ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

DeepSkin: A Deep Learning Approach to Skin Cancer Classification

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Abstract: This study addresses the urgent global problem of rapidly spreading skin cancer, emphasizing the significance of accurate detection for effective prevention. Dermatologists are utilizing deep learning, namely Convolutional Neural Networks (CNNs), because of their difficulties with early detection. The work employs data preparation techniques such autoencoder-based segmentation, dull razor, and sampling using the MNIST: HAM10000 dataset, which has 10,015 samples and seven types of skin diseases. It is demonstrated that when DenseNet169 and ResNet50 models are employed for transfer learning, DenseNet169's undersampling results in high accuracy and F1-measure, whereas ResNet50's oversampling technique works well in both measures. Building on the primary paper's use of ResNet50, DenseNet161, and VGG16 (achieving 91% accuracy), this extension explores additional models including Xception, DenseNet201, and InceptionV3. The study shows how different models and parameter modifications may improve the classification of skin cancer, offering a workable way to increase diagnosis accuracy and preventative measures. It expects an increase in accuracy of 95%.

***Index Terms* -** *Skin cancer, segmentation, deep learning, CNN, Densenet169, Resnet50, Xception, Densenet201, InceptionV3.*

1. INTRODUCTION

A tumour forms when healthy cells change and multiply uncontrolled. Tumors can be cancerous or not. Malignant tumors are those that can spread [1]. Although they can form, benign tumors seldom spread. Skin cancer results from abnormal cell growth. The most prevalent cancer today, it may be discovered anywhere. About 3.5 million melanomas are diagnosed annually [2], [3]. This number exceeds lung, bone, and colon cancer cases. Actually, one melanoma sufferer dies every 57 seconds. Early dermoscopy cancer detection dramatically improves survival. Thus, accurate automated skin excrescence identification will help pathologists improve their skills and productivity. Dermoscopy improves melanoma patients' performance. Dermoscopy is a noninvasive skin imaging method that magnifies and illuminates regions on the affected skin to diminish facial reflection [4]. Early skin cancer detection is valued. Because all skin lesions seem same, identifying them as benign or malignant can be difficult. UV tanning beds and sun exposure are the main causes of skin cancer. The little difference between lesions and skin makes it harder for physicians to distinguish melanoma from non-melanoma lesions [5]. Comparable opinions are difficult to replicate and heavily rely on human judgment. Deep literacy procedures and robotization can provide an early opinion report and refer the case to dermatologists [6]. Skin cancer therapy is limited and needs early identification. A skin cancer prevention approach must incorporate accurate evaluation and detection. Even in unsupervised literacy activities, deep literacy is widely used [7]. CNNs dominate bracket issues and object detection. CNNs are trained end-to-end in a controlled environment, therefore they don't need feature sets. Recently, Convolutional Neural Networks (CNNs) have outperformed highly qualified human specialists in skin cancer lesion categorization.

Develop a deep learning-based automated skin cancer detection system that employs CNNs to enhance early diagnosis utilizing dermoscopy images. Identifying benign and malignant cancers more accurately should improve survival and prompt treatments. The technology helps pathologists and improves melanoma therapy by providing fast, accurate analysis.

Skin cancer, especially melanoma, is spreading worldwide, posing a severe health risk. The difficulty of distinguishing benign from malignant tumors hinders early detection and treatment. Although valuable, dermoscopy relies on human judgment, which can lead to variability and poor reproducibility. This underscores the need for an automated, deep learning-based solution to improve diagnosis precision, speed up action, and reduce the skin cancer prevention and treatment gap.

2. LITERATURE SURVEY

1. Detection of skin cancer using CNN algorithm:

Melanoma and focal cell carcinoma can be prevented with early detection. However, several variables reduce detection accuracy. Medical applications of machine vision and image processing are growing. This study suggests using image processing to detect early skin cancer. This is done using an ideal CNN. This paper improves CNN utilizing updated whale optimization. Comparing the offered strategy to others on two datasets evaluates it. Simulations show the recommended strategy outperforms the others.

2. Skin lesion classification based on deep convolutional neural networks architectures:

Skin cancer is one of the most common cancers caused by dermatological problems. It may be classified by morphology, color, structure, and texture. Early detection and diagnosis of malignant skin cancer cells reduces skin cancer mortality. Noise, artifact, and shadow weaken dermoscopic images and may make detection harder. To solve these challenges, deep learning neural networks analyze images and identify skin cancer. The authors explore authoritative deep learning concepts for skin cancer detection and categorization.

3. Skin cancer classification using image processing and machine learning:

Skin cancer spreads quickest among the numerous types of cancer known. Melanoma, the most dangerous type of skin cancer, begins on the skin's surface and spreads. If diagnosed early, melanoma patients have a 96% survival rate with simple and economical treatments. Traditional melanoma diagnosis involves biopsies, technology, and expert dermatologists. Machine learning may detect skin cancer early and accurately, saving doctors money. This study uses image processing and machine learning to classify and segment benign and malignant skin lesions. Pixel mean values and standard deviation are used to contrast stretch dermoscopic images in a novel way. After that, OTSU thresholding segments the image. The histogram of oriented gradients (HOG) object, color identification features, and Gray level Co-occurrence Matrix (GLCM) features for texture identification are retrieved from segmented images. PCA reduces HOG feature dimensionality. The synthetic minority oversampling approach (SMOTE) addresses class imbalance. The feature vector is then resized and standardized. A wrapper-based feature selection procedure is recommended before categorization. For classification, Random Forest, SVM (Medium Gaussian), and Quadratic Discriminant are used. This approach is validated using the public ISIC-ISBI 2016 dataset. The Random Forest classifier is most accurate. The recommended system's Random Forest classifier classification accuracy on ISIC-ISBI 2016 is 93.89%.The recommended contrast stretching before segmentation yields decent results. Compared to other popular classifiers, the wrapper-based feature selection strategy performs well with the Random Forest classifier.

4. Skin cancer detection using machine learning techniques:

The number of deaths from skin cancer, which is thought to be one of the deadliest types of the illness, has sharply increased due to a lack of knowledge about the symptoms and how to prevent them. Early detection is therefore crucial to preventing cancer from spreading. The three most serious types of skin cancer are squamous cell carcinoma, basal cell carcinoma, and melanoma. This work identifies and categorizes several types of skin cancer using machine learning and image processing techniques. During the pre-processing stage, dermoscopic images are considered as input. A Gaussian filter is used to smooth the image once all unwanted hair particles on the skin lesion have been eliminated using the dull razor technique. The median filter preserves the margins of the lesion while lowering noise. Since color is a key factor in identifying the kind of cancer, color-based k-means clustering is used during the segmentation stage. The statistical and textural feature extraction is accomplished using the Gray Level Co-occurrence Matrix (GLCM) and Asymmetry, Border, Color, Diameter (ABCD). The experimental work makes use of the ISIC 2019 Challenge dataset, which comprises eight different types of dermoscopic images. For classification applications, the Multi-class Support Vector Machine (MSVM) has an accuracy of about 96.25.

5. Deep learning solutions for skin cancer detection and diagnosis:

In the United States alone, about 5,000,000 new cases of skin cancer are found annually, making it a concerning public health concern. The two primary types of skin cancer are melanoma and non-melanoma. Melanoma, also known as malignant melanoma, is the 19th most prevalent kind of cancer in both men and women. The most lethal kind of skin cancer is this one [1]. In 2015, there were over 350,000 cases of melanoma recorded globally, and the illness claimed the lives of about 60,000 individuals. The most prevalent non-melanoma malignancies are squamous cell carcinoma and basal cell carcinoma. Non-melanoma skin cancer is the fifth most frequent kind of cancer, with over 1 million cases detected globally in 2018 [2]. By 2019, an estimated 1.7 million more cases are expected to be diagnosed [3]. Despite the extremely high death rate, the survival rate exceeds 95% when discovered early. This motivates us to create a method for early detection of skin cancer so that millions of lives can be saved. A subclass of deep neural networks known as convolutional neural networks (CNNs) or ConvNets are essentially an extended form of multi-layer perceptrons. CNNs have shown the highest accuracy in visual imaging tasks [4]. The objective of this research is to develop a CNN model for skin cancer diagnostics that can recognize the many types of skin cancer and help with early detection [5]. The backend of the Python CNN classification model creation process will make use of Tensorflow and Keras. The model is developed and assessed using several network topologies by varying the types of layers used to train the network, such as convolutional, dropout, pooling, and dense layers, among others. The model will also use Transfer Learning techniques for early convergence. The model will be trained and tested using the dataset collected from the International Skin Imaging Collaboration (ISIC) challenge archives.

3. METHODOLOGY

i) Proposed Work:

Our proposed system outperforms prior standards for item recognition and classification while providing a state-of-the-art approach for skin cancer detection through the use of Convolutional Neural Networks (CNNs). The work uses HAM10000, a carefully chosen dataset from MNIST that includes 10,015 samples with seven distinct types of skin diseases. Important data pre-processing techniques such autoencoder-based segmentation, dull razor, and sampling are utilized to get the dataset ready for trustworthy testing.

Our approach is based on the use of transfer learning techniques, namely training the CNN using the DenseNet169 and ResNet50 models. A number of transfer learning models are evaluated by carefully using undersampling and oversampling techniques, revealing how each influences performance metrics.

Building on the study of ResNet50, DenseNet161, and VGG16 (generating 91% accuracy) in the basic paper, our contribution offers more advanced models such as Xception, DenseNet201, and InceptionV3. This study aims to raise the classification accuracy to 95% by examining novel model architectures and classification techniques, suggesting the potential for future improvements in skin cancer diagnosis.

ii) System Architecture:

The proposed skin cancer detection system design incorporates Convolutional Neural Networks (CNNs) for precise object recognition and classification. Pre-processing methods include autoencoder-based segmentation, dull razor, and sampling, starting with the MNIST-sourced dataset HAM10000, which contains 10,015 samples of seven distinct kinds of skin lesions. The system's core employs transfer learning using DenseNet169 and ResNet50 models trained on the pre-processed data. A comparison study using both undersampling and oversampling techniques is used to assess the performance of these models. The system architecture, which is designed for flexibility and scalability, shows its potential to significantly advance the field of dermatological diagnostics through complex neural network configurations and model selection.

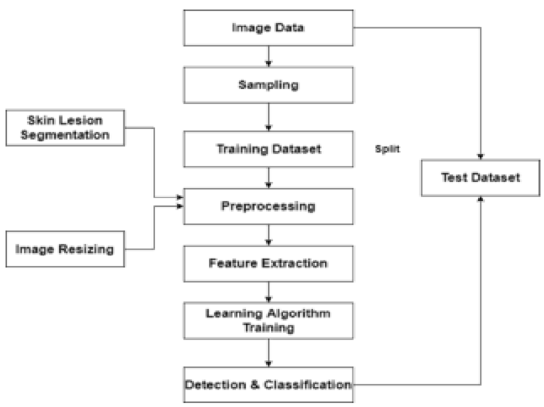

Fig 1 System Architecture

iii) Dataset Collection:

The Skin Cancer Data dataset was made specifically for a notebook project and was reuploaded from the HAM10000 dataset. This carefully chosen dataset has undergone processing to increase its usability and usefulness. It contains comprehensive information about many types of skin lesions that might lead to skin cancer. With 10,015 samples in all, the dataset provides a sizable and varied collection for study and experimentation. The processing steps include sampling, ensuring a representative sample of data, and employing methods such as dull razor and autoencoder-based segmentation for optimal data quality. This carefully curated dataset is a priceless resource for scholars and professionals working on dermatological investigations, with a refined and processed collection that permits important insights and advancements in the field of skin cancer detection and categorization.

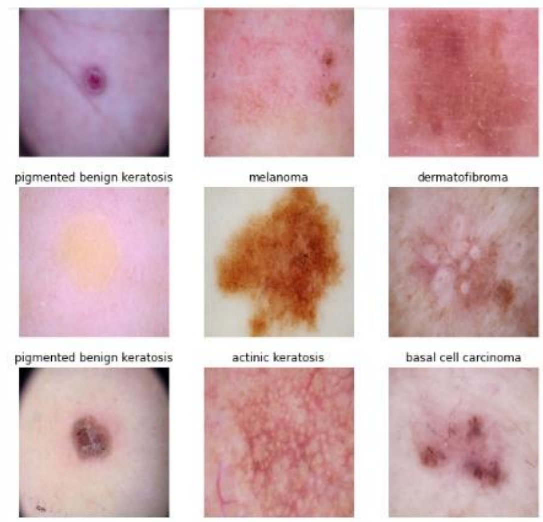

Fig 2 Dataset images

iv) Image Processing:

The image processing pipeline uses the adaptable ImageDataGenerator to augment and improve images, which contributes to the model's increased robustness. Images are initially rescaled to equalize pixel values in order to guarantee consistent feature extraction across the dataset. By applying controlled deformations, shear transformation aids the model in identifying variations in the types of skin lesions. Zooming enhances the dataset by simulating several perspectives and magnifications.

Horizontal flip expands and diversifies the training set by producing mirror images. By allowing for varying input dimensions, image reshaping guarantees compatibility with the model design. Additionally, segmentation techniques that use the Morphological Black-Hat transformation to highlight small structures are used to identify lesions. A mask is created for inpainting tasks to guide the algorithm in restoring damaged or missing portions of images. Last but not least, inpainting methods are utilized to seamlessly fill in any holes or defects, producing a more comprehensive and trustworthy dataset for skin cancer detection models. By addressing potential problems in real-world situations and enhancing model generalization, this multimodal approach to image processing improves the model's diagnostic skills.

v) Algorithms:

ResNet50:

One well-known solution to the vanishing gradient problem is the 50-layer ResNet50 convolutional neural network architecture. By allowing information to flow directly between layers, skip connections enhance gradient flow during training. In deep learning competitions and real-world applications, this architecture excels, especially in image classification tasks.

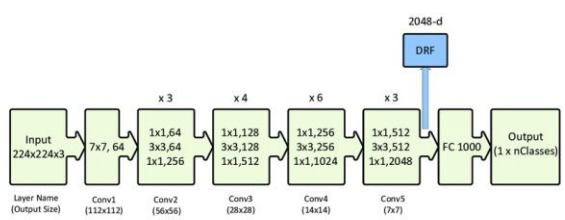

Fig 3 ResNet50 architecture

DenseNet169:

DenseNet169 is a strongly coupled convolutional network with 169 layers. The thick block, which promotes feature reuse by enabling each layer to directly receive input from every layer that came before it, is its distinctive characteristic. By eliminating vanishing gradient issues and boosting parameter efficiency, this increases accuracy. DenseNet169 excels in image identification tasks and is especially helpful when there is a lack of training data.

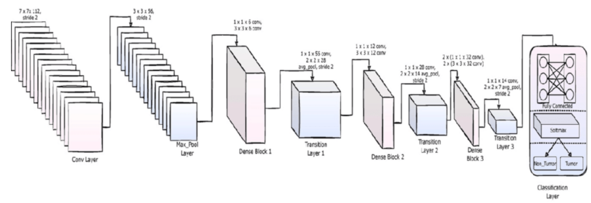

Fig 4 DenseNet169 architecture

VGG16:

VGG16 is a popular and simple convolutional neural network architecture with 16 weight layers. Feature learning is facilitated by its straightforward design, which comprises of several 3x3 convolutional layers. Despite being surpassed by deeper architectures, VGG16 remains a standard for image classification tasks due to its ease of comprehension and training.

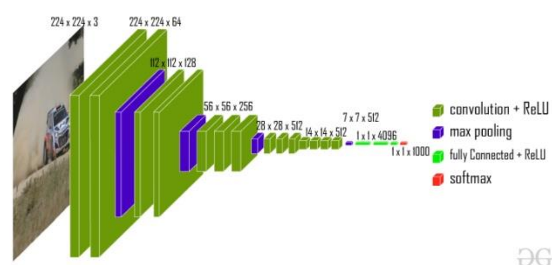

Fig 5 VGG16 architecture

Xception:

An extension of the Inception architecture known as "Extreme Inception," or Xception, substitutes depthwise separable convolutions for traditional convolutional layers. This modification reduces computational complexity while maintaining expressive capability. In image classification and feature extraction tasks, Xception performs better than traditional systems. Its architecture, which enhances the learning of hierarchical features, makes it perfect for a variety of computer vision applications.

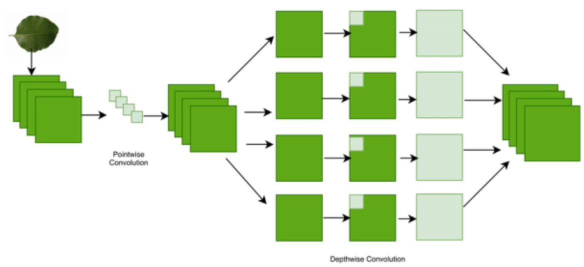

Fig 6 Xception architecture

DenseNet201:

DenseNet201, a 201-layer DenseNet variant, provides a higher model capacity for spotting complex patterns in data. Like previous DenseNet architectures, it has densely connected blocks to facilitate gradient flow and encourage feature reuse. DenseNet201 is particularly useful for image classification tasks where a large number of parameters and deep architectures contribute to improved accuracy when there is an abundance of training data. Its design allows it to easily handle a broad range of intricate visual patterns.

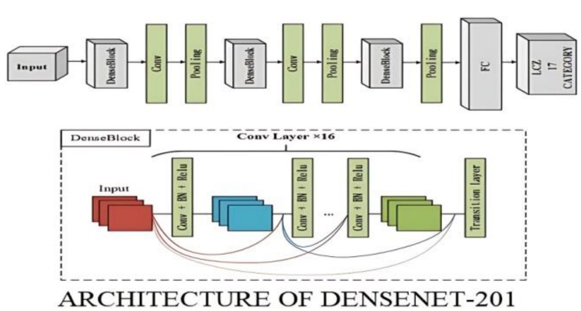

Fig 7 DenseNet201 architecture

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.

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

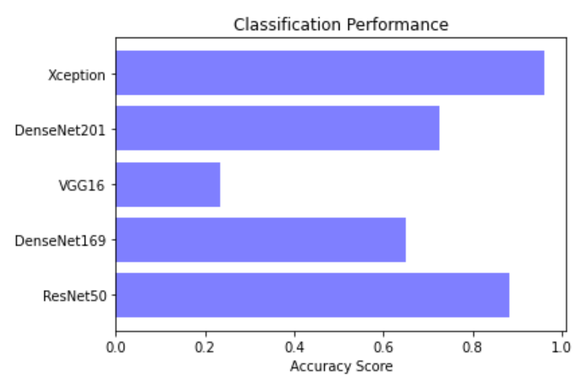

Fig 8 Accuracy Graph

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)

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

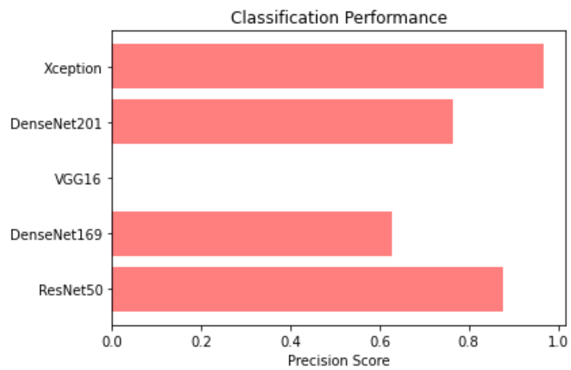

Fig 9 Precision graph

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.

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

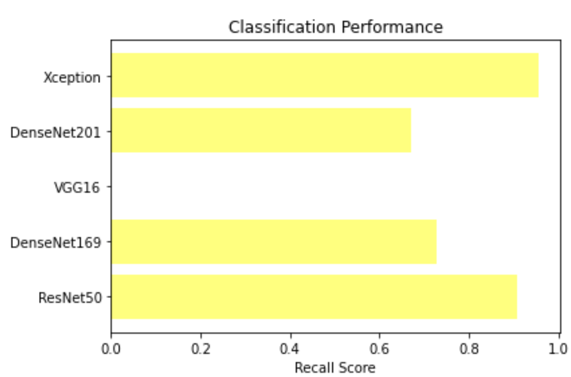

Fig 10 Recall graph

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.

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

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

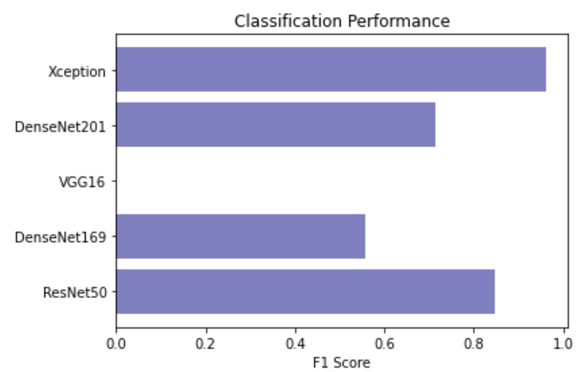

Fig 11 F1 Score graph

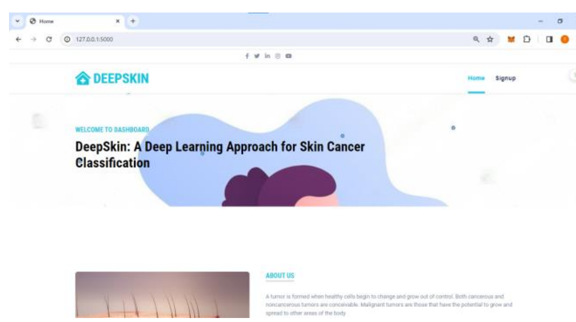

Fig 12 Home page

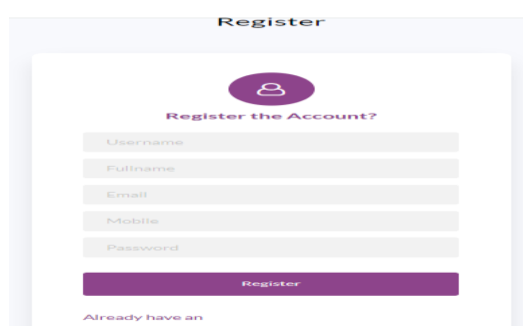

Fig 13 Registration page

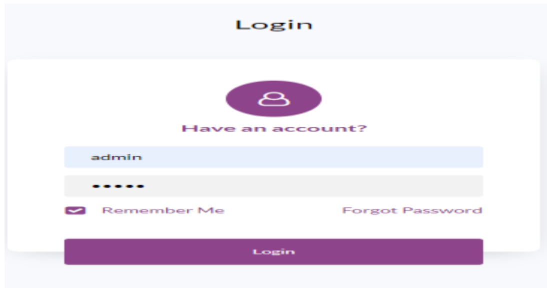

Fig 14 Login page

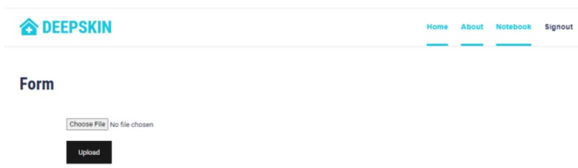

Fig 15 Upload input image page

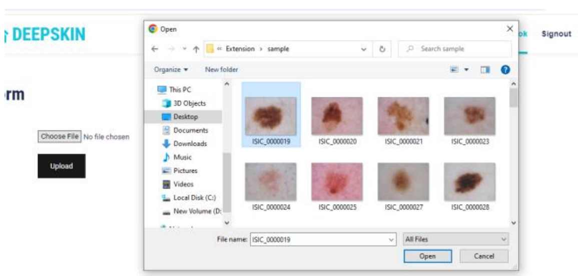

Fig 16 input images folder

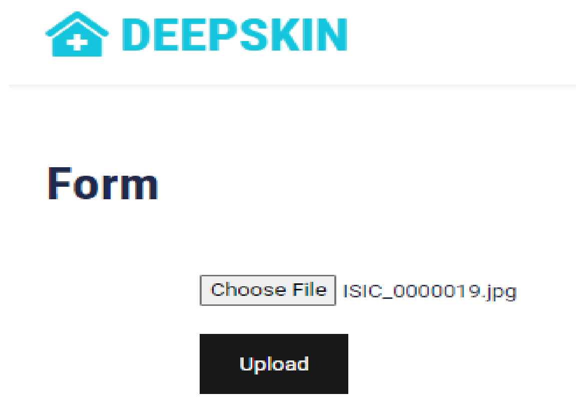

Fig 17 Upload input image to predict result

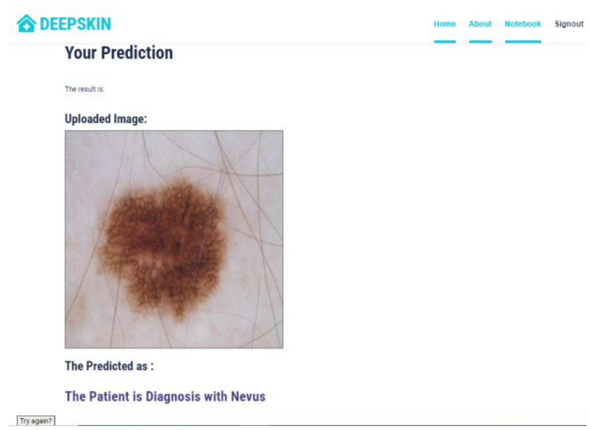

Fig 18 Final outcome as the patient is diagnosis with Nevus

5. CONCLUSION

Finally, our skin cancer detection study demonstrates the efficacy of Convolutional Neural Networks (CNNs) utilizing a meticulously processed dataset from HAM10000. Using transfer learning with DenseNet169 and ResNet50, our models show excellent performance in object recognition and classification. By highlighting nuances in model behavior, the comparison of oversampling and undersampling techniques offers a basis for strategic selection in skin cancer diagnostic applications.

Furthermore, in an effort to boost accuracy by 95%, our expansion explores new models such as Xception, DenseNet201, and InceptionV3. Sophisticated image processing techniques including zooming, morphological modifications, and shear transformations enhance the dataset's diversity and model generalization capabilities. The inpainting procedure promotes completeness by correcting any potential errors in the dataset.

Our work contributes to the evolving area of dermatological diagnostics and emphasizes the importance of further research and development. By employing cutting-edge models and a range of image processing techniques, we anticipate a significant increase in the accuracy of skin cancer detection, paving the way for more effective diagnostic and preventative dermatological therapies.

6. FUTURE SCOPE

The future scope of this research demands for more refinement through the use of state-of-the-art deep learning architectures, complex parameter tuning, and ensemble model exploration. Furthermore, the incorporation of real-world information and continuous technological adaptation will enhance the system's accuracy and usefulness in a range of therapeutic scenarios.

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