Advancing Skin Cancer Diagnosis with Deep Learning: A Multi-Algorithm Approach

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Abstract: This study looks at the serious global problem of skin cancer that is growing very quickly and stresses how important it is to get a correct diagnosis in order to prevent it. Dermatologists have trouble finding problems early on, which is why deep learning, especially Convolutional Neural Networks (CNNs), is used. The study uses the MNIST: HAM10000 dataset, which has 10,015 samples of seven different types of skin lesions, and uses data preparation methods such as sampling, dull razor, and autoencoder-based segmentation. We use transfer learning with the DenseNet169 and ResNet50 models. The results show that DenseNet169's undersampling method gives great accuracy and F1-measure, while ResNet50's oversampling method does better in both. The main paper used ResNet50, DenseNet161, and VGG16 to get 91% accuracy. This add-on looks at more models, such as Xception, DenseNet201, and InceptionV3. With the goal of improving accuracy by 95%, the study shows that using different models and fine-tuning parameters can help with skin cancer classification, opening up a promising path for better diagnosis accuracy and preventative measures.

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

1. INTRODUCTION

When good cells start to change and grow too fast, you have a growth. Tumors can be either dangerous or not cancerous. Cancerous tumors are ones that can get bigger and spread to other parts of the body [1].

There is a chance of getting a benign growth, but they don't generally spread. Skin cancer happens when skin cells grow in the wrong way. It is the most common type of cancer today, and it can happen anywhere. More than 3.5 million cases of different types of melanomas are thought to be found every year [2, 3]. More people have this number than have lung, bone, or stomach cancers put together. In fact, every 57 seconds, someone with melanoma dies. The chance of life is greatly increased when cancer is found early on in dermoscopy pictures. As a result, accurate automatic skin excrescence finding will definitely help doctors get better at their job and get more done. The goal of the dermoscopy method is to help each melanoma patient do better. Dermoscopy is a noninvasive skin imaging method that uses a brightened and enlarged picture of the affected area of skin to make the spots easier to see, which lowers the image on the face [4]. Finding skin cancer early is still a valuable skill. It's hard to tell if a growth on the skin is normal or cancerous because they all look the same. UV (ultraviolet) rays from the sun and UV tanning beds are the two main things that cause skin cancer. Dermatologists have a hard time telling the difference between melanoma and non-melanoma tumors because the differences between them and skin are so small [5]. The main problem with having similar opinions is that they rest a lot on personal judgment and are hard to copy. With the help of deep reading operations and robotization, the case can get an early opinion report. Based on this report, the case can then see a dermatologist for treatment [6]. It is very important to find skin cancer early because there are only a few treatments that can be used. Accurate review and the ability to correctly spot skin cancer are important parts of a plan to stop skin cancer. Deep literacy is used a lot, even in literacy jobs that aren't controlled [7]. Convolutional Neural Networks (CNN) have been the best at finding objects and making brackets. Because CNNs are taught from start to finish in a controlled setting, people are no longer needed to make feature sets by hand. A few years ago, Convolutional Neural Networks (CNNs) did a better job than skilled human experts at classifying skin cancer spots.

Create a computer system that can automatically find skin cancer using deep learning methods, especially Convolutional Neural Networks (CNNs), to help with early discovery using dermoscopy pictures. The goal is to make it easier to tell the difference between cancerous and noncancerous growths, so that treatment can begin sooner and more people survive. The method is meant to help doctors by giving them fast and accurate results, which will eventually make care for melanoma patients more efficient as a whole.

Skin cancer, especially melanoma, is a major health risk, and the number of cases is rising around the world. The problem right now is that it's hard to tell the difference between normal and cancerous tumors, which makes early discovery and treatment more difficult. Even though dermoscopy is useful, it depends a lot on subjective human opinion, which means that results aren't always the same. This shows how important it is to have an automatic, deep learning-based system to improve the accuracy of diagnoses, allow quick action, and fill in the important gaps in skin cancer prevention and treatment.

2. LITERATURE SURVEY

[5] This study shows a new way to use image processing to find skin cancer early on. It uses an improved whale optimization method to make a

Convolutional Neural Network (CNN) work better. Comparative tests on two datasets show that the better results. The suggested system has better recognition accuracy thanks to an improved CNN and an improved whale optimization algorithm, showing better results than other methods. Some problems that could happen are algorithms that are hard to understand and optimize, which can use a lot of resources and take a long time. Problems include the need for a lot of computing power for optimization, the fact that algorithms might be hard to understand, and the need for a wide range of datasets that show how well the system works on all skin types and situations. The study shows a potential way to find skin cancer early on by using an optimized CNN and the improved whale optimization algorithm. This method works better than other options, but it needs a lot of computing power and has a lot of different datasets, which are problems.

[9]This article talks about the newest deep learning ideas for finding and classifying skin cancer. It focuses on using deep convolutional neural network designs to solve problems like poor picture quality in dermoscopic images. The suggested method uses advanced deep learning neural networks, more specifically convolutional structures, to provide a more complex way to classify skin lesions. A problem with dermoscopic pictures is that shadows, artifacts, and noise can make them less useful. Deep convolutional neural networks are very complicated and need a lot of computing power, which could cause problems. Also, the model's interpretability and any worries about overfitting may need careful thought. Some problems with this method are that it might not be able to accurately classify skin lesions, it might need a lot of computing power, and it needs strong solutions that can deal with different skin lesions and their shapes. This article talks about deep convolutional neural networks in skin cancer diagnosis and how they might be able to help with problems in dermoscopic pictures. Even though it looks good, tackling computing challenges and making sure it is reliable are important for making it work in real life.

[14]This work shows how image processing and machine learning can be used to make a method for classifying skin cancer. It does contrast stretching, segmentation with OTSU thresholding, feature extraction (GLCM, HOG, color), PCA reduction, SMOTE sampling, and classification with Random Forest. On the ISIC-ISBI 2016 dataset, it got 93.89% of the answers right. The method is very good at classifying skin cancer (93.89%), which helps find it early. It uses contrast stretching, feature selection, and Random Forest classification well, giving doctors a strong answer. The system may have trouble with scaling and real-time handling even though it is very accurate. It needs a lot of computing power, and how well it works may change depending on the information and the clinical setting. The suggested system might have trouble with skin diseases that aren't in the collection that was used, and the fact that it depends on certain methods might make it less flexible. Also, putting it into action in the real world might need more testing and proof.It works well to classify skin cancer when contrast stretching, feature selection, and Random Forest classification are all used together. The method shows promise in helping doctors find skin problems early, but it needs to be tested and worked out in the real world before it can be used.

[6]The main goal of this project is to use machine learning and picture processing to find and classify

skin cancer. For segmentation, color-based k-means clustering is used after dermoscopic picture pre-processing, which includes removing hair and applying Gaussian filters. GLCM and ABCD conditions are used in feature extraction. This is the ISIC 2019 Challenge dataset that Multi-class Support Vector Machine (MSVM) gets 96.25% of right. The method is very good at putting different kinds of skin cancer into groups (96.25%). It combines thorough pre-processing methods, color-based segmentation, and strong feature extraction, which makes it better at early spotting and classification. Even though the system is very accurate, it may have trouble scaling up and adapting to different datasets. Because it depends on certain pre-processing methods and algorithms, it might not work as well in real-life situations where conditions change. The suggested method might not be able to handle skin problems that weren't included in the information that was looked at. It depends on the idea that dermoscopic pictures are all the same, and using it in real life might need more testing and adjustments to fit different clinical situations. This system is very good at finding and classifying skin cancer (96.25%) thanks to its powerful pre-processing, segmentation, and MSVM classification. Its all-around method makes early identification better, but it needs to be tested more and be changed to work in different clinical situations before it can be used in real life.

[7]Using Python, Keras, and Tensorflow, this project's main goal is to create a Convolutional Neural Network (CNN) model for finding skin cancer. The model uses deep learning to sort skin cancer types so that they can be found early. It does this by using different network designs, such as Convolutional, Dropout, Pooling, and Dense layers. Transfer Learning makes convergence better, and the sample comes from the challenge files of the International Skin Imaging Collaboration (ISIC). Convolutional Neural Networks (CNNs), which are known for being very accurate at image tasks, are used in the system. It gives you freedom and speed by using Keras and Tensorflow in Python. Transfer Learning speeds up convergence, and testing on the ISIC dataset gives you a strong way to judge performance. Even though the suggested system works, it might be hard to understand because deep learning models are so complicated. Also, training that uses a lot of resources and problems with overfitting may happen, which needs careful planning and tuning. The method might not be able to work well with different skin diseases that aren't well represented in the ISIC collection. Problems with interpretability, the need for big named datasets, and the amount of work that needs to be done on computers could make execution difficult. This project shows how CNNs could be used to find skin cancer, stressing how important it is to find the disease early. Transfer Learning and different network designs make models work better. Even though it looks good, problems like interpretability and dataset representativeness need to be fixed before it can be used in the real world.

3. METHODOLOGY

i) Proposed Work:

Using Convolutional Neural Networks (CNNs), our suggested system is the most cutting-edge way to find skin cancer. It beats previous records in finding objects and classifying them. The study uses a carefully chosen dataset from MNIST called HAM10000, which has 10,015 examples of seven different types of skin lesions. Some important data pre-processing methods are used to make the dataset better for stable testing. These include sampling, dull razor, and autoencoder-based segmentation.

One important part of our method is using transfer learning techniques, especially the DenseNet169 and ResNet50 models to teach the CNN. It is possible to compare these transfer learning models by carefully using undersampling and oversampling methods, which show how they affect performance measures in different ways.

The base paper looked at ResNet50, DenseNet161, and VGG16 (which had a 91% success rate). Our addition includes more complex models like Xception, DenseNet201, and InceptionV3. The goal of this diversity is to raise the classification accuracy to 95%. This shows that skin cancer detection could keep getting better by trying out new classification methods and model designs.

ii) System Architecture:

Convolutional Neural Networks (CNNs) are used in the suggested skin cancer detection system design to accurately find and classify objects. Pre-processing starts with a dataset from MNIST called HAM10000, which has 10,015 samples of seven different types of skin lesions. It includes methods like sampling, dull razor, and autoencoder-based segmentation. Transfer learning with DenseNet169 and ResNet50 models that were learned on pre-processed data is what the method is based on. Both undersampling and oversampling methods are used in a comparison study to test how well these models work. The structure of the system is made to be flexible and expandable, showing that it has the potential to make a big difference in the field of dermatology tests by using advanced neural network setups and model choice.

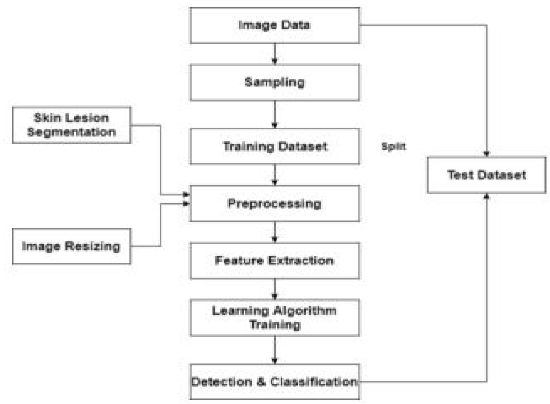

Fig 1 System Architecture

iii) Dataset Collection:

The Skin Cancer Data dataset is a reuploaded version of the HAM10000 dataset that has been changed to fit the needs of a notebook project. This carefully chosen information has been carefully processed to make it more useful and important. With knowledge from different types of skin lesions, it has a lot of information about skin cancer. The dataset has a total of 10,015 samples, which makes it a very useful set for research and testing. Some of the steps in the processing process are sampling, making sure that a group of the data is representative, and using techniques like dull razor and autoencoder-based segmentation to get the best quality data. This carefully chosen dataset is a useful tool for dermatology researchers and practitioners, as it provides a polished and processed collection that helps researchers and practitioners make important discoveries and progress in the field of finding and classifying skin cancer.

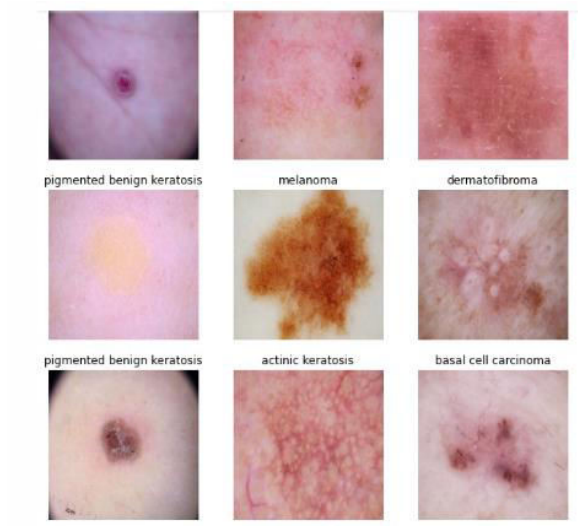

Fig 2 Dataset images

iv) Image Processing:

The ImageDataGenerator is used in the image processing chain to add to and improve images, which makes the model more stable. First, pictures are re-scaled to make the pixel values more uniform across the dataset. This makes feature extraction more consistent. Shear transformation adds controlled deformations that help the model see how skin disease forms change. By modeling different points of view and magnifications, zooming improves the dataset.

By making mirror copies, horizontal flip diversifies the dataset and increases the size of the training set. When you reshape pictures, you can use different input measurements, which makes sure they work with the model layout. Segmentation methods are also used to separate tumors, and Morphological Black-Hat transformation is used to bring out small details. For inpainting jobs, a mask is made that tells the program how to fix parts of pictures that are missing or broken. Lastly, inpainting algorithms are used to fill in any holes or flaws in the data. This makes the information for skin cancer detection models more complete and reliable. This multifaceted approach to picture processing not only makes the model more general, but it also takes into account problems that might come up in the real world, which improves the model's ability to diagnose problems.

v) Algorithms:

ResNet50:

It is known for solving the disappearing gradient problem. ResNet50 is a convolutional neural network design with 50 layers. It adds skip links that let data move straight between layers, which improves gradient flow during training. This design does great at classifying images, showing that it is the best in both deep learning competitions and real-world use.

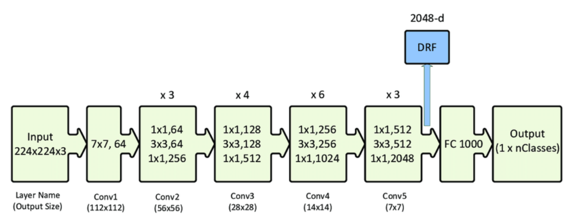

Fig 3 ResNet50 architecture

DenseNet169:

DenseNet169 is a neural network with 169 layers that is very tightly linked. The thick block is what makes it unique; each layer gets direct input from all the levels below it, which encourages feature repetition. This makes the parameters work better and fixes problems with disappearing gradients, which leads to better accuracy. DenseNet169 is great at recognizing images and is especially useful when there isn't a lot of training data available.

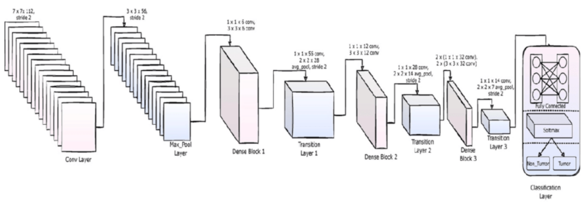

Fig 4 DenseNet169 architecture

VGG16:

The VGG16 design is a standard convolutional neural network with 16 weight layers that is known for being easy to use and successful. Its simple design, which includes several 3x3 convolutional layers, makes it easy to learn features. Deeper models have since topped VGG16, but it is still used as a standard for picture classification jobs because it is simple to understand and train.

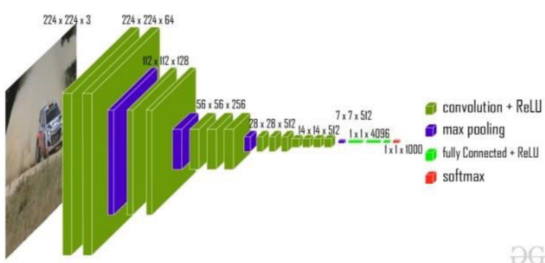

Fig 5 VGG16 architecture

Xception:

"Extreme Inception," or "Xception," is an addition to the Inception design that swaps out normal neural layers for ones that can be separated by depth. This change makes computations simpler while keeping the descriptive power. When compared to standard designs, Xception is much better at picture recognition and feature extraction jobs. Its form makes it easier to learn hierarchical features, which makes it useful for many computer vision tasks.

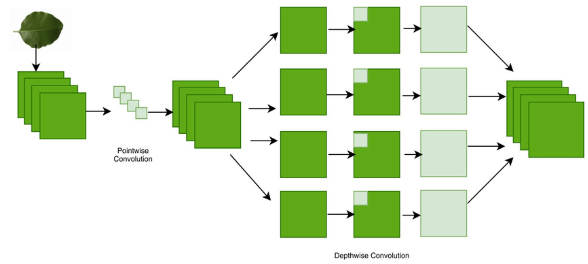

Fig 6 Xception architecture

DenseNet201:

DenseNet201 is a version of DenseNet that has 201 levels, which makes it easier for the model to find complex trends in data. Like other DenseNet designs, it has tightly connected blocks that make it easier to reuse features and let gradients run. DenseNet201 works really well for sorting pictures into groups. Its many features and deep designs help it be more accurate, especially when there is a lot of training data. Its structure makes it strong enough to handle a wide range of complex visual patterns.

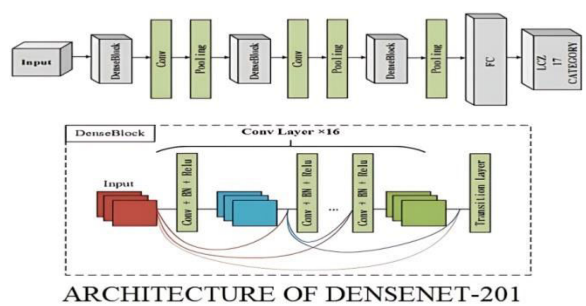

Fig 7 DenseNet201 architecture

4. EXPERIMENTAL RESULTS

Accuracy: The correctness of a test is how well it can tell the difference between weak and strong examples. To figure out how accurate a test is, we should keep track of the very small number of real positive and negative results in all cases that were looked at. This could be shown with numbers as:

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

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

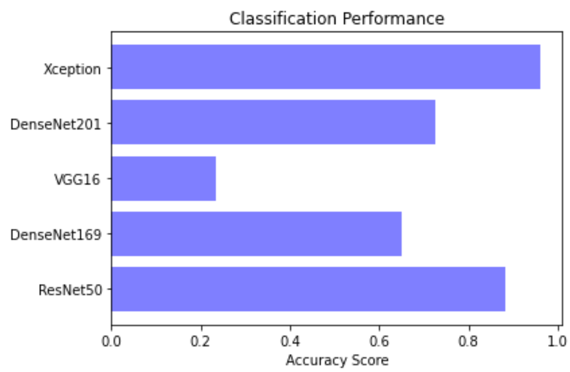

Fig 8 Accuracy Graph

Precision: Precision is the percentage of correctly classified events or samples that are among the hits. So, the following method can be used to figure out the accuracy:

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

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

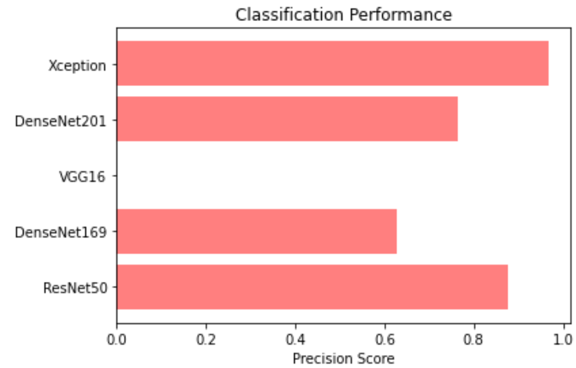

Fig 9 Precision graph

Recall: Recall is a machine learning variable that measures how well a model can recognize all relevant examples of a certain class. It's the percentage of expected positive feelings that turn out to be real positive feelings. This tells us how well a model can catch instances of a certain class.

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

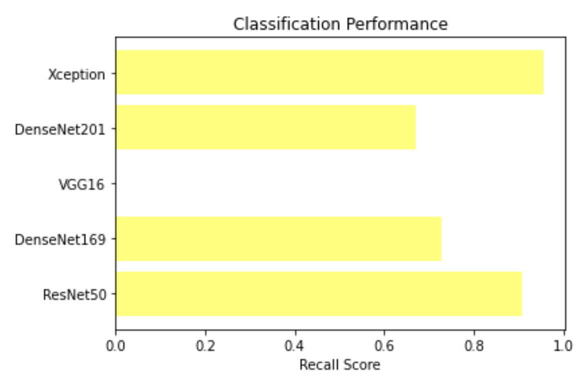

Fig 10 Recall graph

F1-Score: There is a machine learning rating tool called the F1 score that measures how accurate a model is. It adds up the accuracy and review scores of a model. The accuracy measurement figures out how often, across the whole collection, a model correctly predicted what would happen.

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

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

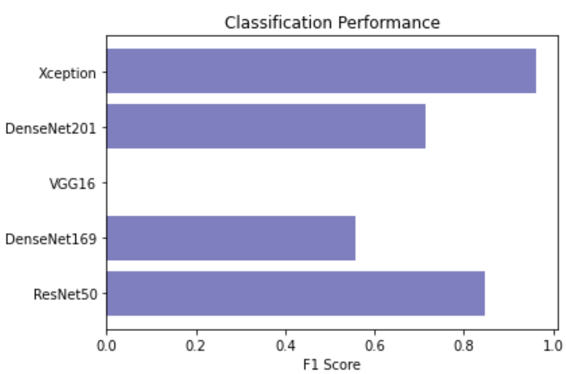

Fig 11 F1 Score graph

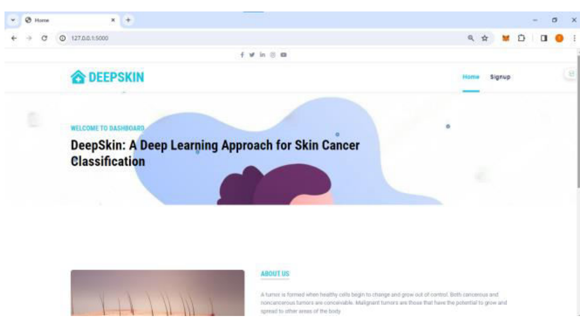

Fig 12 Home page

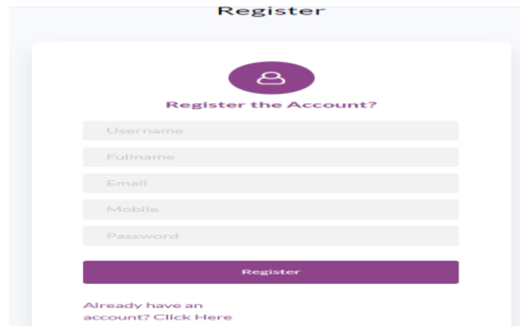

Fig 13 Registration page

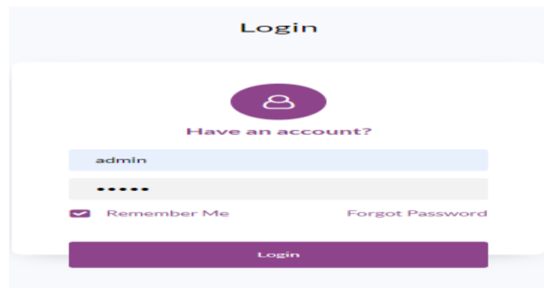

Fig 14 Login page

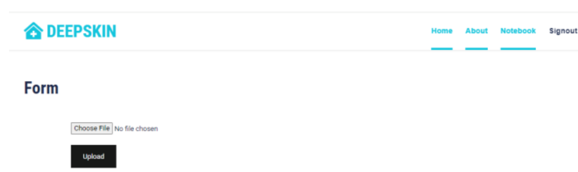

Fig 15 Upload input image page

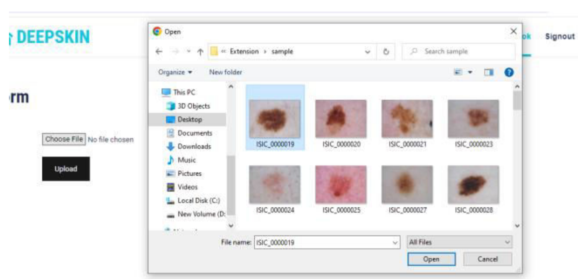

Fig 16 input images folder

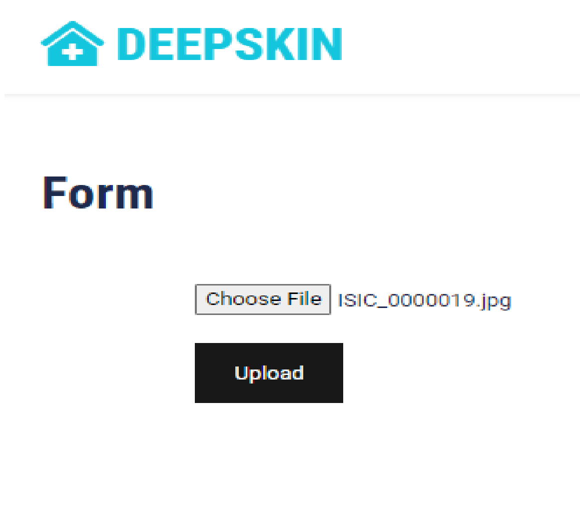

Fig 17 Upload input image to predict result

Fig 18 Final outcome as the patient is diagnosis with Nevus

5. CONCLUSION

Finally, our skin cancer diagnosis project shows how well Convolutional Neural Networks (CNNs) work when combined with a carefully handled dataset from HAM10000. Our models do a great job of finding objects and putting them into groups by using transfer learning with DenseNet169 and ResNet50. Comparing the undersampling and oversampling methods gives us more detailed information about how models behave, which can be used for strategic selection in skin cancer detection uses.

In addition, our update looks at new models like Xception, DenseNet201, and InceptionV3, with the goal of making the accuracy 95% better. Using complex image processing methods like shear transformations, zooming, and morphological transformations improves the variety of the dataset and the ability of the model to generalize. The inpainting method helps make the information full by fixing any mistakes that might be there. Our project not only adds to the changing field of skin testing, but it also shows how important it is to keep researching and improving things. By using cutting-edge models and a variety of image processing techniques, we expect a big improvement in the accuracy of skin cancer diagnosis. This will lead to better ways to avoid and diagnose skin cancer in the field of dermatology.

6. FUTURE SCOPE

The next steps for this project are to make it even better by setting more advanced parameters, looking into group models, and adding new deep learning structures. Adding real-world information and constantly updating the system to keep up with new technologies will also make it more accurate and useful in a wider range of healthcare settings.

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