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Research

DeepSkin: A Deep Learning Method for Categorizing Skin Cancer

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Abstract: This study tackles the pressing worldwide issue of fast spreading skin cancer, highlighting how important a precise diagnosis is to successful prevention. Due of their challenges with early detection, dermatologists are using deep learning, namely Convolutional Neural Networks (CNNs). Utilizing the MNIST: HAM10000 dataset, which has 10,015 samples and seven kinds of skin lesions, the study uses data preparation methods such as autoencoder-based segmentation, dull razor, and sampling. When DenseNet169 and ResNet50 models are used for transfer learning, it is shown that while ResNet50's oversampling strategy performs well in both metrics, DenseNet169's undersampling produces high accuracy and F1-measure. This expansion investigates other models such as Xception, DenseNet201, and InceptionV3, building on the main paper's usage of ResNet50, DenseNet161, and VGG16 (reaching 91% accuracy). The study highlights the potential of various models and parameter adjustment to enhance skin cancer categorization, providing a viable path for improving diagnostic precision and preventive tactics. It anticipates a 95% accuracy increase.

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

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1. INTRODUCTION

When healthy cells start to alter and proliferate uncontrollably, a tumor is created. It is possible for tumors to be either malignant or noncancerous. Tumors with the potential to develop and spread to other parts of the body are known as malignant tumors [1]. Although they can develop, benign tumors typically do not spread. Unusual development of skin cells leads to skin cancer. These days, it is the most common cancer and may be found anywhere. It is estimated that about 3.5 million instances of melanomas of various types are found each year [2], [3]. This figure is higher than the total number of lung, bone, and colon cancer cases. In actuality, one melanoma patient passes away every 57 seconds. The survival rate is greatly increased when cancer is identified early on in dermoscopy pictures. As a result, precise automated skin excrescence detection will surely aid pathologists in improving their proficiency and output. Enhancing the performance of each melanoma patient is the aim of the dermoscopy procedure. Dermoscopy is a noninvasive skin imaging procedure that reduces face reflection by increasing visibility of the spots on the afflicted skin region through a magnified and illuminated image [4]. Early identification of skin cancer is still highly valued. Because all skin lesions seem same, it can be challenging to determine whether they are benign or cancerous. The two most frequent causes of skin cancer are exposure to the sun's damaging ultraviolet (UV) radiation and using UV tanning beds. The modest degree of difference between lesions and skin makes it more challenging for dermatologists to differentiate between melanoma and non-melanoma lesions [5]. The primary issue with comparable opinions is that they are rarely replicable and heavily rely on personal judgment. With the use of deep literacy operations and robotization, the case can receive an early opinion report and, based on that report, consult dermatologists for treatment [6]. Skin cancer has few accessible treatment options and requires an early diagnosis. A skin cancer preventive strategy must include accurate assessment and the ability to recognize skin cancer. Deep literacy has been extensively employed, even in unsupervised literacy tasks [7]. Convolutional Neural Networks (CNN) have been the dominant technology for bracket problems and object detection. Therefore, CNNs do not require humans to manually construct feature sets since they are trained end-to-end in a controlled setting. In recent years, Convolutional Neural Networks (CNNs) have surpassed highly qualified human professionals in the classification of skin cancer lesions.

Create a deep learning-based automated skin cancer detection system that uses Convolutional Neural Networks (CNNs) to improve early diagnosis using dermoscopy pictures. Enhancing the precision of distinguishing between benign and malignant tumors is intended to increase survival rates and allow for prompt intervention. By offering quick and accurate analysis, the technology seeks to support pathologists and eventually improve the overall effectiveness of melanoma patient treatment.

The number of incidences of skin cancer, particularly melanoma, is rising globally, making it a serious health concern. Early identification and prompt treatment are hampered by the existing problem of differentiating between benign and malignant tumors. Despite its value, dermoscopy is highly dependent on human judgment, which might result in variability and poor repeatability. This emphasizes the necessity of an automated, deep learning-based solution to increase diagnostic precision, facilitate prompt action, and close the crucial gap in the prevention and treatment of skin cancer.

2. LITERATURE SURVEY

1. Detection of skin cancer using CNN algorithm:

Certain types of skin cancer, including melanoma and focal cell carcinoma, can be avoided with early identification. However, there are a number of factors that negatively affect the accuracy of detection. The use of machine vision and image processing in medical applications has grown recently. This research proposes a novel approach to early skin cancer diagnosis based on image processing. For this, the technique makes use of an ideal convolutional neural network (CNN). This study optimizes the CNN using an updated whale optimization technique. The suggested approach is evaluated by contrasting it with a few other approaches on two distinct datasets. According to simulation findings, the suggested approach is better than the other approaches under comparison.

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

One of the main cancer kinds that arises from a variety of dermatological conditions is skin cancer, which may be further divided into other forms according to morphological characteristics, color, structure, and texture. The early and prompt identification and diagnosis of malignant skin cancer cells is essential for reducing the death rate of skin cancer patients. Current dermoscopic picture limitations, such as noise, artifact, and shadow, degrade image quality and might make detection more difficult. In an effort to address these issues, deep learning neural networks have been used to analyze the photos and diagnose skin cancer. The state-of-the-art in authoritative deep learning principles relevant to the diagnosis and classification of skin cancer is reviewed by the writers in this work.

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

Among the many different kinds of cancer that people are aware of, skin cancer spreads the fastest. The scariest and most serious kind of skin cancer is melanoma, which often starts on the skin's surface before spreading deeper into the skin's layers. However, with straightforward and affordable therapies, the survival rate for people with melanoma is 96% if they are discovered early. The traditional approach to diagnosing melanoma includes biopsies, technology, and skilled dermatologists. The field of machine learning has shown itself to offer state-of-the-art methods for skin cancer identification at an earlier stage with high accuracy, helping dermatologists avoid the costly diagnosis. This research proposes an image processing and machine learning approach for classifying and segmenting skin lesions as either benign or malignant. A brand-new technique for contrast stretching dermoscopic pictures is put forward, which is based on pixel mean values and standard deviation. After that, picture segmentation is done using the OTSU thresholding technique. Following segmentation, characteristics such as the histogram of oriented gradients (HOG) object, color identification features, and Gray level Co-occurrence Matrix (GLCM) features for texture identification are recovered from the segmented pictures. To reduce dimensionality, HOG features are reduced using principal component analysis (PCA). To address the issue of class imbalance, sampling using the synthetic minority oversampling method (SMOTE) is used. After that, the feature vector is scaled and standardized. Prior to classification, a unique feature selection strategy based on the wrapper technique is suggested. For classification, classifiers such as Random Forest, SVM (Medium Gaussian), and Quadratic Discriminant are employed. The suggested method is validated using the ISIC-ISBI 2016 publically available dataset. The Random Forest classifier achieves the highest accuracy. On ISIC-ISBI 2016, the suggested system's classification accuracy using the Random Forest classifier is 93.89%.Segmentation results are good when the suggested method of contrast stretching before to segmentation is used. Furthermore, when paired with the Random Forest classifier, the suggested wrapper-based feature selection method yields encouraging outcomes when compared to other widely used classifiers.

4. Skin cancer detection using machine learning techniques:

Lack of awareness about the signs and how to prevent them has led to a sharp rise in the number of fatalities from skin cancer, which is regarded as one of the most deadly forms of the disease. In order to stop cancer from spreading, early identification at an early stage is therefore essential. There are other varieties of skin cancer, but the three most dangerous ones are melanoma, basal cell carcinoma, and squamous cell carcinoma. This study uses machine learning and image processing methods to identify and classify different forms of skin cancer. Dermoscopic pictures are taken into consideration as input during the pre-processing phase. After all undesirable hair particles on the skin lesion have been removed using the dull razor approach, the picture is smoothed using a Gaussian filter. The median filter is used to reduce noise and maintain the lesion's margins. Color-based k-means clustering is carried out during the segmentation step as color is a crucial characteristic in determining the kind of malignancy. The Gray Level Co-occurrence Matrix (GLCM) and Asymmetry, Border, Color, Diameter (ABCD) are used to achieve the statistical and textural feature extraction. The ISIC 2019 Challenge dataset, which includes eight distinct kinds of dermoscopic pictures, is used for the experimental study. The accuracy of the Multi-class Support Vector Machine (MSVM), which was used for classification purposes, is around 96.25.

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

Over 5,000,000 new instances of skin cancer are discovered each year in the United States alone, making it a worrying public health issue. Melanoma and non-melanoma are the two main kinds of skin cancer. Malignant melanoma, another name for melanoma, is the 19th most common kind of cancer in both men and women. This kind of skin cancer is the most deadly [1]. Around 350,000 instances of melanoma were reported worldwide in 2015, and around 60,000 people died from the disease. Squamous cell carcinoma and basal cell carcinoma are the most common non-melanoma tumors. In 2018, more than 1 million cases of non-melanoma skin cancer were diagnosed worldwide, making it the fifth most common kind of cancer [2]. It is anticipated that about 1.7 million additional cases would be diagnosed by 2019 [3]. The survival rate surpasses 95% when diagnosed early, despite the very high death rate. This encourages us to develop a way to identify skin cancer early and save millions of lives. A subclass of deep neural networks known as convolutional neural networks (CNNs) or ConvNets are essentially an extended form of multi-layer perceptrons. When it comes to visual imaging tasks, CNNs have demonstrated the best accuracy [4]. The goal of this study is to create a CNN model for skin cancer diagnosis that can identify the different forms of skin cancer and aid in early detection [5]. Tensorflow and Keras will be used in the backend of the Python CNN classification model development process. By altering the kind of layers used to train the network, such as convolutional, dropout, pooling, and dense layers, among others, the model is created and evaluated using various network topologies. For early convergence, the model will also employ Transfer Learning strategies. The dataset gathered from the International Skin Imaging Collaboration (ISIC) challenge archives will be used to train and test the model.

3. METHODOLOGY

i) Proposed Work:

By using Convolutional Neural Networks (CNNs), our suggested system offers a state-of-the-art method for detecting skin cancer while outperforming previous standards for object identification and classification. The study makes use of a carefully selected dataset from MNIST: HAM10000, which contains 10,015 samples with seven different kinds of skin lesions. To prepare the dataset for reliable testing, important data pre-processing methods are used, such as autoencoder-based segmentation, dull razor, and sampling.

The application of transfer learning techniques, particularly using the DenseNet169 and ResNet50 models to train the CNN, is the basis of our methodology. By carefully utilizing undersampling and oversampling strategies, several transfer learning models are compared, illuminating how each affects performance measures.

Our addition presents more sophisticated models including Xception, DenseNet201, and InceptionV3, building on the base paper's investigation of ResNet50, DenseNet161, and VGG16 (producing 91% accuracy). By investigating new classification methods and model architectures, this research seeks to increase the classification accuracy to 95%, indicating the possibility of further advancements in skin cancer diagnosis.

ii) System Architecture:

Convolutional Neural Networks (CNNs) are integrated into the suggested skin cancer detection system architecture to provide accurate object recognition and categorization. Starting with the MNIST-sourced dataset HAM10000, which includes 10,015 samples of seven different types of skin lesions, pre-processing techniques include autoencoder-based segmentation, dull razor, and sampling. Using DenseNet169 and ResNet50 models that were trained on the pre-processed data, the system's core uses transfer learning. These models' performance is evaluated by a comparative analysis that makes use of both undersampling and oversampling methods. Through sophisticated neural network setups and model selection, the system architecture, which is built for flexibility and scalability, demonstrates its potential to make a substantial contribution to the field of dermatological diagnostics.

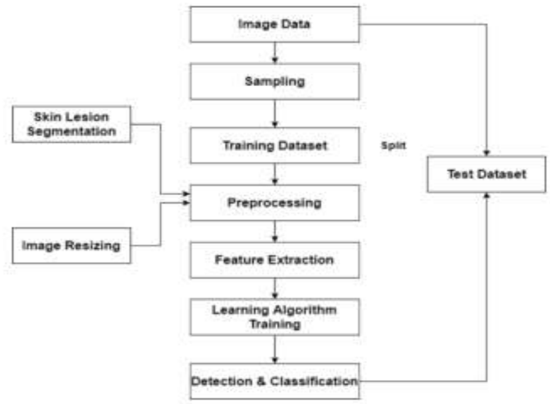

Fig 1 System Architecture

iii) Dataset Collection:

Reuploaded from the HAM10000 dataset, the Skin Cancer Data dataset was created especially for a notebook project. This carefully selected dataset has been processed to improve its usefulness and applicability. It includes thorough information about skin cancer that is derived from a variety of skin lesion kinds. The dataset offers a large and diverse collection for research and experimentation, with 10,015 samples in total. Sampling, guaranteeing a representative selection of data, and using techniques like autoencoder-based segmentation and dull razor for the best possible data quality are all part of the processing phases. With a refined and processed collection that enables significant insights and developments in the field of skin cancer detection and classification, this curated dataset is an invaluable tool for academics and practitioners working on dermatological investigations.

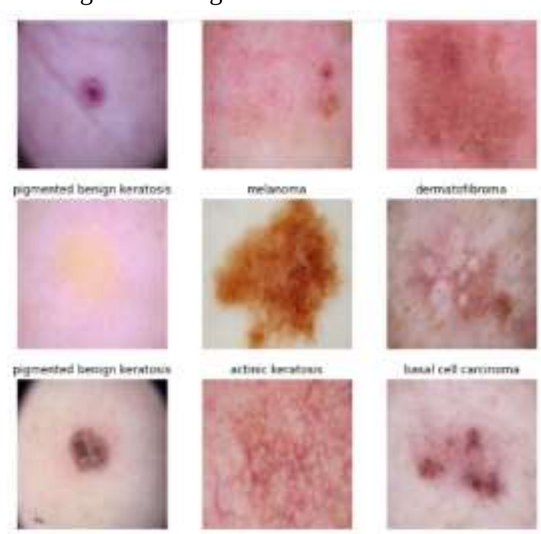

Fig 2 Dataset images

iv) Image Processing:

The flexible ImageDataGenerator is used in the image processing pipeline to enhance and supplement pictures, which helps to increase the resilience of the model. To ensure uniform feature extraction throughout the dataset, pictures are first rescaled to equalize pixel values. Shear transformation helps the model identify differences in the forms of skin lesions by introducing controlled deformations. Zooming simulates several viewpoints and magnifications, which improves the dataset.

By creating mirror images, horizontal flip broadens the training set and diversifies the dataset. Image reshaping ensures consistency with the model design by accommodating different input dimensions. Lesions are also isolated using segmentation methods, which emphasize tiny structures using Morphological Black-Hat transformation. For inpainting jobs, a mask is made to direct the algorithm in reconstructing areas of pictures that are damaged or missing. Lastly, inpainting techniques are used to smoothly fill in any gaps or flaws, creating a more complete and reliable dataset for models that identify skin cancer. This multifaceted approach to image processing enhances the diagnostic capabilities of the model by addressing possible issues in real-world circumstances and improving model generalization.

v) Algorithms:

ResNet50:

The 50-layer ResNet50 convolutional neural network design is well-known for solving the vanishing gradient issue. By introducing skip connections, it improves gradient flow during training by enabling information to go directly across layers. This architecture performs exceptionally well in deep learning contests and practical applications, particularly when it comes to image categorization tasks.

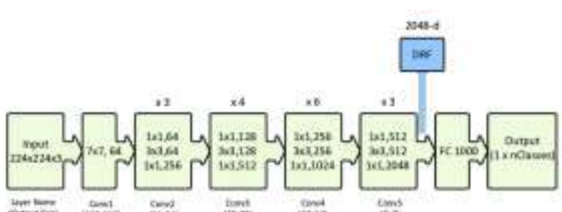

Fig 3 ResNet50 architecture

DenseNet169:

DenseNet169 is a 169-layer convolutional network that is tightly linked. Its unique feature is the thick block, which encourages feature reuse by allowing each layer to accept direct input from every layer that came before it. This improves accuracy by increasing parameter efficiency and resolving vanishing gradient problems. DenseNet169 is particularly useful in situations with little training data and performs exceptionally well on image recognition tasks.

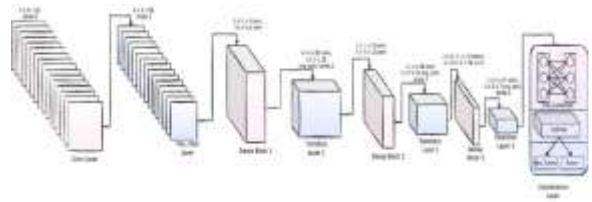

Fig 4 DenseNet169 architecture

VGG16:

With 16 weight layers, VGG16 is a well-known and straightforward convolutional neural network design. Its simple architecture, which consists of many 3x3 convolutional layers, makes feature learning easier. Because of its simplicity in understanding and training, VGG16 continues to be a benchmark for image classification tasks, despite being overtaken by deeper architectures.

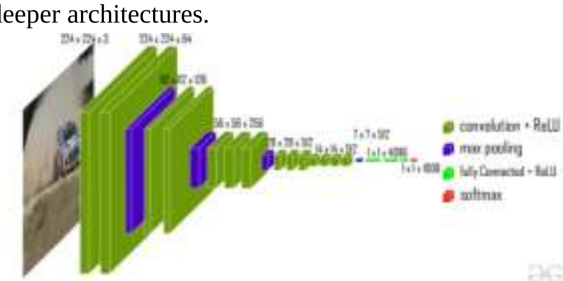

Fig 5 VGG16 architecture

Xception:

"Extreme Inception," or Xception, is an augmentation of the Inception architecture that uses depthwise separable convolutions in place of conventional convolutional layers. This change preserves expressive capacity while lowering computational complexity. When compared to conventional architectures, Xception exhibits more performance in picture categorization and feature extraction tasks. It is ideal for a range of computer vision applications because of its architecture, which improves the learning of hierarchical features.

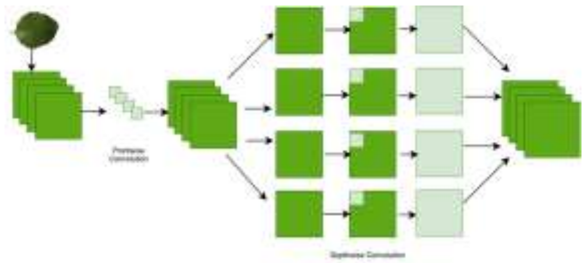

Fig 6 Xception architecture

DenseNet201:

A DenseNet variation with 201 layers, DenseNet201 has a larger model capacity for identifying intricate patterns in data. It has tightly linked blocks to promote feature reuse and ease gradient flow, just as other DenseNet designs. In situations where there is a wealth of training data, DenseNet201 is especially helpful for image classification jobs where a high number of parameters and deep architectures contribute to enhanced accuracy. Because of its construction, it can handle a wide variety of complex visual patterns with ease.

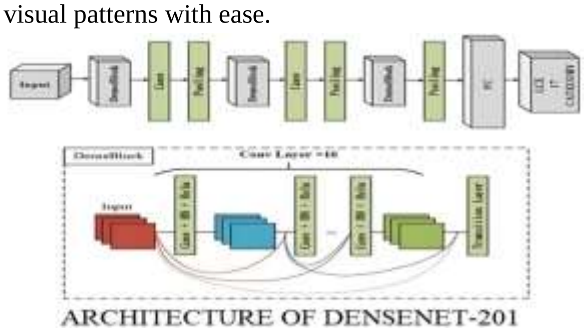

Fig 7 DenseNet201 architecture

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.

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

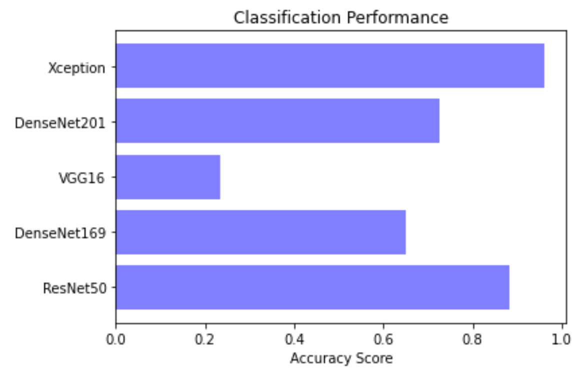

Fig 8 Accuracy Graph

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)

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

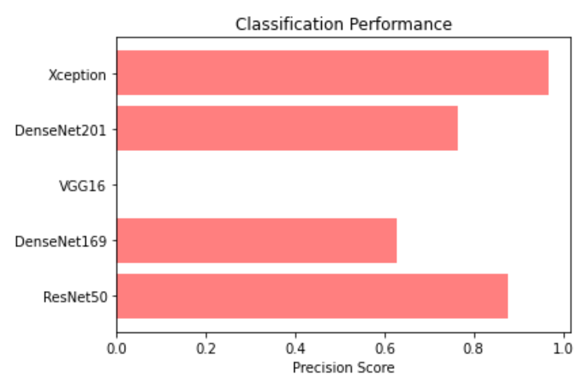

Fig 9 Precision graph

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.

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

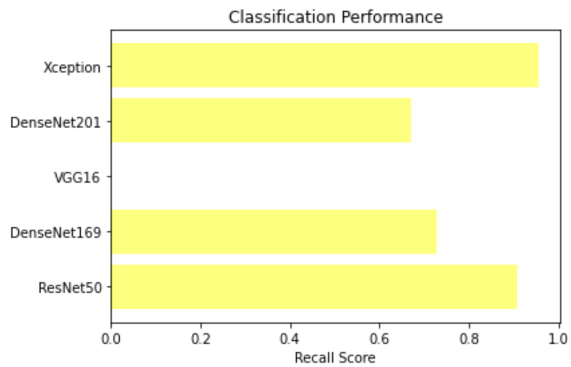

Fig 10 Recall graph

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.

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

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

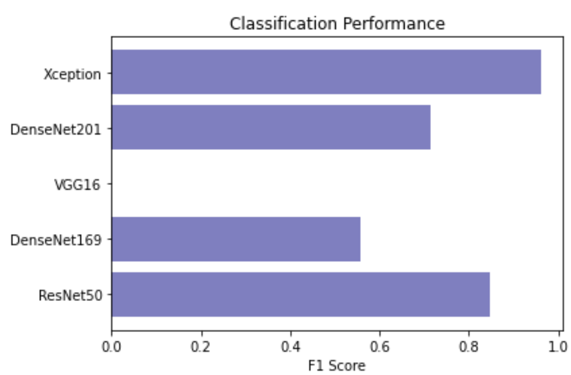

Fig 11 F1 Score graph

Fig 12 Home page

Fig 13 Registration page

Fig 14 Login page

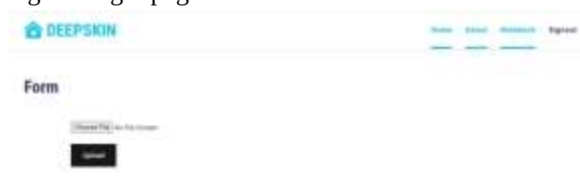

Fig 15 Upload input image page

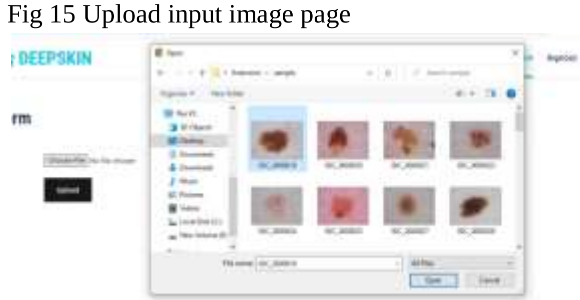

Fig 16 input images folder

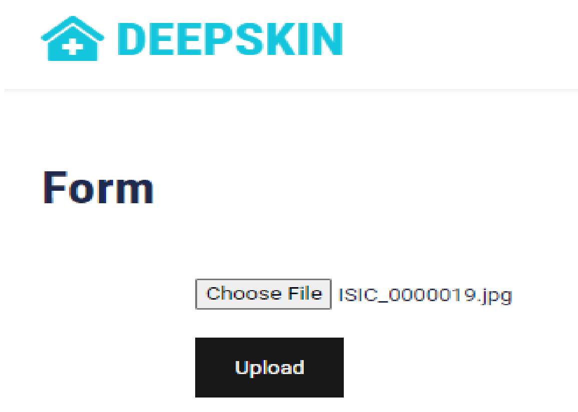

Fig 17 Upload input image to predict result

Fig 18 Final outcome as the patient is diagnosis with Nevus

5. CONCLUSION

Finally, using a carefully processed dataset from HAM10000, our skin cancer detection study shows the effectiveness of Convolutional Neural Networks (CNNs). Our models demonstrate strong performance in object identification and classification by utilizing transfer learning with DenseNet169 and ResNet50. The comparison of oversampling and undersampling methods provides a foundation for strategic selection in skin cancer diagnostic applications by illuminating subtleties in model behavior.

Additionally, our expansion investigates new models including Xception, DenseNet201, and InceptionV3, with the goal of achieving a 95% accuracy increase. The dataset's variety and model generalization capabilities are improved by the use of sophisticated image processing techniques, such as zooming, morphological changes, and shear transformations. The inpainting process fixes any possible flaws in the dataset, hence promoting completeness.

Our effort highlights the value of ongoing research and development in addition to adding to the changing field of dermatological diagnostics. We expect a substantial improvement in the accuracy of skin cancer diagnosis by utilizing state-of-the-art models and a variety of image processing techniques, opening the door for more efficient diagnostic and preventative dermatological procedures.

6. FUTURE SCOPE

This project's future scope calls for more refinement via sophisticated parameter tweaking, ensemble model exploration, and incorporation of cutting-edge deep learning architectures. Furthermore, the system's accuracy and suitability in a variety of therapeutic contexts will be improved by the integration of real-world datasets and ongoing technological adaptation.

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