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DETECTION AND DIAGNOSING OF SKIN CANCER USING DEEP LEARNING TECHNIQUES

Juthi Biswas

Department of computer science and engineering, Chandigarh university mohali Punjab

Paurav Goyal

Department of computer science and engineering, Chandigarh university mohali Punjab

Dr. Navneet Kaur Walia

Department of computer science and engineering, Chandigarh university mohali Punjab

Abstract— Skin cancer is the most common form of cancer in the world and early detection is essential for successful treatment. Deep learning techniques have been widely used to detect and diagnose skin cancer. This research paper explores the potential of deep learning techniques for the detection and diagnosis of skin cancer. We review existing methods and propose new techniques to improve the accuracy and robustness of the detection and diagnosis process. We evaluate a range of existing deep learning models, such as convolutional neural networks, and analyze their performance on three publicly available datasets. Segmentation and feature extraction is carried out with the help of PSO algorithm. We also investigate the effects of transfer learning, data augmentation, and model ensemble on the accuracy of the models. Our results demonstrate that the use of deep learning techniques can significantly improve the detection and diagnosis of skin cancer. We provide insights and findings to help practitioners develop more effective and reliable systems for skin cancer detection and diagnosis.

Keywords— Deep Learning, Skin Cancer, accuracy.

INTRODUCTION

Skin cancer is the most prevalent kind of cancer overall, yet it is still one of the major causes of mortality across the globe. The early identification and diagnosis of skin cancer is very necessary for the therapy to be effective. The development of automated methods for identifying and diagnosing skin cancer has been made possible by recent advancements in artificial intelligence, notably Deep learning. [1] These devices are able to do medical image analysis, such as dermoscopy image analysis, and provide precise diagnosis.

The purpose of this study is to provide an overview of the use of deep learning methods for the early detection and accurate diagnosis of skin cancer. The purpose of this study is to investigate the most recent developments in the field of automated skin cancer detection and to examine the benefits and drawbacks of these approaches and technologies.[2]

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Deep learning

Deep learning use algorithms to find data patterns. Deep learning algorithms uncover patterns in complex datasets like photographs, audio, and movies, whereas Deep learning algorithms find patterns and make predictions from massive datasets. Both learning techniques boost machine intelligence.[3] Medical imaging has become more interested in deep learning. Medical pictures have been processed using deep learning algorithms to detect skin cancer. Deep learning systems can analyze complex medical images and provide more accurate diagnoses. Information for Authors.[4]

Detection and Diagnosis of skin cancer using Deep learning

In order to identify and diagnose skin cancer, a variety of alternative deep learning algorithms have been developed. Support vector machines, deep neural networks, convolutional neural networks, and recurrent neural networks are all examples of these types of neural networks. [5]The aforementioned algorithms each come with their own set of benefits and drawbacks. Support vector machines, often known as SVMs, are a specific kind of algorithm that belong to the field of Deep learning. These machines can divide data into many different categories. SVMs are especially well adapted for the identification and diagnosis of skin cancer since they are able to analyze complicated medical pictures and provide reliable diagnoses. This makes them an excellent choice for this application.[6]

A potential area of study is the application of deep learning algorithms for the detection and diagnosis of skin cancer.[7] Recent research has shown that automated systems have the capacity to identify and diagnose skin cancer using medical photographs. The use of these algorithms has the potential to enhance diagnostic precision and speed, eventually leading to improved clinical results for patients.[8]

Contribution of the study:

This study uses ensemble learning to classify data with the main objective of detecting skin cancer. The research investigates the potential of utilizing an ensemble model to identify skin cancer in an individual's body.

Objectives:

- To detect the skin cancer using deep learning techniques.
- To make the comparative analysis between previous methods and our proposed method.

Related Works:

This article discussed recent researches in Skin cancer detection and the problems and potential for improving existing skin cancer detection models. some of them are presented below.

Authors proposed a transfer learning-based intelligent Region of Interest (ROI) system to distinguish melanoma from nevus malignancy. Images are ROI-extracted using an updated k-mean technique. Melanoma-only photos are utilized to train the ROI-based technique to find discriminative features. A CNN-based transfer learning model with data augmentation was applied for ROI pictures of DermIS and DermQuest datasets. [9]

This study discussed melanoma detection from cutaneous lesions. Pre-processing and segmentation of skin lesion pictures were addressed. They compared current technologies. They addressed categorization methods for skin lesions into skin cancer classifications. [10]

In this paper, the author's suggested system uses three prediction methods: Two traditional deep learning classifiers and a convolutional neural network trained on skin lesion boundaries, texture, and colour. Through majority vote, these approaches are then integrated to enhance their results. These tests have shown that the maximum degree of accuracy is obtained when all three approaches are used simultaneously. [11]

An integrated deep feature fusion approach for skin cancer detection was presented. Alex Net and VGG-16 extract characteristics from segmented skin lesion pictures and fuse them for classification. Model training and validation utilized selected data. Authors identified integrated deep feature fusion approach for skin cancer detection was presented. Alex Net and VGG-16 extract characteristics from segmented skin lesion pictures and fuse them for classification. Model training and validation utilized selected data. [12]

This study provides a comprehensive overview of deep learning methods for detecting skin cancer in its earliest stages. In its earliest stages. In order to better understand how to diagnose skin cancer, a number of high-quality research publications were analysed. Authors of this study identified CNN performs better than other neural network types for identifying picture data because it is more directly associated with computer vision. [13]

Background:

In this part, Background of Skin Cancer describes the architecture of the existing models Alex Net and Res Net 50 and our proposed model VGG16.

Alex Net Architecture:

The architecture consists of a total of eight layers, with the final three being completely connected and the first five being convolutional. The first two convolutional layers of the network are linked to overlapping layers of max-pooling to extract the maximum number of features possible.[14] There are direct connections between the third, fourth, and fifth convolutional layers and the fully connected layers. The outputs of both the convolutional and fully connected layers are linked to the ReLU nonlinear activation function.[15]

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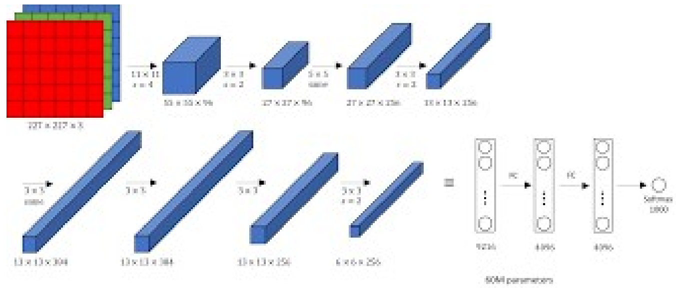

Figure 1 Alex Net Architecture

A SoftMax activation layer coupled to the final output layer of the network provides a distribution of one thousand class labels. A 256x256 RGB (3-channel) image is submitted to Alex Net. There are around 650 thousand neurons and sixty million architectural components. Reduce overtraining via dropout layers. Dropped neurons have no effect on forward or reverse propagation. These layers comprise the first two levels that are completely linked.[16]

Res Net 50 Architecture:

Microsoft Research created a convolutional neural network (CNN) architecture called ResNet-50. It is a deep neural network with 50 layers comprised of numerous residual blocks with shortcut connections. ResNet-50 is designed to enhance the precision of image classification tasks.[17]

A convolutional layer is followed by many residual blocks in the ResNet-50 architecture. Each residual block consists of three convolutional layers with a direct input link. The fast connection is used to deepen the network, enabling the learning of more complicated elements. The convolutional layers use batch normalization and ReLU activation algorithms to enhance the network's precision and speed. Many applications, such as image classification, object identification, and semantic segmentation, have used the ResNet-50 architecture.[18] In numerous benchmark datasets, including ImageNet, CIFAR-10, and Pascal VOC, it has achieved state-of-the-art performance. Moreover, the network is often used for transfer learning. Because to its precision and scalability, ResNet-50 has emerged as one of the most prominent deep learning architectures. It has become a vital component of many computer vision applications and is an excellent option for anyone seeking to develop a deep learning model.[19]

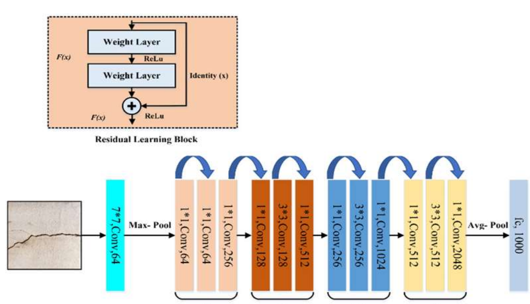

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Figure 2 Res Net 50 Architecture

VGG16 Architecture:

VGG16 proved to be a defining moment in humanity's attempt to make computers "see" the world. For decades, a lot of work has been invested into enhancing this capacity under the field of Computer Vision (CV). The major development known as VGG16 paved the way for several other developments in this field. Andrew Zisserman and Karen Simonyan of the University of Oxford created the Convolutional Neural Network (CNN) model. Back in 2013, the concept for the vehicle was first introduced, but the final model wasn't submitted until the ILSVRC ImageNet Challenge in 2014. An annual contest called the ImageNet Wide Scale Visual Recognition Challenge (ILSVRC) evaluated image categorization (and object identification) techniques on a significant scale.[20]

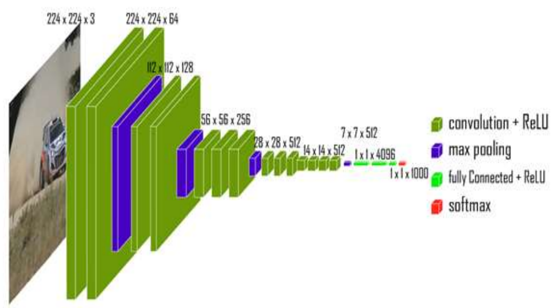

Figure 3 VGG 16 Architecture

Research Methodology:

The primary objective of this work is to identify images of skin cancer using VGG16 Architecture. Utilized were image pre-processing techniques including morphological image processing and the Hough transform.

Dataset Description:

We gathered data from this website.

https://www.kaggle.com/datasets/farjanakabirsamanta/skin-cancer-dataset We must choose images of Skin cancer from the given dataset.

Pre-processing steps for image classification:

The objective is to demonstrate how the accuracy changes when some well-known pre-processing methods are applied to certain basic convolutional networks. The following lists a few pre-processing methods.

- Read image
- Resize image

- Remove noise
- Morphology

Read image

To read the image, we constructed a method to load picture-containing folders into arrays after storing the path to our image dataset in a variable.

Resize image

In resizing image, we will write two methods to show the photos in this phase, one to display one image and the other to display two images, in order to see the change. Following that, we develop a method called processing that only accepts the photos as an input.

Remove noise

To Remove the noise a Gaussian function is used to blur a picture, producing a gaussian blur. It is a typical graphics application effect that is often used to decrease visual noise. In order to improve picture structures at various sizes, computer vision algorithms also use gaussian smoothing as a pre-processing step.

Morphology

The processing of pictures based on forms encompasses a wide range of image processing processes. The output image produced by morphological processes is the same size as the input image after it has had a structural element applied to it.

Image Segmentation using PSO

Image segmentation is one of the pre-processing steps which is conducted before the pattern recognition, feature extraction, and image reduction process. There are various kinds of segmentation methods based on supervised and unsupervised learning methods that are currently being used by researchers. In this study, we developed a segmentation method to divide the skin images into its background and foreground using correlation-based feature selection method i.e., Particle swarm optimization (PSO) and we will then use PSO method to extract the features from images. The brief description about PSO is described below.

particle swarm optimization (PSO)

The particle swarm optimization (PSO) algorithm is a population-based search algorithm based on the simulation of the social behavior of birds within a flock. The initial intent of the particle swarm concept was to graphically simulate the graceful and unpredictable choreography of a bird flock, to discover patterns that govern the ability of birds to fly synchronously, and to suddenly change direction by regrouping in an optimal formation. From this initial objective, the concept evolved into a simple and efficient optimization algorithm.

$$X_{i,n} = (Z_{i,n,0}, Z_{i,n,1} \ldots\ldots, Z_{i,n,K-1}) \quad (2)$$

where n is the number of iterations for the ith particle location.

This particle's velocity vector V toward its next point in the jth dimension is indicated by

$$V_{i,j,n+1} = wV_{i,j,n} + c_1 r_1 (P_{i,j,n} - X_{i,j,n}) + c_2 r_2 (G - X_{i,j,n}) \quad (3)$$

where w is an inertia weight; P is the ith particle's best location; G is the swarm's overall best position; c1 and c2 are acceleration factors; and r1 and r2 are two random values among [0, 1]. The velocity is regulated once it has been updated to prevent it from exceeding its maximum velocity. The revised velocity vector is used to update the particle location as follows:

$$X_{i,n+1} = X_{i,n} + V_{i,n+1} \quad (4)$$

Segmentation

Image segmentation is the technique of effectively grouping pixels that have comparable texture, colour, and form attributes into a small number of units. Because all the succeeding steps, including the extraction of features, choice of features, and classifying phase, rely on segmentation's effectiveness, it is true that segmentation efficiency should be quick and accurate. The segmentation stage in dermoscopy images constitutes one of the most crucial and difficult steps because of a number of factors, including the presence of the hairs with the previously mentioned artefacts and the wide ranges in size and colour of the lesions, in addition to the lack of contrast among the lesion area and the surrounding healthy skin.

Building a reliable, effective, and automatic segmentation method for lesion detection is the primary goal of our strategy. In order to distinguish the lesion area against the healthy skin, image segmentation is used. By using the right segmentation approach, beneficial outcomes can be obtained. In order to execute the final segmentation of the images by minimising the energy function, the PSO algorithms was employed.

The approach is used to define the image segmentation into an energy function optimisation problem. For this, the author executes the tagging using the PSO approach. The core concept of this method is a population of artificial particles working cooperatively to get the optimal class label for each of the pixels in the image. Based on the fitness function, every particle iteratively assigns pixels to a class. Initialization involves determining the number of particles, setting the position value of each particle to an arbitrary spot inside the area of search, and setting the speed of each particle to zero. The highest value of intensity L, which indicates that the number of particles is dispersed randomly, will be used to define the search space between 0 and 255. When the image is clustered according to the fitness function, each particle in the swarm reflects one possible solution. The entire swarm thus reflects a variety of potential clustering options for the entire image. Each particle evaluates its current fitness value according to the measurement for its own Pbest resolution as well as the overall fitness value of the swarm at each stage of the suggested method. GbesQ solution. The obtained results of segmentation has been shown in figure

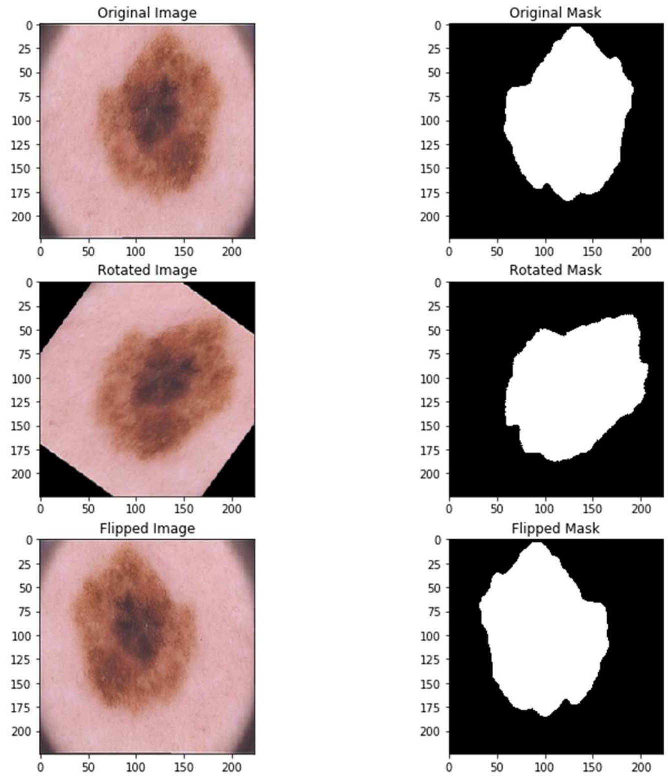

Figure 4 Skin lesion segmentation using PSO

Train test split:

After all the pre-processing steps are done, the data set is split into training and testing sets based on the user's split ratio. Later, this split train data will be used to train the models, and the test data will be used to test the models.

Train the network:

The suggested VGG-16 model and Alex, ResNet 50 are trained using the train data. The suggested model's performance is evaluated and compared using these two extra Alex and Res Net 50.

The following metrics may be used to assess the model's performance.

Performance Matrices:

The effectiveness of a technique is assessed in view of the confusion matrix's accuracy, sensitivity, precision, and F1-score

Accuracy: It is the quantity of subjects that were effectively recognized out of all the subjects.

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

Sensitivity: The percentage of accurately positive labels that our computer recognizes as being labels is called recall, also known as sensitivity.

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

Precision: By factoring in the overall number of precise predictions, it is feasible to determine the accuracy of an outlook. This idea also goes by the name of predictive value.

$$\Pr ecision = \frac{TP}{TP + FP} \quad (3)$$

F1-Score: The F1-score integrates precision and recall into a single score.

$$F1 - score = 2 * \frac{\Pr ecisison * \text{Re} call}{\Pr ecision + \text{Re} call} \quad (4)$$

Specificity: The negative has been correctly categorized by the algorithm as specificity.

$$Specificity = \frac{TN}{TN + FP} \quad (5)$$

results:

To assess the efficacy of the architectures, the performance metrics, such as Accuracy, Sensitivity, and Specificity, are computed and represented as follows:

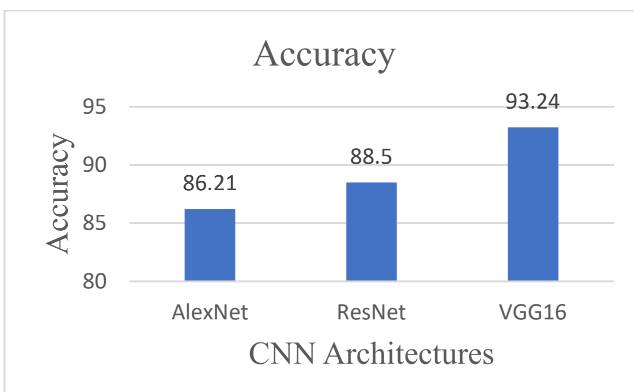

Figure 5 Accuracy

The average accuracy of VGG Net architectures is 93.24 percent, Res Net 50 architectures are 88.5 percent, and Alex Net architectures are 86.2 percent. This demonstrates that the VGG Net architecture are more accurate in detecting Skin cancer.

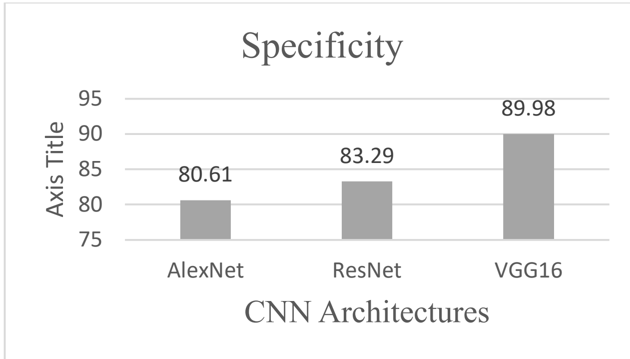

Figure 6 Specificity

The average Specificity of VGG Net architectures is 89.98 percent, Res Net 50 architectures are 83.29 percent, and Alex Net architectures are 80.61 percent. This demonstrates that the VGG Net architecture are more accurate in detecting Skin cancer.

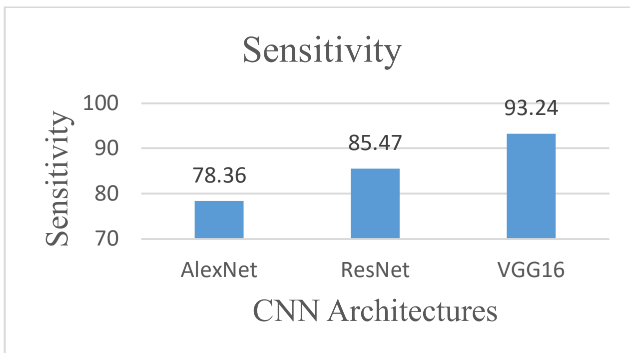

Figure 7 Sensitivity

The average Sensitivity of VGG Net architectures is 93.24 percent, Res Net 50 architectures are 85.47 percent, and Alex Net architectures are 78.36 percent. This demonstrates that the VGG Net architecture are more accurate in detecting Skin cancer.

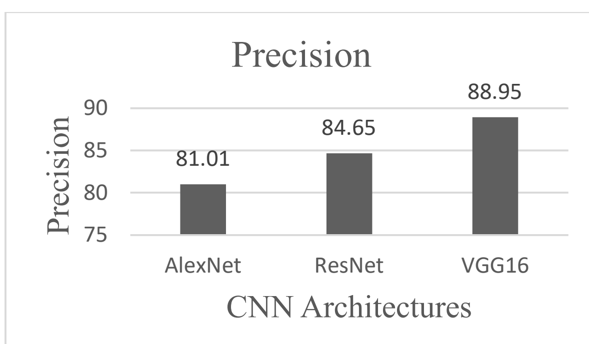

Figure 8 Precision

The average Sensitivity of VGG Net architectures is 88.95 percent, Res Net 50 architectures are 84.65 percent, and Alex Net architectures are 81.01 percent. This demonstrates that the VGG Net architecture are more accurate in detecting Skin cancer.

Architectures	Accuracy (%)	Specificity (%)	Sensitivity (%)	Precision (%)
VGG Net	93.24	80.61	93.24	88.95
Res Net 50	88.5	83.29	85.47	84.65
Alex Net	86.21	89.98	78.36	81.01

Conclusion

In this study, we developed a CNN architecture based on the VGG 16 model for detecting skin cancer. After pre-processing, the split train data is used to train the models, while the test data is utilized to evaluate the model. In addition to Alex and ResNet50, the train data is utilized to train the proposed VGG-16 model. These two Alex and Res Net 50 are used to evaluate and compare the proposed model's performance as assessed by the performance metrics. And we obtained 93.24 percent accuracy, 80.61 percent specificity, 93.24 percent sensitivity, and 88.95 percent precision, which is higher than past models.

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