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Applications of Deep Learning to the Diagnosis and Classification of Skin Cancer.

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1. ABSTRACT

The most prevalent cancer in the world today is skin cancer. It develops when the body's skin cells grow without control. Due to the fact that no two cases of skin cancer are alike, it is possible that some cases may not show many early indications. However, abnormal skin changes may be a warning sign of many different types of cancer. By being vigilant in the detection of these alterations, an early diagnosis is made feasible. The rising rates of skin cancer, its high mortality rate, and the high expense of treatment make it critical to catch the disease early via vigilant symptom detection. Researchers have developed a variety of skin cancer screening technologies in light of the seriousness of the disease. Several deep learning and machine learning-based techniques have been developed to aid with skin

2. INTRODUCTION

During a clinical screening, the majority of skin cancer cases are discovered visually. A biopsy, a thermoscopic examination, and histological tests may then be performed. The most prevalent type of malignancy in people is skin cancer. Given the fine-grained visual heterogeneity of skin lesions, automated classification of skin lesions using photographs is a difficult job. Melanoma skin cancer is also known as malignant skin cancer. Its frequency has increased during the last 30 years. The most recent statistics show that 1 in 10 people will have cancer at some point in their lives. The two primary forms of skin cancer that can be identified are benign skin cancers without melanoma and malignant skin

cancers with melanoma (see figure 1). The two skin cancer lesions are categorized as.

Dermatologists have utilized a range of image processing techniques to detect this malignancy early. Dermatologists employ microscopic (clinical) photos obtained with a digital camera or an image from a mobile device for the early detection and evaluation of skin cancer. ii) Thermoscopic photos captured with a certain camera or piece of gear known as a Thermoscopic device that can show the pigmentation of the skin lesion Numerous computational methods have been developed specifically to help physicians identify skin cancer with accuracy.

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Computer-aided diagnosis is one instrument dermatologists use to categorize distinct types of skin cancer (CAD). These tools can provide reliable skin cancer screenings automatically. The (CAD) method's features extraction stage is one that should normally identify the lesion and help differentiate between skin cancer lesions that are melanoma and those that are not. This technique is very important and has a significant bearing on those that follow.

Convolution neural networks, or CNNs, have gained popularity recently for application in object detection and image categorization. Deep learning is divided into several subfields. It includes LSTM among a wide range of convolutional and recurrent neural networks. These neural networks may learn from training data and assist in classifying photos into several groups. They learn from the neural network layers, including their own layers of max-pooling, activation units, convolution, and fully linked layers.

The symptoms of melanoma have already been discussed. With a precision of 0.8–0.9, these serious disorders were detected using SVM, KNN, and decision tree approaches. In order to finish the challenge, CNN and Resnet, which has a precision of 0.91, were both used. In an effort to improve accuracy and hasten the process of early disease detection, Resnet was included to the classification of skin diseases in 2017. These categorization techniques improve over time, and the accuracy results follow suit. Deep learning advancements are tremendously beneficial to the medical sector. To accurately assess the severity and spread of the skin disease, specialists are required.

3. LITERATURE SURVEY

The objective of this comprehensive review of the

literature was to compile a ranking and classification of the best neural network skin cancer diagnosis techniques (NNs). Systematic literature reviews assemble and evaluate previously published studies using predetermined evaluation criteria. These evaluations help identify what is known about the relevant study area already. All data assembled from primary sources is organized and reviewed. When the systematic literature is complete, it provides a more logical and convincing answer to the central research topic. Deep neural network (DNN) techniques were applied to one of the studies in the population taken into account for the current systematic literature review to detect skin cancer.

It is a reality that skin cancer rates have risen in recent years. Given that the majority of the human body is covered with skin, it makes sense to think that skin cancer is the most common disease among people. The efficacy of skin cancer treatment depends on early detection. Skin cancer symptoms can now be promptly and simply identified using computer-based procedures. There are many non-invasive ways to evaluate skin cancer symptoms.

4. PROBLEM IDENTIFICATION AND OBJECTIVES

It is crucial to establish an early diagnosis by keeping an eye out for any harmful symptoms because of the increased prevalence of skin cancer, the high death rate, and the expensive cost of medical care. Given the severity of these problems, researchers have created a number of methods for early skin cancer screening. Many techniques based on deep learning and machine learning have been created to aid in the diagnosis of skin cancer. The objective of this tiny study is to create a reliable machine learning model for detecting skin cancer early using image processing techniques like ResNet50 and VGG16.

The model will be built in Python using any flexible libraries that are required. Anyone seeking a preliminary assessment of unusual developments on The project was developed using Tensor flow, an open-source end-to-end platform and framework for multiple machine learning applications. In addition, Keras, an advanced neural network built on top of Tensor Flow, is utilized. These libraries provide high-level APIs for rapidly constructing models, although this package is more useful due to its Python origins.

5. SYSTEM METHODOLOGY

A. TYPICAL IMAGE CLASSIFICATION SYSTEM

Image classification methods are typically trained to classify images instantaneously. When performing them, the following activities are frequently taken:

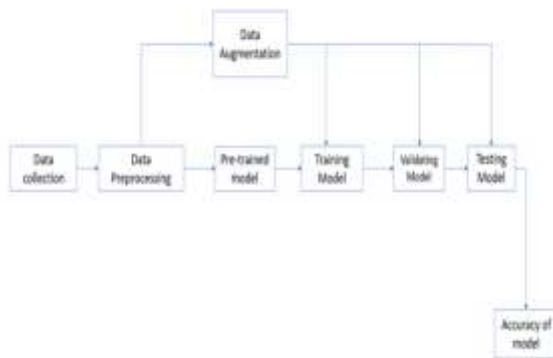


Fig.2 Typical Image Classifier

B. Data Collection

The machine learning model's performance depends heavily on the method used to gather the data. The AI model's decisions are directly impacted by the size and quality of the dataset. These two elements affect how effectively, precisely, and robustly the AI algorithms work. As a result, gathering and organizing data demands

C. Data preparation.

The most elementary abstraction level of actions on images is referred to as "image pre-processing." If

entropy is a measure of information, then these operations reduce the information content of the image rather than enhancing it. By removing undesired distortions or improving particular characteristics of the image that are crucial for further processing and analysis, pre-processing seeks to enhance the picture data task. Pictures being restored, being transformed into Fourier form, being segmented and filtered, having their geometry changed, and having their pixel brightness adjusted.

D. Data Augmentation

A common technique is data augmentation, which involves randomly changing a vast amount of training data in believable ways. Other instances include rotating, flipping, and resizing. This method makes it possible to obtain more varied data that is already available, which improves the training set and the model under training.

E. Training Model

We require the following in order to validate the model: Images for validation and the accurate labels that go with them Training images and their corresponding true labels (we use these labels only to validate the model and not during the training phase) At this point, we additionally provide the total number of epochs. Ten iterations of the model will be run initially.

At this level, validation is done concurrently. The model is changed to account for fresh information that was not previously considered. Initial checks for missing data are made using validation data. The model's hyperparameters and settings are modified using the outcomes of this approach.

F. Testing Model

There are already data sets for training and testing. We set aside 15% of the training data, which we refer to as the test dataset, in order to evaluate the model's precision.

6. MODELIMPLEMENTATION

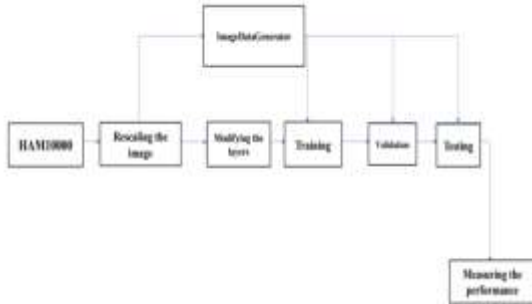


Fig3Implementation Architecture

7. VGG 16 ARCHITECTURE

The 16 convolution layers of VGGNet-16 are quite appealing, and the architecture is incredibly dependable. It includes a number of filters but only use 3x3 convolutions, similar to Alex Net. On four GPUs, it can be taught for two to three weeks. The community today regards it as the best technique for extracting characteristics from images. The weight configuration of the Vignette is easily accessible and has been employed as a typical feature extractor in a variety of applications and issues.

However, managing Genet's 138 million parameters can be a little difficult. VGG is made possible through the application of transfer learning. The parameters are changed for greater accuracy once the model has been pre-trained on a dataset, and the parameter values can then be applied.

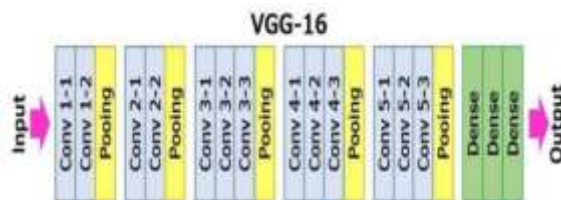


Fig.4VGG16Architecture

8. RESNET50ARCHITECTURE

The ResNet-34 design, which featured 34 weighted layers, was added to the original Resnet architecture. By utilizing the idea of shortcut connections, it presented an innovative method to expand the quantity of convolution layers in a CNN without encountering the vanishing gradient problem. A shortcut connection changes a standard network into a residual network by "skipping over" some levels.

The regular network was built using the VGG neural networks (VGG-16 and VGG-19), each of which includes a 3x3 filter. A ResNet, on the other hand, is simpler and contains fewer filters than a Vignette. A smaller 18-layer ResNet can function at 1.8 billion FLOPs and a larger 34-layer ResNet can operate at 3.6 billion FLOPs in comparison to a VGG-19 Network's 19.6 billion FLOPs.

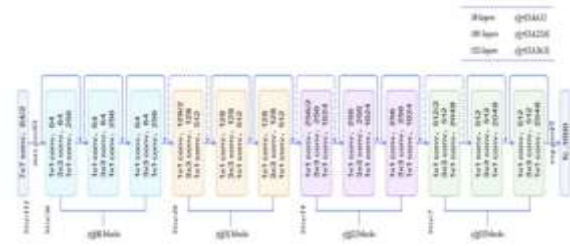


Fig.5ResNet50Architecture

9. TESTING

A. Functional Testing

QAs employ the technique of functional testing to determine whether software is acting in compliance with established requirements. It uses "black-box" testing techniques, in which the tester is not informed of how the system is designed to operate. Functional testing just determines whether a system performs as intended.

Functional Testing – Test Case Report

Table 1 : Functional Testing – Test Case Report



Test case ID	Specifications	Steps to execute	Expected Output	Actual Output	Remark
1	Check whether the input image is being read or not	-Browse files -Upload an image type of only JPG, JPEG, PNG	Displays the image	Displays the image	Pass
2	Check whether the image is being classified into melanoma or non-melanoma	-Browse files -Upload an image type of only JPG, JPEG, PNG	- Displays the image - Displays the output as melanoma or non-melanoma	- Displays the image - Displays the output as melanoma or non-melanoma	Pass
3	Know whether the ResNet50 model is read properly or not	-Browse files -Upload an image type of only JPG, JPEG, PNG -Check the output	- Displays the output as melanoma or non-melanoma	- Displays the output as melanoma or non-melanoma	Pass

Test case ID	Test Description	Test Steps	Actual Output	Expected Output	Remarks
1	Check whether the model is running or not	-Browse files -Upload an image type of only JPG, JPEG, PNG	Classifying melanoma or non-melanoma	Classifying melanoma or non-melanoma	Pass
2	Check if image size exceeds 200MB	- input file - 202MB	- Displays error message: File Size Exceeds	- Displays error message: File Size Exceeds	Pass
3	Check if image size is less than 200MB	- input file - 9MB	- Displays the image	- Displays the image	Pass

10. Unit Testing

Unit testing, a type of software testing, involves testing individual program units or components. Verifying that every line of software code executes as intended is the goal. Unit testing is done by developers while they work on an application (the coding phase). A specific piece of code is identified and its correctness is validated by unit tests. A unit can be classed as a procedure, method, module, or object.

Unit testing, a type of software testing, involves testing individual program units or components. Verifying that every line of software code executes as intended is the goal. Unit testing is done by developers while they work on an application (the coding phase). Unit tests locate and confirm the accuracy.

Unit Testing - Test Case Report

Table 2: Unit Testing - Test Case Report

11. RESULTS AND DISCUSSIONS

Because it enables radiologists to diagnose patients accurately and without human error, the automated skin cancer detection system, which uses deep learning algorithms and image processing techniques, represents a significant advancement in the field of medicine. This enables timely and relatively simple disease cure.

Melanoma and non-melanoma classes of the HAM10000 dataset, which comprises a total of 10,335 pictures, were separated for the training procedure. Only 3,300 images were initially used. It was separated once more into the train-validate-test ratios (70-15-15). Both models were trained on 2 473 images, and they were tested on 473 images. ResNet50's accuracy is 83%, while VGG16's is 77%.

In the second experiment, the remaining 7,045 pictures were used to retrain the models, again splitting them into the ratio of 70-15-15 to train-validate-test. Both models were retrained using 5 097 shots, and they were tested using 974 images. The effectiveness of the proposed framework was assessed using a small number of samples, and it ultimately yielded accuracy values of 79% for VGG16 and 84% for ResNet50. ResNet50 outperformed VGG16 for our problem despite a slight improvement.

Table 7.1: Model Performance Evaluation

Table 7.1: Model Performance Evaluation

Deep Learning Networks	Trial 1 (Accuracy)	Trial 2 (Accuracy)
VGG16	77%	79%
ResNet50	83%	84%

12. CONCLUSION

This essay focuses on diagnosing skin cancer utilizing several traits, such as the extent, diameter, lesion color, etc. of the spread. A machine learning algorithm can be used to perform the analysis, in which the system learns from the past of the images saved in the database and evaluates the current image to determine whether it qualifies as melanoma or not and, if so, to determine its stage. Machine learning is less computationally complex than present systems. The procedure can be completed more rapidly as a result.

We explored a computer-aided diagnosis technique for melanoma skin cancer in this study. Based on the findings, it can be said that the suggested system for diagnosing skin cancer will work better for patients and doctors. In rural locations where there might not be any close medical personnel, this technology is very helpful. The instrument has been enhanced so that it is more user-friendly and robust for images taken in any circumstance, enabling it to be utilized for the automatic diagnosis of skin cancer. The majority of skin cancer detection research focuses on determining the malignancy of a particular lesion picture. However, a patient's question about whether a certain skin cancer symptom appears elsewhere in their body cannot be answered by the most current studies.

The research's sole focus up until now has been the classification of a single image. The project's future scope may involve increasing the model's accuracy by classification using many photographs in order to produce the most accurate results. The basal cell

carcinoma and squamous cell carcinoma, which are the two most common skin cancers, can be added to the model to classify more skin cancer forms.

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