DeepSkin: A Deep Learning Approach for Skin Cancer Classification

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Abstract: This study looks at the urgent global problem of skin cancer spreading quickly and stresses how important it is to have the proper diagnosis in order to stop it from happening. Dermatologists have trouble finding skin problems early, which is why they use deep learning, especially "Convolutional Neural Networks (CNNs)". using the "MNIST: HAM10000 dataset, which has 10,1/2 samples of seven different types of skin lesions", This study uses data preparation methods such as random samples, dull razors, and car code-based segmentation. Uses transfer learning on the dennenet169 and resnet50 models. The results show that the Densenet169 subgenus method results in good accuracy and F1 measurements, and the ResNet50 oversampling method is well performed with both metrics. This expansion builds on the main paper's "usage of ResNet50, DenseNet161, and VGG16 (which got 91% accuracy) by looking at other models like Xception, DenseNet201, and InceptionV3". The study shows that using several models and modifying parameters could enhance "skin cancer classification by 95%". this is a viable way to increase diagnostic accuracy and prevention methods.

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

1. INTRODUCTION

Healthy cells change too quickly, and if they expand too quickly, tumors begin to form. They have both cancer-like and non-cancerous tumors. Malignant tumors are tumors that grow and spread to other areas of the body [1]. It is thought that a benign tumor will form, but it will not spread normally. Skin cancer occurs when strange cells grow too quickly in the skin. This type of cancer is the most frequent right now and can happen anywhere. about 3.5 million melanomas are found each year, and it is thought that different forms of melanomas are to blame for this [2, 3]. This number is higher than the overall number of cases of lung, bone, and colon cancer. "The data say that someone with melanoma dies every 57 seconds". using dermoscopy photos to find cancer early on greatly increases the number of people who survive the disease. So, pathologists will definitely be able to do their jobs better and more quickly if they can discover skin excrescences accurately and automatically. The goal of the dermoscopy method is to improve the health of each person who has been diagnosed with melanoma. Dermoscopy is a skin imaging test that doesn't hurt and uses a magnified and lit snapshot of the damaged area of skin. This makes the spots easier to see, which in turn makes the face less reflective [4]. Being able to find skin cancer early on is still a valuable skill. because all skin lesions seem the same, it can be hard to tell if one is benign or cancerous. two main things that can cause skin cancer are being in the sun's "ultraviolet (UV)" rays and using tanning beds that give out UV rays. The small differences between lesions and skin make it very hard for "doctors to tell the difference between melanoma and non-cancer lesions [5]". this is because there aren't many differences between the two. one of the biggest troubles with similar beliefs is that they depend a lot on personal judgment and are hard to repeat. . With the assist of robotization and deep literacy, the case can accumulate an early opinion report. primarily based totally on that report, the case may match to dermatologists for treatment [6]. Getting a skin cancer diagnosis early is highly crucial because there aren't many treatment choices. a good plan to stop skin cancer includes being able to accurately diagnose it and do appropriate evaluations. people have widely accepted deep literacy. even when people do literacy tasks on their own, this is still true [7]. "Convolutional Neural Networks (CNN)" have been the most popular manner to handle tasks that include identifying objects and putting them in groups. because of this, CNNs don't need people to manually build feature sets because they are trained in closed settings from start to finish. CNNs have been better than trained human doctors at classifying skin cancer lesions for the past few years.

To make early diagnosis more accurate utilizing dermoscopy photographs, we need to create an automated skin cancer detection system that uses DL techniques, especially "Convolutional Neural Networks (CNNs). We want to improve the accuracy of recognizing malignant and benign lesions" so that we can treat them at the right time and raise the number of people who survive breast cancer. The method is meant to help pathologists by giving them speedy and precise analysis. The ultimate goal is to make treatment for melanoma patients more effective overall.

Skin cancer, especially melanoma, is becoming more common all over the world. this is a big threat to public health. The current problem is that it's hard to tell the difference between benign and malignant tumors, which makes it hard to find them early and treat them effectively. Dermoscopy is very beneficial, but it relies heavily on people's subjective judgment, which leads to variable results and a limited ability to repeat. This shows how crucial it is to have an automated solution based on DL to improve the accuracy of diagnoses, allow for quick action, and fill the important gap in effective skin cancer prevention and treatment.

2. LITERATURE SURVEY

[5] this article talks about a way to use image processing to find skin cancer early. The method uses an optimized "Convolutional Neural network (CNN)" that has been improved using the whale optimization technique. The findings of comparing datasets show that the quality of performance is better. The suggested system works better than other methods since it has a higher detection accuracy. this is because it uses an optimized CNN and a better whale

optimization algorithm. One possible drawback is that it can want a lot of computer power and time. other possible problems include that optimization takes a lot of resources and algorithms are hard to understand. The challenges include the need for a lot of computer power for optimization, the possibility of algorithm complexity, and the need for a variety of datasets that accurately represent the skin types and conditions being studied. The study suggests a possible way to find skin cancer early by using an optimized CNN and a better whale optimization method. even if processing needs and the variety of datasets make things harder, the methodology works better than other methods.

[9] This study looks at the newest and most advanced DL methods for finding and classifying skin cancer. It focuses on using deep convolutional neural network architectures to overcome problems "like picture quality issues in dermoscopic images. The recommended approach uses advanced neural networks that are built using DL", especially convolutional architectures, to create a more advanced way to sort skin lesions. This software fixes the problems with dermoscopic photos that are produced by shadows, artifacts, and noise. Deep convolutional neural networks are pretty complex and need a lot of processing power, so problems may come up. also, it may be vital to think carefully about how clean it is to understand the model and any complications that could come up with overfitting. one of the problems is that problems with the quality of dermoscopic pictures can make it hard to classify them efficaciously. another problem is that strong remedies may be needed to handle A huge variety of morphological developments and kinds of pores and skin lesions. This paper offers a radical examine how deep convolutional neural networks may be used to discover pores and skin cancer. The research also talks about how these networks could help with problems that come up in dermoscopic imagery. even though they offer a possible chance, addressing computational issues and ensuring robustness are necessary for real-world use.

it is [14] This paper talks about a way to sort skin cancer using image processing and ML. "It got 93.89% accuracy on the ISIC-ISBI 2016 dataset by using contrast stretching, OTSU thresholding for segmentation, GLCM, HOG, and color for feature extraction, principal component analysis reduction, SMOTE sampling, and Random forest for classification. The system is very accurate (93.89%)" when it comes to categorizing skin cancer, which helps with early diagnosis. "It combines contrast stretching, feature selection, and Random forest classification in a way" that gives dermatologists a complete answer. even if it is quite accurate, the system could have trouble with scalability and processing data in real time. It takes a lot of computational power to do this, and its performance may change based on the datasets and clinical situations that are being looked at. The suggested system might have trouble dealing with a lot of other skin disorders that weren't included in the dataset that was used. also, because it relies on precise algorithms, it might not be able to adapt to new situations as well. it might also be required to do more testing and validation before putting it into use in the real world. "it has been proven that using contrast stretching, feature selection, and Random forest classification" together helps to correctly classify skin cancer. To be useful in the real world, though, the machine needs to get beyond a few practical problems and be tested again. The technology looks like it could help dermatologists find things early on.

[6] the main focus of this work is how to use ML and image processing to find and classify skin cancer. After using color-based ok-means clustering to divide the image into parts, it uses dermoscopic image pre-processing, which involves getting rid of hair and using Gaussian filtering. For feature extraction, the ABCD criterion and GLCM are used. “The Multi-class support Vector machine (MSVM) gets 96.25% accuracy” when utilized “on the ISIC 2019 challenge dataset”. The system is quite good at figuring out what kind of skin cancer someone has “(96.25 percent of the time)”. It includes a full set of” pre-processing algorithms, color-based segmentation, and strong feature extraction to make it better” at finding and classifying things early. even though it is very accurate, the system may have trouble scaling and adapting to a large range of datasets. because it relies on precise pre-processing techniques and classifiers, it could not work as well in real-world situations where things can change. The suggested strategy might not work as well for treating skin disorders that are not in the dataset that was investigated. it is based on the idea that dermoscopic photos are the same, and using it in the real world could need more testing and adjustments for different clinical situations. “This system has a very high accuracy rate (96.25%)” when it comes to finding and classifying skin cancer. It uses advanced pre-processing, segmentation, and MSVM classification. Even while it needs further testing and customization for a wide range of clinical contexts before it can be used in real life, its holistic approach makes it easier to find problems early.

[7]: This project will utilize Python, Keras, and Tensorflow to construct a “Convolutional Neural network (CNN)” model that can help doctors figure out if someone has skin cancer. The model uses multiple types of network topologies, “like Convolutional, Dropout, Pooling, and Dense layers”, to find different types of skin cancer so that they can be diagnosed early. DL makes this possible. transfer learning makes convergence better, and the dataset came from the archives of the “international skin Imaging Collaboration (ISIC) competition. The system uses Convolutional Neural Networks (CNNs)”, which are known for being very accurate in visual imaging applications, to make the most of their power. it is both bendy and efficient because it uses Python and the ML packages Keras and Tensorflow. transfer learning is utilized to speed up convergence, while testing on the ISIC dataset is employed to create a strict assessment framework. even though the suggested approach may work well, it may be hard to understand because DL models are inherently complex. in addition, there is the prospect of training that takes a lot of resources and concerns about overfitting, both of which need careful optimization and modification. The system might not be able to generalize to a large range of skin conditions that aren't well represented in the ISIC dataset. There are a lot of problems that make it hard to use in real life, such as the fact that it's hard to understand, it takes a lot of computer resources, and it needs enormous datasets that have been labeled. This experiment shows how important it is to find skin cancer early and how CNNs could help with this. using transfer learning and different network designs could make the model work better. even if these problems will be promising, it is important to find solutions to problems like interpretability and dataset representativeness in order to use them in the actual world.

3. METHODOLOGY

i) Proposed Work:

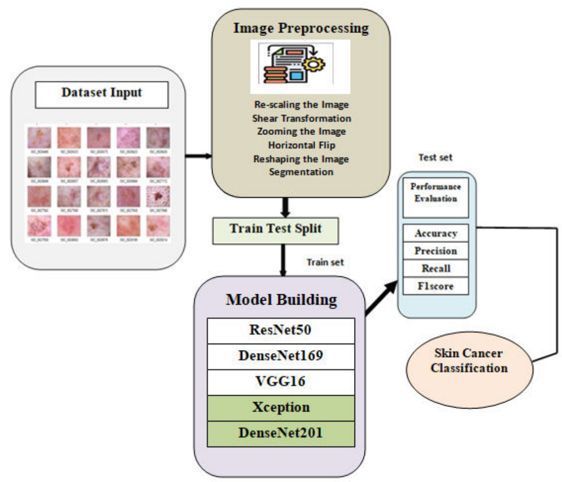
Our suggested technique uses “Convolutional Neural Networks (CNNs)” to find skin cancer in a new way that beats the best methods for finding and classifying objects. The study uses a carefully chosen “dataset from MNIST: HAM10000, which has 10,1/2 samples of seven different types of skin lesions”. To make the dataset better for robust testing, We use critical information pre-processing techniques such sampling, stupid razor, and autoencoder-primarily based totally segmentation.

switch studying strategies are on the coronary heart of our solution. “We use the DenseNet169 and ResNet50 fashions to educate the CNN”. while evaluating those switch studying fashions, we use undersampling and oversampling techniques in a deliberate manner to look how they have an effect on overall performance measures.

Our addition adds more complex “models like Xception, DenseNet201, and InceptionV3 to the main paper's study of ResNet50, DenseNet161, and VGG16, which had a 91% accuracy rate”. The goal of this diversification is to raise “the classification accuracy to 95%”. This shows that skin cancer detection can usually get better by trying out new classification methods and model architectures.

ii) System Architecture:

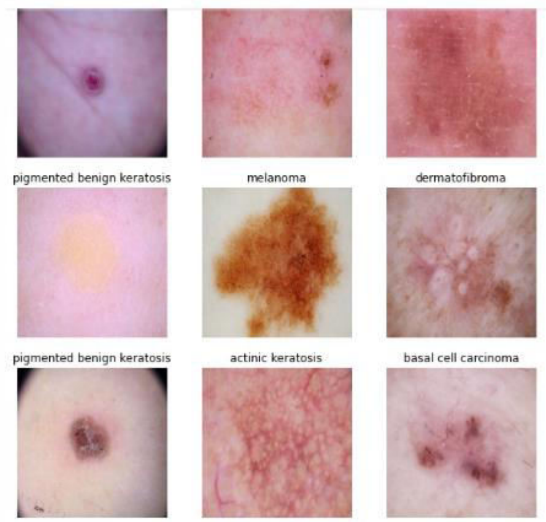
The suggested architecture for a skin cancer detection system uses “Convolutional Neural Networks (CNNs) to accurately find and classify objects. The dataset used is MNIST: HAM10000, which has 10,0.5 samples of 7 different types of skin lesions”. Preprocessing consists of techniques like sampling, stupid razor, and autoencoder-primarily based totally segmentation. “the principle a part of the machine makes use of DenseNet169 and ResNet50 fashions which have been trained” at the pre-processed records to study from different records. A assessment evaluation appears at how properly those fashions paintings with the aid of using the usage of each undersampling and oversampling techniques. The machine structure is made to be bendy and scalable, which suggests how it can assist the sector of dermatological diagnostics lots with the aid of using the use of superior neural community setups and version selection.



“Fig 1 System Architecture”

iii) “Dataset Collection:”

The “skin cancer data dataset is a re-uploaded version of the HAM10000 dataset that has been changed to work with a notebooks project”. This carefully chosen dataset has been carefully processed to make it more useful and relevant. It has a lot of information about skin cancer that comes from many sorts of skin lesions. The dataset has 10,1/2 samples, which makes it a rich and diversified collection for testing and analysis. Sampling is one of the phases in processing that makes sure the data is representative. other steps include “using dull razor and autoencoder-based segmentation to get the best data quality”. This carefully chosen dataset is a useful tool for researchers and practitioners working in dermatology. it is a cleaned-up and processed collection that makes it easier to gain significant insights and make “progress in the field of skin cancer detection and classification”.



“Fig 2 Dataset images”

iv) Image Processing:

The ImageDataGenerator is a powerful tool that the image processing pipeline uses to add to and improve images, which makes the model more resilient. First, the photos are re-scaled to make sure that the pixel values are the same, which helps with feature extraction throughout the whole dataset. Shear transformation adds controlled changes to the model, which helps it recognize differences in the forms of skin lesions. Zooming improves the dataset by making it look like it has different angles and sizes. by making mirror images, horizontal flip adds variety to the dataset and increases the size of the training set. Reshaping photos makes them fit different input sizes, which makes sure they work with the model design. Morphological Black-Hat transformation is one of the segmentation methods used to separate lesions and bring out fine details. A mask is made for inpainting jobs, which tells the algorithm how to fill in missing or broken parts of images. finally, inpainting techniques are used to fill in gaps or flaws in the data, making it more complete and strong for pores and skin most cancers detection models. This multi-faceted method to photo processing now no longer best makes the version higher at generalizing, however it additionally solves troubles that might arise withinside the real world, which makes the version higher at diagnosing.

v) “Algorithms:”

“ResNet50:” ResNet50 is a 50-layer convolutional neural community structure this is acknowledged for fixing the vanishing gradient problem. It provides bypass connections, which permit data glide directly among layers, which facilitates the gradient glide higher in the course of training. This structure is super at classifying images, and it has carried out higher than different architectures in DL contests and real-international applications.

“DenseNet169:” DenseNet169 is a convolutional community with 169 layers which can be tightly coupled. The dense block is what makes it unique. on this block, every layer receives enter from all of the ranges earlier than it, which inspires characteristic reuse. This makes parameters work better and helps with the problem of disappearing gradients, which leads to better accuracy. DenseNet169 is great at recognizing images, and it's especially useful when there isn't a lot of training data available.

“VGG16: VGG16 is a convolutional neural network design with 16 weight layers”. it is known for being simple and effective. It is easy to learn features because it has a simple design with several 3x3 convolutional layers. VGG16 is still a standard for image classification problems because it is easy to learn and train, even though deeper architectures have taken its place.

Xception: Xception, which stands for "extreme Inception," is an augmentation of the Inception architecture that uses depthwise separable convolutions instead of regular convolutional layers. this change makes the computation less complicated while keeping the expressive capacity. Xception is great at classifying images and extracting features, and it does these things more quickly than standard systems. Its design makes it easier to learn hierarchical features, which makes it great for a wide range of computer vision tasks.

“DenseNet201: DenseNet201 is a version of DenseNet with 201 layers”. It has more capacity to capture complicated patterns in data. It has tightly connected blocks like previous DenseNet architectures to encourage feature reuse and make it easier for gradients to flow. DenseNet201 is great for classifying images since it has a lot of parameters and deep architectures that make it more accurate, especially when there is a lot of training data. Its design makes it strong enough to handle a wide range of complex visual patterns.

4. EXPERIMENTAL RESULTS

“Accuracy:” A test is accurate if it can correctly tell the difference between ill and healthy people. To figure out how accurate a test is, we need find the ratio of true positives to true negatives in all the cases that were tested. this can be said in math as:

$$"Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP + FP + TN + FN}} (1)"$$

Precision: Precision looks at the percentage of accurately labeled instances or samples among those that were labeled as positives. So, the formula for figuring out the precision is:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{ False Positive}} (2)$$

Recall: In ML, recall is a measure of how well a model can find all the relevant examples of a certain class. it is the ratio of accurately predicted positive observations to the total number of real positives. This tells you how well a model captures all occurrences of a certain class.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP\ +\ FN}} (3)$$

F1-Score: The F1 score is a way to check how accurate a ML model is. It takes the precision and recall scores of a model and combines them. The accuracy statistic counts how many times a model produced a valid prediction on the whole dataset.

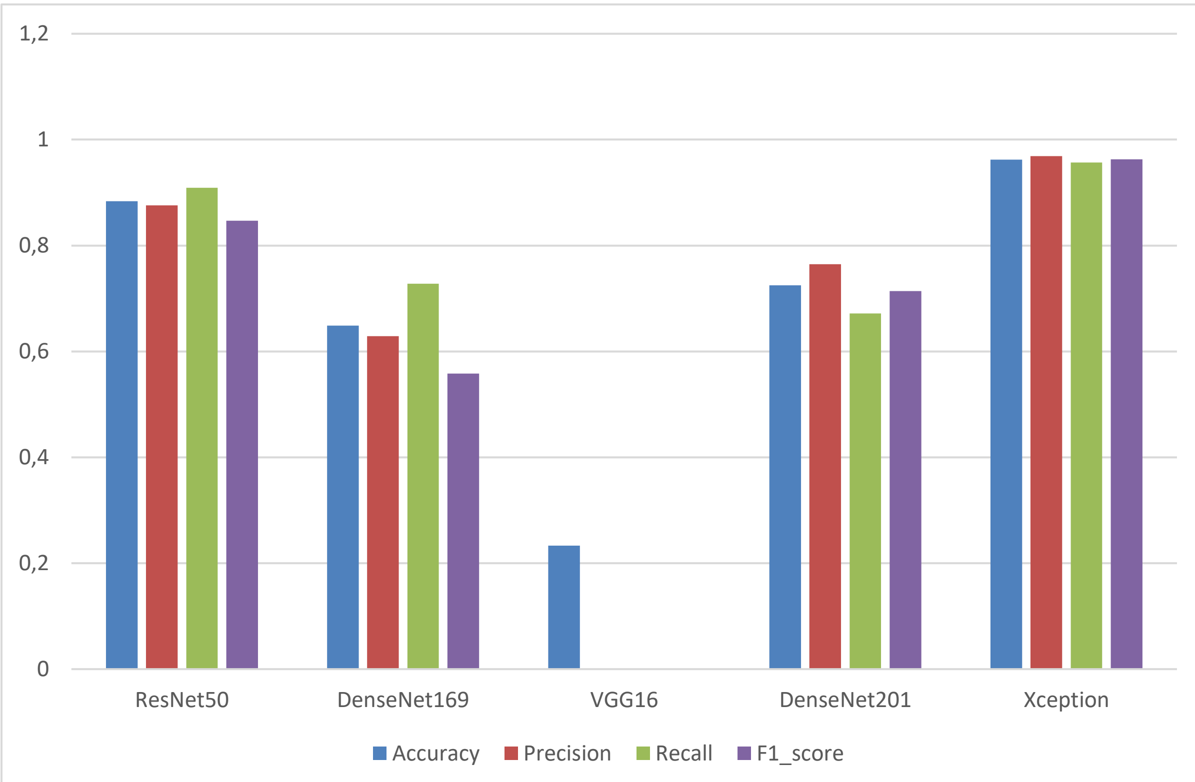
$$"F1\ Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100(4)"$$

“Table (1)” check the performance metrics for each method, such “as accuracy, precision, recall, and F1-score. The Xception always does better than all other algorithms on all criteria”. The tables also show how the metrics for the different algorithms compare to each other.

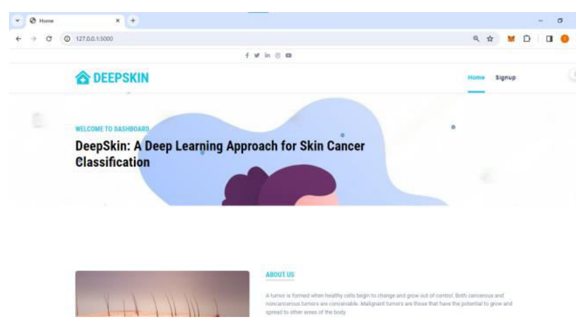
“Table.1 Performance Evaluation Table”

ML Model	Accuracy	Precision	Recall	F1_score
ResNet50	0.884	0.876	0.909	0.847
DenseNet169	0.649	0.629	0.728	0.558
VGG16	0.233	0.000	0.000	0.000
DenseNet201	0.725	0.765	0.672	0.714
Xception	**0.962**	**0.969**	**0.957**	**0.963**

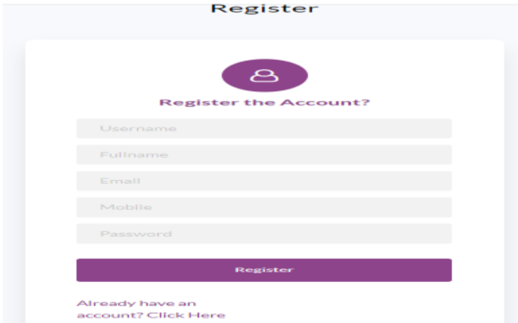
"***Graph.1*** Comparison Graph"



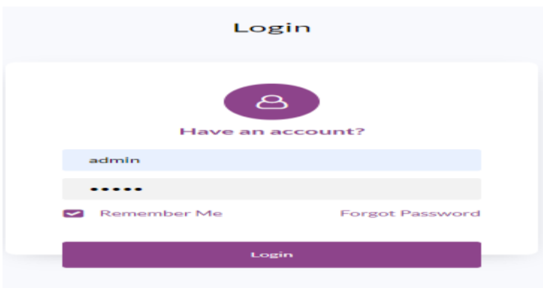
In Graph (1), blue shows "accuracy, red shows precision, green shows recall, and purple shows F1-score". The Xception outperforms all the other models on all criteria, reaching the highest values. The graphs above show these results in a way that is easy to understand.



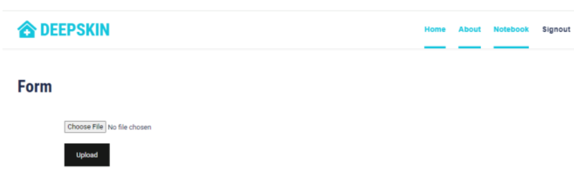
"Fig 3 Home page"



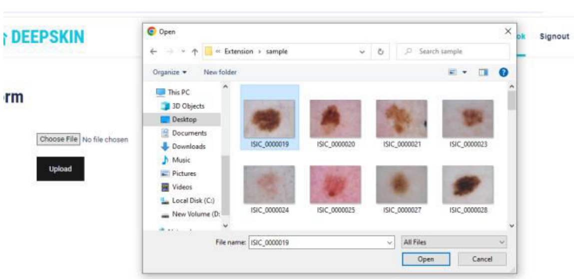
"Fig 4 Registration page"



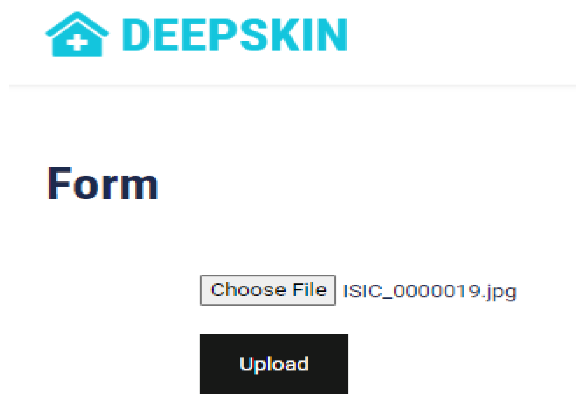
"Fig 5 Login page"



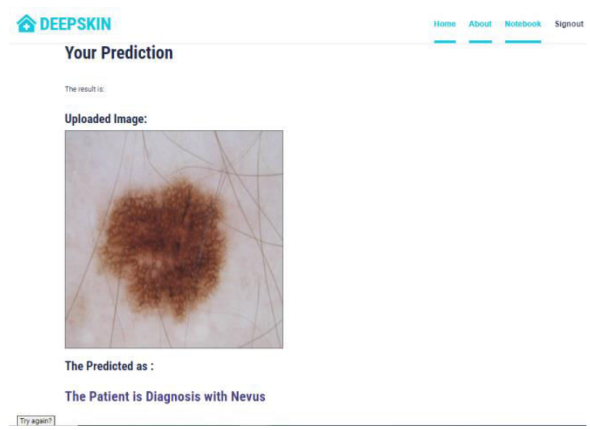
"Fig 6 Upload input image page"



"Fig 7 input images folder"



"Fig 8 Upload input image to predict result"



"Fig 14 Final outcome as the patient is diagnosis with Nevus"

5. CONCLUSION

In conclusion, our skin cancer diagnosis experiment shows that "Convolutional Neural Networks (CNNs)" operate well when "used with a carefully processed dataset from HAM10000. by using transfer learning with DenseNet169 and ResNet50, our models" show that they can recognize and classify objects quite well. A comparison study of undersampling and oversampling methods gives us more detailed information about how models work, which can help us choose the best one for skin cancer diagnosis.

Our expansion also looks into "new models like Xception, DenseNet201, and InceptionV3, with the goal of reaching an accuracy of 95%. adding complex image processing techniques like shear transformations, zooming, and morphological transformations makes the dataset" more diverse and helps the model work better on new data. The inpainting approach helps make the dataset complete by fixing any problems that could be there.

Our effort not only adds to the field of dermatological diagnostics, but it also shows how important it is to keep exploring and improving. by using the latest models and a variety of image processing techniques, we hope to significantly enhance the accuracy of pores and skin most cancers diagnosis. this could result in higher preventive and diagnostic measures in dermatology.

6. FUTURE SCOPE

In the future, this venture gets higher via superior parameter tweaking, the usage of ensemble models, and the addition of recent DL architectures. Adding real-international datasets and continuously adapting to new technology may also make the machine extra correct and beneficial in a much broader variety of scientific contexts.

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