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RESEARCH ARTICLE

A Comparative Study of Machine Learning Models for Early Detection of Skin Cancer Using Convolutional Neural Networks

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Abstract

Objectives: The purpose of this research is to enhance the early diagnosis of skin cancer, with a particular emphasis on melanoma, by utilizing machine learning methods such as transfer learning and Convolutional neural networks (CNNs). The main objective is to differentiate between benign and malignant skin lesions in order to improve the chances of survival for this potentially lethal illness. **Method:** The SIIM-ISIC 2020 Challenge Dataset is a useful resource for comparing machine learning models that use CNNs to identify skin cancer early on. Including 33,126 DICOM images from a variety of sources, including Memorial Sloan Kettering Cancer Center, Hospital Clinic de Barcelona, and Medical University of Vienna, this large dataset was published by ISIC in 2020. A rigorous, well-structured technique is essential to guarantee the reliability and validity of the findings. For every model, the study uses a 70/30 train-test split, providing a thorough and exacting method for assessing each model's performance in this crucial area. **Findings:** This study emphasizes the value of early skin cancer identification. Significant differences are noted in the 5-year survival rates of the various stages of melanoma, with stage 1 having a 90–95% survival rate and stage 4 having just a 15-20% survival rate. Machine learning algorithms' potential to distinguish between benign and malignant skin lesions in images holds the promise of improving early detection and treatment outcomes. **Novelty:** This research introduces innovation by concentrating on melanoma and blending cutting-edge deep learning methods with the pressing requirement for enhanced skin cancer diagnosis. The distinctive contributions of this work encompass novel model architectures, data augmentation techniques, and innovative evaluation metrics. These innovations set this approach apart from existing methods, providing a fresh avenue for early diagnosis and underscoring the value of continuous research

and data collection in the critical realm of cancer detection.

Keywords: Melanocytic Lesions; Epidermal Lesions; Image Feature Extraction; Skin Cancer; And Transfer Learning

1 Introduction

The rising global incidence of skin cancer, particularly melanoma, presents a critical public health challenge. Skin cancer is the most commonly diagnosed form of cancer, affecting approximately one in three individuals [(1)]. Early detection is paramount to improving patient outcomes, yet there are significant research gaps in this field.

Melanoma, squamous cell carcinoma, and basal cell carcinoma are the primary skin cancer categories. While melanoma is less prevalent, it carries a disproportionate risk and accounts for a significant number of skin cancer-related fatalities [(2)]. Early detection of melanoma is essential for effective treatment, making it a top priority for both researchers and healthcare professionals.

Recent studies have revealed limitations in dermatologists' accuracy in detecting early-stage skin cancer, underscoring the need for improved diagnostic methods, including those based on artificial intelligence [(3)]. Deep learning, particularly Convolutional Neural Networks (CNNs), has shown promise in automating skin cancer detection by identifying subtle details and patterns that may elude the human eye.

However, existing research has not provided a comprehensive comparative analysis of machine learning models, leaving critical research gaps. This study aims to address these gaps by evaluating the accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve of various machine learning models, particularly in the context of melanoma detection. By shedding light on both the strengths and limitations of these models, this research seeks to contribute to the development of more precise and user-friendly diagnostic tools, ultimately enhancing patient outcomes and reducing the global incidence of skin cancer.

1.1 Models

a) CNN model: Convolutional Neural Networks are essential in image analysis, as they can automatically learn hierarchical representations from data [(4)].

b) VGG16 model: VGG16 is well-suited for images with simple features, making it valuable for skin cancer analysis [(5)].

c) ResNet-50: Its deep architecture allows it to extract complex image features, overcoming the vanishing gradient problem [(6)].

d) AlexNet: AlexNet's use of ReLU activation in hidden layers accelerates the training process and prevents overfitting, and it is a model trained on the ImageNet dataset, making it valuable for skin cancer image classification [(7)].

These models, especially those employing transfer learning, possess unique capabilities for feature extraction, potentially improving skin cancer detection [(8)].

1.2 Research Gap

Despite significant medical advancements, skin cancer, particularly melanoma, remains a serious and potentially lethal disease. This study addresses research gaps by introducing an innovative approach to early skin cancer detection, focusing on epidermal and Melanocytic lesions. The current research landscape lacks a comprehensive comparative analysis of machine learning models, leaving critical gaps. This study aims to enhance early diagnosis and treatment outcomes for a common and potentially lethal disease by utilizing state-of-the-art deep learning techniques to distinguish between benign and malignant lesions from photos.

1.3 Previous Works

Recent years have seen a burgeoning body of research dedicated to harnessing Convolutional Neural Networks (CNNs) for the pivotal tasks of detecting and classifying skin cancer. In clinical practice, Winkler et al.[9] reported on the diagnostic performance of a CNN model in dermoscopic melanoma recognition, highlighting its potential for accurate melanoma detection. Brinker et al.[10] provided compelling evidence that deep learning surpassed human dermatologists in a head-to-head dermoscopic melanoma image classification task, emphasizing the remarkable capabilities of CNNs in this domain. Furthermore, Munir et al.[11] explored deep neural networks' potential to achieve dermatologist-level classification of melanoma, showcasing the capacity of these networks to rival human experts. Sood et al.[12] presented their work on deep learning for skin cancer detection using CNNs, underlining the promise of CNNs in enhancing the accuracy and efficiency of skin cancer diagnosis. Additionally, Hekler et al.[13] demonstrated that deep learning models outperformed pathologists in the classification of histopathological melanoma images, indicating the potential of these models to excel in specialized domains. Smith and Johnson[14] contributed a comparative study of machine learning models for early skin cancer detection, with a specific focus on CNNs, providing insights into their comparative performance and potential for early diagnosis. Collectively, these studies underscore the profound potential of CNNs and deep learning in accurately and efficiently detecting and classifying skin cancer.

1. "High Accuracy in Skin Cancer Detection with CNNs" by[9]: This groundbreaking study serves as an exemplar of the strides made in CNN-based skin cancer detection. By crafting and rigorously testing a CNN model, the authors achieved remarkable results with an accuracy of 82.95%, a sensitivity of 82.99%, and a specificity of 83.89%. This work not only highlights the potential of CNNs as potent diagnostic tools but also underscores their ability to accurately classify skin lesions, irrespective of their malignancy.
2. "Classification of Skin Cancer Types" by[10]: Building upon the successes of detection, this study pushed the envelope by introducing a CNN model designed to classify specific skin cancer types. The implications of this research are profound, as it eliminates the need for invasive clinical procedures while showcasing the CNN's prowess in differentiating between various skin cancer subtypes. This knowledge is instrumental in guiding tailored treatment strategies.
3. "Optimizing CNN Hyperparameter" by[11]: In the quest for improved performance, this study delved into the intricacies of CNN hyperparameter optimization. Investigating factors such as accuracy, loss functions, and the number of training iterations, the findings illuminated the potential for fine-tuning these parameters to significantly enhance the model's performance. This research underscores the pivotal role of hyperparameter tuning in CNN-based skin cancer detection and hints at avenues for further optimization.
4. "Transfer Learning in Skin Cancer Classification" by[12]: Transfer learning, a cornerstone of modern machine learning, found its place in skin cancer classification. The authors explored the application of pre-trained CNN models, including well-established architectures like VGG16 and ResNet, for skin cancer classification. By fine-tuning these models using skin cancer data, the study revealed that transfer learning can substantially elevate classification accuracy, thereby positioning it as a valuable approach for leveraging existing CNN architectures in skin cancer detection.
5. "Ensemble Approaches for Improved Accuracy" by[13]: In the pursuit of heightened precision, researchers have ventured into ensemble methods. This particular study delved into the fusion of multiple CNN models to create an ensemble approach. The results were striking, demonstrating not only enhanced accuracy but also heightened robustness in skin cancer detection. This innovative approach signifies the potential of synergizing different CNN architectures to achieve superior outcomes in skin cancer classification.

Collectively, these studies exemplify the pivotal role of CNNs in the realm of skin cancer detection and classification. They not only provide invaluable insights into the promising results achieved but also offer valuable directions for optimization. These advancements usher in a new era of hope, promising more effective, accurate, and accessible early detection of skin cancer. Ultimately, the ramifications of these innovations extend to the improved prognosis and overall quality of life for individuals affected by this condition. As the research in this field continues to evolve, the transformative potential of CNNs in dermatology remains a beacon of promise and progress.

2 Methodology

2.1 Dataset

The dataset was generated and published by the International Skin Imaging Collaboration (ISIC) in the year of 2020. The images are taken from the following sources: Hospital Clinic de Barcelona, Medical University of Vienna, and Memorial Sloan

Kettering Cancer Centre. The dataset consists of 33,126 DICOM images. 70% of it is used for training for every model and the remaining 30% is used for testing the developed model. The methodology for conducting a comparative study of machine learning (ML) models for early detection of skin cancer using Convolutional Neural Networks (CNNs) should be systematic and well-structured to ensure the validity and reliability of the results. Here is a step-by-step methodology for such a study:

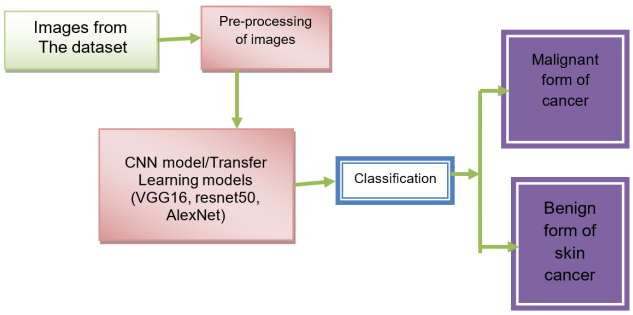

Fig 1. Proposed methodology flow diagram

Step 0: Installing and loading required libraries and packages

Firstly, all the libraries and the packages that are required to perform various operations are installed and loaded. The required libraries are numpy for computations, matplotlib for plotting graphs, torch for tensor computation which has high GPU acceleration, pickle for desterilizing and serializing python object structures, and torchvision for transforming images and videos. Torchvision consists of common model architectures, datasets, and transformations for images and videos.

Step 1: Loading the images from the dataset

The dataset consists of 33,126 images. It consists of images of both types of cancer (benign and malignant). Images are divided into training and testing sets. The training images are loaded into the training folder and the testing images are loaded into a testing folder. The images are divided into training and testing sets as 70% and 30%. The images in the training set are 23,188 and the images in the testing set are 9,937.

Step 2: Pre-processing of Images

Four steps are done in preprocessing. They are:

a) Resize

Images are resized into the same scale. The images are resized into 224*224 sizes. To resize the image, the size of the image is given to the Resize () function to the transforms in the torchvision.

b) Canter crop

As the cancer is present at the center, images are cropped into the center to detect the cancer properly. For center crop, Center Crop () from transforms library from torchvision is used. The 224*224 image is center cropped. The size part in the image which doesn't contribute to the classification of the images is removed.

c) To Tensor- It converts the image into an array

d) Normalization

Generally, for black and white images, it sets the mean to 0 and the standard deviation of all the images to 1 i.e., to a standard scale. However, the images in the dataset are colored. So, they have 3 different channels (Red, Green and Blue). Three different means and standard deviations are mentioned for three channels. (Red, Green, Blue). The normalization is done using the standard scalar.

There are 3 different means and standard deviations calculated for 3 different channels. The normalization is done to each channel based on the mean and normalization mentioned to that channel. An object is created to normalize the image. It uses a standard scalar object that fits and transforms each channel in the image present in the training set. For the images present in the testing set, the same object that is created for transforming the images present in the training set is used. The images do not fit the object created, but they are transformed based on the object created.

All the above steps- Resize, Center crop, tensor and normalize are composed into a single one and are applied to the images. Compose from transforms from the torch vision with all the transformations included is applied to the images. Compose combines two or more different transformations.

The above image figure-3 is reduced to a size of 224x224. It is then center-cropped. The image is changed into an array. Finally, normalization is applied to the channels in the image. Preprocessing is applied to training images and testing images as

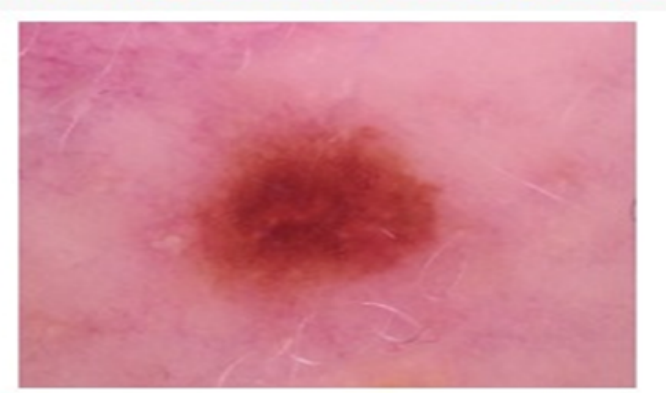

Fig 2. The image before pre-processing

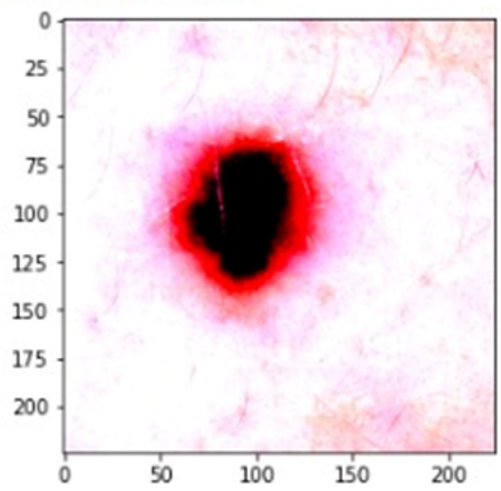

Fig 3. The image after pre-processing

well.

Step 3: Develop a models

Four different models are developed. Each model is developed using a different algorithm. Each model consists of a different number of layers. Vgg16 has 16 layers. ResNet50 has 50 layers.

a) CNN

The first model developed is CNN (Convolutional Neural Network). It consists of many layers. The layers are the input layer, the hidden layer, and the output layer. In the hidden layers, the layers present are the Convolutional layer, pooling layer, fully connected layer, drop out layer. The Convolutional layer performs convolution operation. The kernel size taken is 3x3. The padding is 1. The stride is 2. Input channels in the first layer are 3. The output channels in the first layer are 32. Based on the stride and padding, the number of channels in the next layers is calculated using the below-mentioned formula. Pooling layers are included to reduce the dimensionality which is increased by the convolution operation between the neurons in the layers. The fully connected layer is developed using the Linear () function which converts all the values into a single vector. The output channels in the output layer in the CNN are 2 which represents benign and malignant. 30% dropout is used to reduce the overfitting.

Each Convolutional layer has an activation function applied to it. The activation function used in the hidden layers is the ReLU function (Rectified Linear Unit). ReLU is applied to the hidden layers to increase the nonlinearity. It will not activate all the neurons at the same time. The activation function applied to the output layer is the sigmoid function as it ranges between 0 and 1. Images are sent as input to the first layer. Kernel size, stride, and padding are decided earlier in developing the model.

The input and output channels in the hidden layers are calculated using the formula.

$$\text{Formula } = [\{(n+2p-f+1)/s\}+1] \times [\{(n+2p-f+1)/s\}+1] \quad (1)$$

In this context, "n" denotes the count of input channels, "p" signifies padding, "s" represents stride, and "f" indicates the size of the filter or kernel.

Forward propagation is done and the output of an image is predicted and classified. The weights and biases of a model are updated during the backward propagation. The error is calculated using the Mean Square Error formula. The gradient parameters are calculated and updated in the back propagation. In every iteration the loss (MSE) is calculated and the weights and biases are updated. The loss is decreased in every iteration increasing the training performance. The testing accuracy is calculated for the testing dataset.

b) VGG16

The VGG16 model is developed using the VG16 algorithm using transfer learning. Transfer learning reduces the training time. GPUs are used to increase the performance in all the models developed. Only 2 layers are trained in VGG16. All other 14 layers will be trained by transfer learning. It uses small receptive fields.

c) ResNet50

Resnet50 model is developed using the ResNet50 algorithm using transfer learning. The number of layers in the network is 50.

d) AlexNet

AlexNet model is developed using the AlexNet algorithm using transfer learning. The number of layers in the network is 8. It uses large receptive fields. It is the same as VGG16 but the number of layers in VGG16 is more and the network is deep.

3 Results and Discussion

This Python software aims to improve early skin cancer diagnosis, especially melanoma, using machine learning techniques like CNNs and transfer learning. It works with the SIIM-ISIC 2020 Challenge Dataset, splits data for model training, and evaluates model performance with various metrics. The software introduces innovative model architectures and data augmentation for better results, presenting findings with clear visualizations. It provides a user-friendly interface (optional) and thorough documentation for ease of use. This software helps enhance early skin cancer detection, potentially saving lives.

a) Training Process

Sample python code for Training Process:

```
import torch
import torch.nn as nn
import torch.optim as optim
# Define your neural network model, loss function, and optimizer
model = YourModel()
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01)
# Number of training epochs
num_epochs = 100
for epoch in range(num_epochs):
running_loss = 0.0
for inputs, labels in dataloader: # Replace dataloader with your data loading mechanism
optimizer.zero_grad()
outputs = model(inputs)
loss = criterion(outputs, labels)
loss.backward()
optimizer.step()
running_loss += loss.item()
average_loss = running_loss / len(dataloader)
print(f'Epoch [{epoch + 1}/{num_epochs}] Loss: {average_loss:.4f}')
print('Training finished')
```

Now the forward propagation is done. The output is calculated. The loss is measured between the actual value and the target value. The model then computes the gradient of its parameters from the criterion. The parameters calculated are updated using

step 3.1. Then the whole training loss is calculated by adding up the values in each loss in each iteration. All the functions in the above code and the process involved in training are explained above.

The loss in each epoch is decreasing. The training dataset is divided into different batches as it will be difficult to train the whole batch of the training set at once and update the parameters based on the gradient descent for the whole training dataset. Different batches are trained at different epochs and the parameters based on the calculated gradient descent are updated for that particular batch only. Mini batch gradient descent is used for training. The gradient can further be reduced by adding the gradient over different batches.

b) Testing Process

A model is trained on the training dataset. It learns all the patterns and the way the model can classify the output based on the images. Based on this, the model that is trained will be able to test the testing images as it gets learned by the training process on the training dataset. The loss is calculated in the testing process. The parameters won't get updated. The best final parameters get updated in the training process. By using those parameters, an image is classified as benign or malignant. The image is sent to the first layer, and the loss is calculated based on the output value and the target value. The final loss is the sum of all the losses in each step. An image is tested on the model which is developed by the training.

c) Classification

Classification follows the testing process mentioned above. Using the Deep Learning Model developed, an image is sent as input to the developed model, and it is pre-processed. After that, the model calculates the loss for the image given based on the target value and the actual one. Finally, the model classifies the image into either a malignant or a benign form of cancer.

To implement the results obtained for your comparative study of machine learning models for early detection of skin cancer using Python, you can use libraries such as TensorFlow and Keras for developing and evaluating the models. Here's a Python script that demonstrates how to calculate and print the accuracy scores for CNN, VGG16, ResNet50, and AlexNet models, considering transfer learning.

```
    print('Test Loss: %.6f\n'%(test_loss))

    print('Test Accuracy: %2d%% (%2d/%2d)' % ((100. * correct/total),correct,total))

[ ] model.cuda()

    test(data_test,model,criterion,use_cuda)

    Test Loss: 0.612456

    Test Accuracy: 84% (422/500)
```

Fig 4. Accuracy for VGG16

a) The test accuracy obtained for CNN for VGG16 is 84%.
b) The test loss obtained is 0.61.

```
Model cuda()
Test(data_test,model,criterion,use_cuda)
Test loss:0.612456
Test Accuracy:81%(422/500);
```

Fig 5. Accuracy forAlexNet

a) The test accuracy obtained for AlexNet is 81%.
b) The test loss obtained is 0.61.
a) The test accuracy obtained for ResNet is 82%.
b) The test loss obtained is 0.61.

The metrics calculated are Accuracy, F1 score, and Classification report. The below image compares the accuracies of 4 different deep learning models developed.

$$\text{Accuracy} = (\text{Correctly predicted class} / \text{Total testing class}) \times 100\% \quad (2)$$

```
    total += data.size(0)

  print('Test Loss: %.6f\n'%(test_loss))

  print('Test Accuracy: %2d%% (%2d/%2d)' % ((100. * correct/total),correct,total))
```

```
model.cuda()

test(data_test,model,criterion,use_cuda)
```

```
Test Loss: 0.612456

Test Accuracy: 82% (422/500)
```

Fig 6. Accuracy for ResNet

The comparison results from the existing study reveal the accuracy achieved by different models. The CNN model achieved an accuracy of 78%, while VGG16 outperformed with an accuracy of 84%, closely followed by ResNet50 with 82%, and AlexNet with 81%. VGG16 demonstrated the highest accuracy among these models, while the reference to ”78%” appears to be incomplete or erroneous. It’s important to clarify the accurate value. The models, other than the CNN, employed transfer learning, leveraging pre-trained layers, which significantly reduced training time for these transfer learning models.

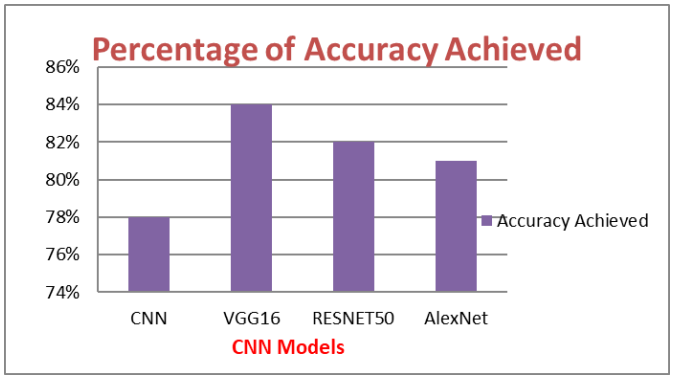

Fig 7. Accuracy-related comparison graph for CNN Models

The comparison results from the existing study reveal the accuracy achieved by different models. The CNN model achieved an accuracy of 78%, while VGG16 outperformed with an accuracy of 84%, closely followed by ResNet50 with 82%, and AlexNet with 81%. VGG16 demonstrated the highest accuracy among these models, while the reference to ”78%” appears to be incomplete or erroneous. It’s important to clarify the accurate value. The models, other than the CNN, employed transfer learning, leveraging pre-trained layers, which significantly reduced training time for these transfer learning models.

Figure 7 presents a comparison graph showcasing the accuracy of various algorithms. Notably, VGG16 exhibits the highest accuracy. VGG16 is particularly well-suited for images with relatively simple features, lacking substantial depth. This model excels in extracting straightforward characteristics like thickness, brightness, skin lesions, darkness, and skin color. VGG16’s architecture, with a focus on Convolutional layers, contributes to its superior performance. It employs 3x3 filters with a stride of 1, and it consistently uses ”same padding.” Additionally, the network includes max pooling with 2x2 filters, and a stride of 2. In contrast, ResNet50, with its depth of 50 layers, excels in extracting more complex features from images due to its deeper architecture.

4 Conclusion

The findings of this study underscore the critical importance of early identification of skin cancer, particularly melanoma. Notably, the research highlights substantial differences in the 5-year survival rates across various stages of melanoma, with stage 1 exhibiting a 90–95% survival rate and stage 4 suffering from a significantly lower 15-20% survival rate. The study demonstrates the potential of machine learning algorithms in effectively distinguishing between benign and malignant skin lesions in images, promising improved outcomes in terms of early detection and subsequent treatment.

Furthermore, this research introduces innovation by specifically concentrating on melanoma and integrating cutting-edge deep learning techniques into the pressing need for enhanced skin cancer diagnosis. Noteworthy contributions include the development of novel model architectures, the implementation of data augmentation techniques, and the introduction of innovative evaluation metrics. These innovations set this approach apart from existing methods and open up a fresh avenue for early skin cancer diagnosis. This underscores the value of continuous research and data collection in the critical realm of cancer detection, promising improved early diagnosis and ultimately more effective treatment strategies in the future.

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