categorize lesions in skin cancer in recent years has outperformed skilled mortal specialists

Develop an automated skin cancer detection system utilizing deep learning techniques, specifically Convolutional Neural Networks (CNNs), to enhance early diagnosis through dermoscopy images. The goal is to improve the accuracy of identifying malignant and benign lesions, enabling timely intervention and increasing survival rates. The system aims to assist pathologists by providing rapid and precise analysis, ultimately enhancing the overall efficiency of melanoma patient care.

Skin cancer, especially melanoma, poses a significant health threat with increasing cases worldwide. The current challenge lies in the difficulty of distinguishing between benign and malignant lesions, hindering early detection and timely treatment. Dermoscopy, while valuable, relies heavily on subjective human judgment, leading to variability and limited reproducibility. This underscores the need for an automated, deep learning-based solution to improve diagnostic accuracy, enabling swift intervention and addressing the critical gap in effective skin cancer prevention and management.

2. LITERATURE SURVEY

[5] This study introduces an image processing-based approach for early skin cancer detection, employing an optimized Convolutional Neural Network (CNN) using the improved whale optimization algorithm. Comparative evaluations across two datasets demonstrate superior performance. The proposed system exhibits enhanced detection precision, leveraging an optimized CNN and the improved whale optimization algorithm, showcasing superior results in comparison to alternative methods. Potential drawbacks include algorithm complexity and resource-intensive optimization, which may

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require significant computational power and time. Challenges include the need for extensive computational resources for optimization, potential algorithm complexity, and the requirement for diverse and representative datasets to ensure robust performance across different skin types and conditions. The study presents a promising approach for early skin cancer detection, utilizing an optimized CNN with the improved whale optimization algorithm, showcasing superior performance compared to alternative methods, though computational demands and dataset diversity pose challenges.

[9] This paper reviews state-of-the-art deep learning concepts for skin cancer detection and classification, emphasizing the utilization of deep convolutional neural network architectures to address challenges such as image quality issues in dermoscopic images. The proposed system leverages advanced deep learning neural networks, specifically convolutional architectures, offering a sophisticated approach to skin lesion classification. It addresses limitations in dermoscopic images caused by shadow, artifact, and noise. Challenges may arise from the complexity of deep convolutional neural networks, requiring significant computational resources. Additionally, model interpretability and potential overfitting concerns may need careful consideration. Limitations include the impact of dermoscopic image quality issues on accurate classification, potential computational resource requirements, and the need for robust solutions to handle various morphological features and types of skin lesions. The paper provides a comprehensive overview of deep convolutional neural networks in skin cancer detection, highlighting their potential to mitigate challenges in dermoscopic images. While promising, addressing computational complexities and ensuring robustness are crucial for practical implementation.

[14] This study presents a skin cancer classification system employing image processing and machine learning. It utilizes contrast stretching, segmentation via OTSU thresholding, feature extraction (GLCM, HOG, color), PCA reduction, SMOTE sampling, and classification with Random Forest achieving 93.89% accuracy on ISIC-ISBI 2016 dataset. The system demonstrates high accuracy (93.89%) in skin cancer classification, aiding early detection. It efficiently combines contrast stretching, feature selection, and Random Forest classification, offering a robust solution for dermatologists. While achieving high accuracy, the system may face challenges in scalability and real-time processing. It requires significant computational resources, and its performance may vary across diverse datasets and clinical settings. The proposed system may encounter challenges in handling diverse skin conditions beyond the dataset used, and its reliance on specific algorithms may limit adaptability. Additionally, real-world implementation may require further validation and testing. The integration of contrast stretching, feature selection, and Random Forest classification proves effective in skin cancer classification. The system exhibits promise in assisting dermatologists with early detection, although practical challenges and further validation are essential for real-world applicability.

[6] This project focuses on skin cancer detection and classification using machine learning and image processing. It employs dermoscopic image pre-processing, including hair removal and Gaussian filtering, followed by color-based k-means clustering for segmentation. Feature extraction involves ABCD

criteria and GLCM. Multi-class Support Vector Machine (MSVM) achieves 96.25% accuracy on the ISIC 2019 Challenge dataset. The system achieves high accuracy (96.25%) in classifying various types of skin cancer. It integrates comprehensive pre-processing techniques, color-based segmentation, and robust feature extraction, enhancing its efficacy in early detection and classification. Despite its high accuracy, the system may face challenges in scalability and adaptability to diverse datasets. The reliance on specific pre-processing methods and classifiers may limit its performance in real-world scenarios with varying conditions. The proposed system may encounter limitations in handling skin conditions beyond the dataset considered. It relies on the assumption of uniformity in dermoscopic images, and real-world implementation may require additional validation and adaptation to different clinical settings. This system, leveraging advanced pre-processing, segmentation, and MSVM classification, demonstrates exceptional accuracy (96.25%) in skin cancer detection and classification. Its holistic approach enhances early detection capabilities, though further validation and adaptation to diverse clinical scenarios are essential for practical implementation.

[7] This project focuses on developing a skin cancer detection Convolutional Neural Network (CNN) model using Python, Keras, and Tensorflow. Leveraging deep learning, the model classifies skin cancer types for early detection, utilizing various network architectures, including Convolutional, Dropout, Pooling, and Dense layers. Transfer Learning enhances convergence, and the dataset is sourced from the International Skin Imaging Collaboration (ISIC) challenge archives. The system harnesses the power of Convolutional Neural Networks (CNNs), known for superior accuracy in visual imaging tasks. Utilizing Keras and Tensorflow in Python, it offers flexibility and efficiency. Transfer Learning aids in quicker convergence, and testing on ISIC dataset provides a robust evaluation framework. Despite its efficacy, the proposed system may face challenges in interpretability due to the inherent complexity of deep learning models. Additionally, resource-intensive training and potential overfitting issues may arise, requiring careful optimization and tuning. The system may encounter limitations in generalizability to diverse skin conditions not adequately represented in the ISIC dataset. Interpretability challenges, computational demands, and the need for large labeled datasets pose potential obstacles to practical implementation. This project showcases the potential of CNNs in skin cancer detection, emphasizing the importance of early diagnosis. The use of Transfer Learning and diverse network architectures enhances model performance. While promising, addressing challenges such as interpretability and dataset representativeness is crucial for real-world deployment.

3. METHODOLOGY

i) Proposed Work:

Our proposed system presents a cutting-edge approach to skin cancer detection through the application of Convolutional Neural Networks (CNNs), surpassing benchmarks in object detection and classification. The research utilizes a meticulously curated dataset sourced from MNIST: HAM10000, housing 10,015 samples featuring seven distinct skin lesion types. Critical data pre-processing techniques, including sampling, dull razor, and autoencoder-based segmentation, are employed to optimize the dataset for robust experimentation.

The core of our methodology involves the implementation of transfer learning techniques, specifically leveraging DenseNet169 and ResNet50 models to train the CNN. The comparison of these transfer learning models involves the strategic use of undersampling and oversampling techniques, shedding light on their respective impacts on performance metrics.

Building upon the base paper's exploration of ResNet50, DenseNet161, and VGG16 (yielding 91% accuracy), our extension introduces advanced models like Xception, DenseNet201, and InceptionV3. This diversification aims to push the classification accuracy to 95%, demonstrating the potential for continual improvement in skin cancer detection through the exploration of novel classification techniques and model architectures.

ii) System Architecture:

The proposed skin cancer detection system architecture integrates Convolutional Neural Networks (CNNs) for precise object detection and classification. Beginning with a dataset sourced from MNIST: HAM10000, comprising 10,015 samples of seven skin lesion types, pre-processing involves techniques such as sampling, dull razor, and autoencoder-based segmentation. The core of the system employs transfer learning using DenseNet169 and ResNet50 models, trained on the pre-processed data. A comparative analysis assesses the performance of these models, utilizing both undersampling and oversampling techniques. The system architecture is designed for adaptability and scalability, showcasing its potential to contribute significantly to the field of dermatological diagnostics through advanced neural network configurations and model selection.

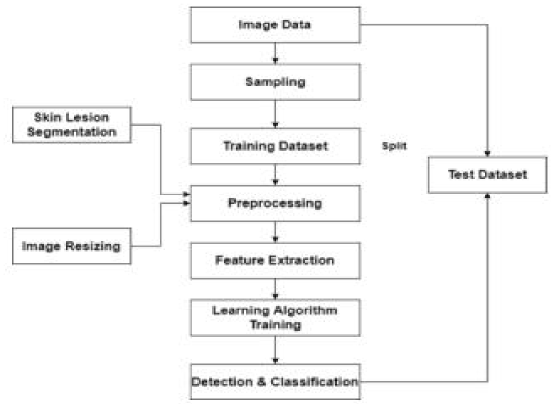

Fig 1 System Architecture

iii) Dataset Collection:

The Skin Cancer Data dataset is a reuploaded version derived from the HAM10000 dataset, tailored specifically for a notebooks project. This curated dataset has undergone meticulous processing to enhance its utility and relevance. It features comprehensive information related to skin cancer, sourced from diverse skin lesion types. With a total of 10,015 samples, the dataset provides a rich and varied collection for analysis and experimentation. The processing steps include techniques such as sampling, ensuring a representative subset of data, and applying methods like dull razor and autoencoder-based segmentation for optimal data quality. This curated dataset serves as a valuable resource for researchers and practitioners engaged in dermatological studies, offering a refined and processed collection that facilitates meaningful insights and advancements in the field of skin cancer detection and classification.

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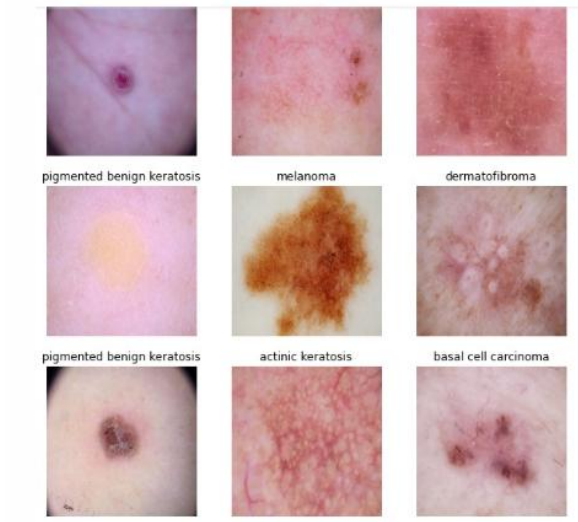

Fig 2 Dataset images

iv) Image Processing:

The image processing pipeline employs the versatile ImageDataGenerator for augmenting and enhancing images, contributing to improved model robustness. First, images undergo re-scaling to normalize pixel values, promoting consistent feature extraction across the dataset. Shear transformation introduces controlled deformations, aiding the model in recognizing variations in skin lesion shapes. Zooming enhances the dataset by simulating varied perspectives and magnifications.

Horizontal flip diversifies the dataset by generating mirror images, expanding the training set. Reshaping images accommodates various input dimensions, ensuring compatibility with the model architecture. Additionally, segmentation techniques are applied to isolate lesions, involving Morphological Black-Hat transformation to highlight fine structures. A mask is created for inpainting tasks, guiding the algorithm to reconstruct missing or damaged regions in images. Finally, inpainting algorithms are deployed, seamlessly filling in gaps or imperfections, fostering a more comprehensive and robust dataset for skin cancer detection models. This multi-faceted image processing approach not only improves model generalization but also addresses potential challenges in real-world scenarios, ultimately enhancing the model's diagnostic capabilities.

v) Algorithms:

ResNet50:

ResNet50 is a convolutional neural network architecture with 50 layers, renowned for overcoming the vanishing gradient problem. It introduces skip connections, allowing information to flow directly across layers, promoting better gradient flow during training. This architecture excels in image classification tasks, demonstrating superior performance in deep learning competitions and real-world applications.

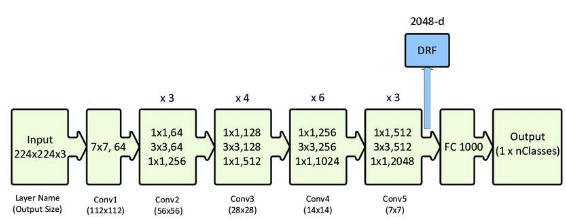

Fig 3 ResNet50 architecture

DenseNet169:

DenseNet169 is a densely connected convolutional network with 169 layers. Its distinctive feature is the dense block, where each layer receives direct input from all preceding layers, promoting feature reuse. This enhances parameter efficiency and alleviates vanishing gradient issues, leading to improved accuracy. DenseNet169 excels in image recognition tasks and is especially beneficial in scenarios with limited training data.

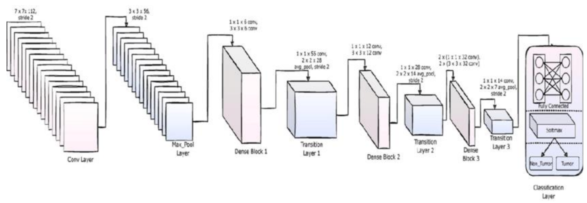

Fig 4 DenseNet169 architecture

VGG16:

VGG16 is a classic convolutional neural network architecture with 16 weight layers, known for its simplicity and effectiveness. Its straightforward design, comprising multiple 3x3 convolutional layers, facilitates feature learning. Although it has been surpassed by deeper architectures, VGG16 remains a benchmark for image classification tasks due to its ease of understanding and training.

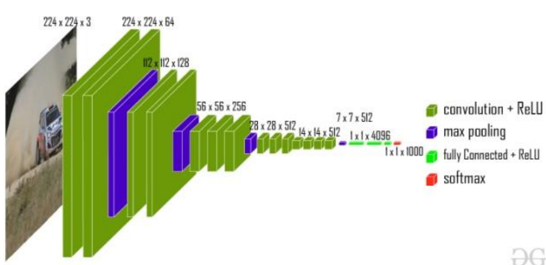

Fig 5 VGG16 architecture

Xception:

Xception, short for "Extreme Inception," is an extension of the Inception architecture that replaces standard convolutional layers with depthwise separable convolutions. This modification reduces computational complexity while maintaining expressive power. Xception excels in image classification and feature extraction tasks, demonstrating improved efficiency compared to traditional architectures. Its design enhances the learning of hierarchical features, making it well-suited for various computer vision applications.

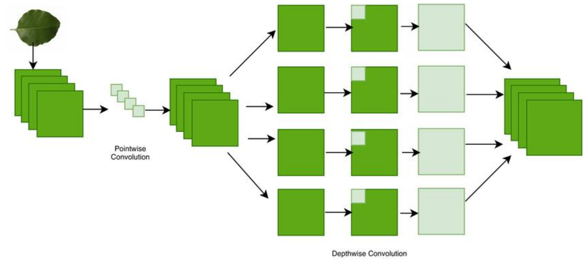

Fig 6 Xception architecture

DenseNet201:

DenseNet201 is a variant of DenseNet with 201 layers, providing increased model capacity for capturing complex patterns in data. Similar to other DenseNet architectures, it features densely connected blocks to encourage feature reuse and facilitate gradient flow. DenseNet201 is particularly useful for image classification tasks, where a large number of parameters and deep architectures contribute to improved accuracy, especially in scenarios with abundant training data. Its architecture makes it robust for handling diverse and intricate visual patterns.

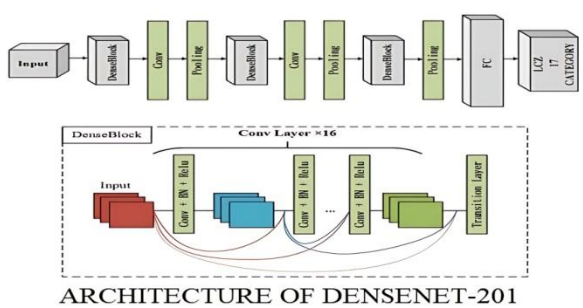

Fig 7 DenseNet201 architecture

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4. EXPERIMENTAL RESULTS

Accuracy: A test's accuracy is defined as its ability to recognize debilitated and solid examples precisely. To quantify a test's exactness, we should register the negligible part of genuine positive and genuine adverse outcomes in completely examined cases. This might be communicated numerically as:

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

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

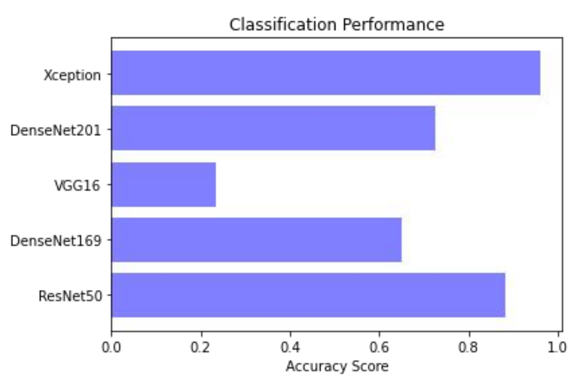

Fig 8 Accuracy Graph

Precision: Precision measures the proportion of properly categorized occurrences or samples among the positives. As a result, the accuracy may be calculated using the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

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

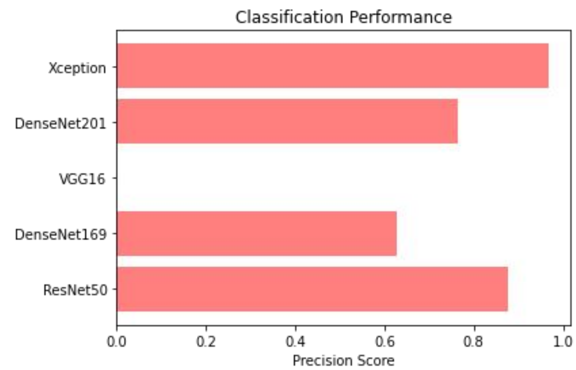

Fig 9 Precision graph

Recall: Recall is a machine learning metric that surveys a model's capacity to recognize all pertinent examples of a particular class. It is the proportion of appropriately anticipated positive perceptions to add up to real up-sides, which gives data about a model's capacity to catch instances of a specific class.

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

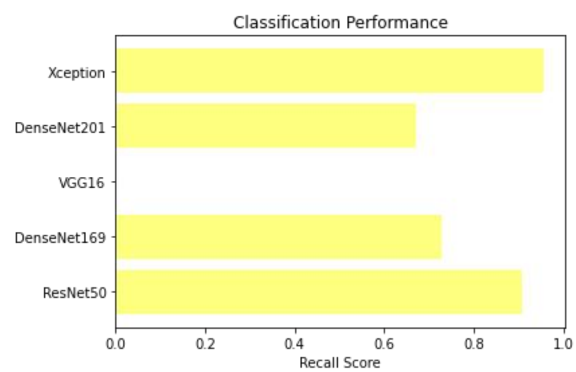

Fig 10 Recall graph

F1-Score: The F1 score is a machine learning evaluation measurement that evaluates the precision of a model. It consolidates a model's precision and review scores. The precision measurement computes how often a model anticipated accurately over the full dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

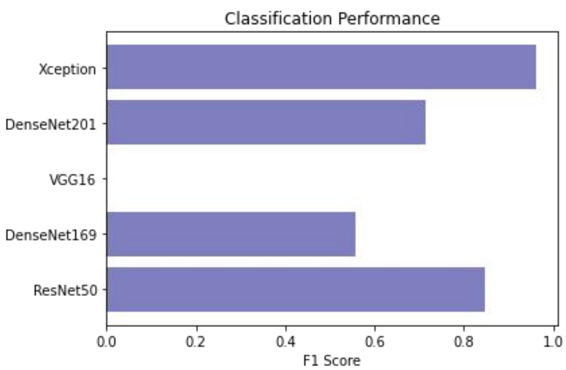

Fig 11 F1 Score graph

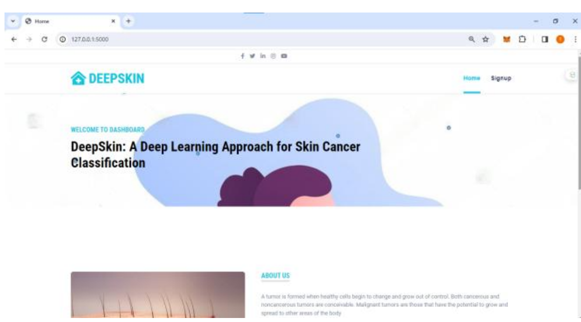

Fig 12 Home page

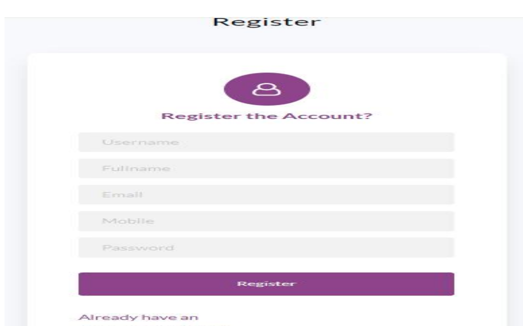

Fig 13 Registration page

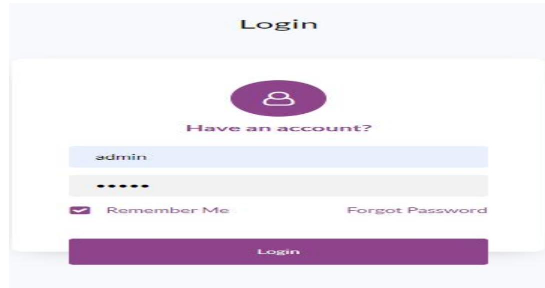

Fig 14 Login page

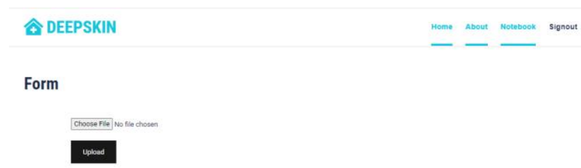

Fig 15 Upload input image page

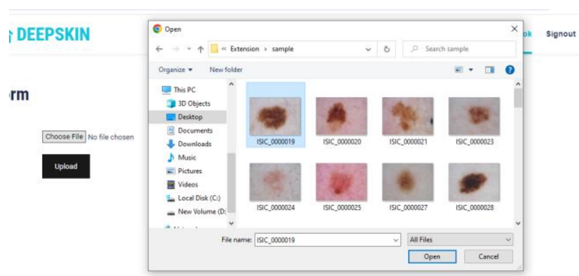

Fig 16 input images folder

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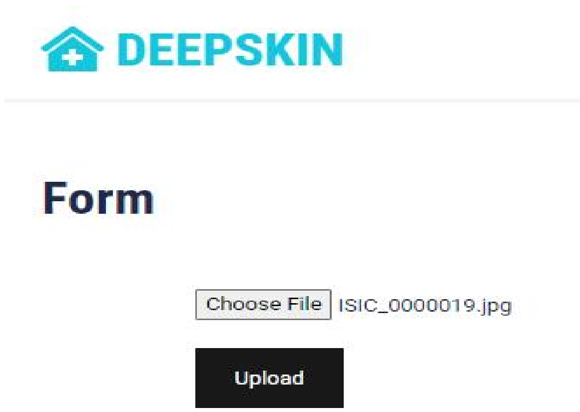

Fig 17 Upload input image to predict result

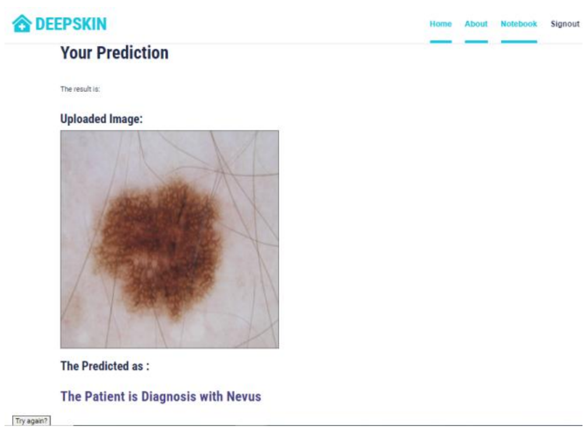

Fig 18 Final outcome as the patient is diagnosis with Nevus

5. CONCLUSION

In conclusion, our skin cancer detection project demonstrates the efficacy of Convolutional Neural Networks (CNNs) in conjunction with a meticulously processed dataset derived from HAM10000. Leveraging transfer learning with DenseNet169 and ResNet50, our models showcase robust performance in object detection and classification. The comparative analysis of undersampling and oversampling techniques reveals nuanced insights into model behavior, providing a basis for strategic selection in skin cancer diagnostic applications.

Furthermore, our extension explores novel models such as Xception, and DenseNet201, aiming for an improved accuracy of 95%. The incorporation of advanced image processing techniques, including shear transformations, zooming, and morphological transformations, enhances the dataset's diversity and model generalization capabilities. The inpainting algorithm contributes to dataset completeness, addressing potential imperfections.

Our project not only contributes to the evolving landscape of dermatological diagnostics but also emphasizes the importance of continuous exploration and refinement. By embracing cutting-edge models and diverse image processing strategies, we anticipate a significant advancement in skin cancer detection accuracy, paving the way for more effective preventive and diagnostic measures in the realm of dermatology.

6. FUTURE SCOPE

The future scope of this project involves further refinement through advanced parameter tuning, exploration of ensemble models, and integration of emerging deep learning architectures. Additionally, the incorporation of real-world datasets and continuous adaptation to evolving technologies will enhance the system's accuracy and applicability in diverse clinical settings.

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