Title: Detection of Skin Cancer Using Modified VGG16 Model

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Detection of Skin Cancer Using Modified VGG16 Model

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Abstract
Skin cancer is one of the most reported cancers across the globe. The main causes of skin cancer is exposure to ultraviolet light, either from sunlight or ultraviolet lamps present in tanning machines or other scientific equipment. Early detection of skin cancer not only helps with treatment but also prevents it from spreading to other parts of the body, resulting in death. The proposed VGG16 model trained, validated and tested using the Ham10000 dataset. As an initial step, the data set is preprocessed by applying class imbalance handling techniques. Image transformation, cropping etc are applied to generate images to aid in correction of class imbalance. Cropping technique is applied to crop the region of interest (ROI) as a small portion is the skin lesion in images. The model needs to be light, efficient and fast, hence the Mobile Net and Efficient Net architectures will be used. To further reduce the size of the model, pruning techniques are applied. The proposed modified VGG16 model is compared with existing models using precision, recall, accuracy and F1-score metrics.

Keywords: Accuracy, Deep Learning, Melanoma, Precision, Recall, Skin Cancer.

Introduction
Skin cancer is the rapid growth of canceroustissue on the skin surface and the layers beneath the skin. These cells grow abnormally and can even propagate to other body parts. There are three major kinds of skin cancers: Basal-cell skin cancer, Squamous-cell skin cancer and Melanoma. About 80% of the skin cancers are Basal Cell Cancer and Squamous Cell Carcinoma.

Melanoma, which is the most aggressive type of cancer, appears as a mole and it changes its shape and size over time. Skin cancer is the most common type of cancer
in the world. 4 out of 10 cancer cases diagnosed are related to skin. More than 90% of the cases are caused by ultraviolet radiation exposure. Melanin content in the skin plays an important role in determining the chances of skin cancer. Exposure to sunlight for extended periods of time without sunscreen can cause skin cancer especially at places where the ozone layer is thin or absent [20][21].

Early detection and treatment can prevent the spread of cancer to other parts of the body and can even prevent death. Many computer-aided systems are already in use. Deep learning based CNN is effective and can be used for diagnosis. Computer assisted diagnosis is much slower as it only takes one image and makes predictions. On the other hand, a CNN based system can make personalized, faster and more reliable predictions. Many CNN networks like Mobile Net, Visual Geometry Group Net and Efficient Net etc., are already being used in the literature to make predictions, object detection and more.

In this research, the method proposed is a deep learning based portable and efficient CNN model using Mobile Net or Efficient Net. This model is light weight, fast and computationally efficient. This model can be a part of an architecture that can be used in mobile phones as an application. Most of the cancer images in the dataset contain skin around the cancer region, which is more than that of the cancer region. To make the model more efficient and effective in the ROI, model parameters are tweaked and certain data augmentation steps are performed on the dataset to get more efficiency than the state of the art models [23].

**Literature Review**

The first step in detecting skin lesions is by visual inspection by a concerned doctor. Most of the serious cases are with the patients who fail to get diagnosed. Differentiating a mole from a dangerous lesion is a near impossible thing for patients. This can only be done by a doctor with the help of medical scans. Although a deep learning based mobile application with SOTA accuracy can aid and alert patients and helps them detect a potentially fatal skin disease.

Z. Jiahao, et. al., (2021) presented a Efficient Net model for classifying melanoma. Their model takes into account all the lesions of a patient to get personalized classification. With some hyper parameter tuning and train time data augmentation, augmentation during
C. A. Hartanto, et. al., (2020) worked with two types of skin cancers, Actinic Keratosis and Melanoma. They have used Mobile Net due to its efficiency. They have also used Faster Regions with CNN which is faster than its predecessors and other architectures like You Only Look Once (YOLO) and Single-Shot object Detection (SSD). In most of the images in the considered dataset, the area of normal skin is more compared to the lesions. Parameter tuning is performed to adjust the model for the required [22].

Srinivasu, et. al., (2021) used Mobile Net with Long Short Term Memory. They used Mobile Net V2 as it is computationally efficient and lightweight which can be used in light weight computational devices like mobile phones or portable camera devices[23].

According to Abbas Hannon and Alasadi Baidaa M.ALSafy (2015), the picture technology approach is used to divide melanoma into quickly distinguishable stages. The first step should be to determine whether the skin damage is malignant, and the second should be done to identify the type of black melanoma. Coup segmentation is used in a similar way to operate the system, but characteristic extraction is used [2].

As stated by Sanjana M and V. Hanuman Kumar (2017), in order to determine the stage of cancer, the images are processed using combinations of desktop discipline and image technology. With the help of a derma scope, images of the affected area are taken. After detecting skin cancer, a number of algorithms have been proposed, but almost all of them require manual input. The primary objective of their work is to create a computer discipline algorithm that doesn't require as much human intervention [3].

According to Nikitha Kaut et. al (2018) the steps like pre-processing, segmentation, classification, or function extraction are all necessary in the melanoma discovery process. This order places an emphasis on unique approaches like the hybrid artificial neural network, genetic algorithm, neuro fuzzy system, hybrid genetic algorithm, artificial neural network (ANN), support vector machine (SVM), CNN, asymmetry, border, color and diameter rule, and unsupervised algorithm – K capacity algorithm, among others. However, the SVM algorithm technique outperforms the rest of the
examined algorithms when it comes to cancer detection because it has the fewest drawbacks. The SVM method is the most effective of all the structures that currently exist up to the expectation[23]. According to Hao Chang (2017), who works in the department of Genetics at Yale university School of Medicine, dermoscopy is one of the most important ways to look at skin lesions or take high-resolution pictures of the skin without surface reflections. High-resolution imaging is only used by well-trained doctors who have already considered the possibility of melanoma at the outset and can achieve diagnostic accuracy of up to 80%. Nonetheless, not all dermatologists can detect skin cancer effectively. In an effort to address the issue, efforts have been made to develop machine-driven image analysis software for the purpose of introducing the academic research Community to specific skin-related conditions by utilizing dermoscopy images[5].

Munya A. Arasi, et al (2016) have focused on an overview of the state of the art in computer-aided detection/diagnosis (CAD) structures for figuring out and diagnosing black melanoma using dermoscopy images. The diagnosing steps proposed involve photo acquisition, preprocessing, and the discrete wavelet transform (DWT), which combines both land and color
features to produce a yield with dead-on high accuracy. Nearest Neighbor, ANN and SVM are the techniques that give better results because of the alignment [6].

Adria Romero Lopez et. al (2015), states that the skin lesions classification, primarily between skin cancer and melanoma detection, provides a deep-learning method-based system for resolving issues related to isolating dermoscopic photographs that contain a skin injury that is either benign or malignant. The Visual Geometry Group Net neural network structure serves as the foundation for this proposed solution. In this work, the focus is on classifying a dermoscopic image of a skin lesion into melanoma, which is considered dangerous[7].

Catarina Barata and Jorge S. Marques (2019) used hierarchical architectures to learn about using deep learning for the diagnosis of skin cancer. They discovered that skin lesions are organized in a hierarchical manner, as dermatologists take into account when diagnosing them. Computerized systems, on the other hand, do not use this information, resulting in a diagnosis based on a one-versus-all approach in which all types of lesions are taken into account [11].

Yoonsik Kim et. al (2017) introduced twin CNN and their training techniques for skin detection. They proposed to mimic the scientific approach or educate a deep-learning structure in order to operate a hierarchical diagnosis. A variant of the VGG network is the forward CNN, which has 23 filters and 20 convolution layers. The second layer is made up of more than twenty networking network layers, which can still be seen as a change to the bottom structure. They first considered patch-based training before moving on to complete image-based training when instructing these networks for human skin detection. The first approach focuses on visible features, such as skin color and texture. Experiments demonstrate that the proposed CNNs outperform both conventional methods and the current deep-learning-based method in terms of propagation performance. Additionally, the CNN structure is found to typically produce better results than the Visual Geometry Group-based structure [12].

A study on the application of computerized skin lesion analysis to the detection of melanoma was conducted by Le Thu Thao and Nguyen Hong Quang (2017). In recent years, deep learning strategies for image evaluation have demonstrated impressive performance. The standard benchmark data sets from
the International Skin Imaging Collaboration (ISIC) 2017 Challenge, which include approximately 2000 coaching samples and 600 checking samples, are used to train and evaluate the proposed models. Jainesh Rathod et al. (2018) used CNNs to learn about skin disease diagnosis, and the results meet expectations for how the proposed methods improve pregnancy performance [13].

Many medical procedures are in practice to detect and diagnose skin cancer. Most of them are based on visual perception. Computer vision based deep neural network models are reliable, fast and most effective ways to detect skin cancer. Even though a lot of research has already been performed, there is still a lot of scope to bring this technology available to people on a large scale.

**Materials and Proposed Method**

The study is conducted on the Ham10000 dataset which consists of multiple classes of skin lesions. The scope of this study is limited to three most common types of skin cancer: Basal cell carcinoma (BCC), Squamous Cell Carcinoma (SCC) and melanoma. The reason for choosing the top three common skin cancers in this study is to focus on the most common cases of cancer. This study also aims to reduce the size of the dataset. The reason for choosing Efficient Net and Mobile Net is they are designed for portable applications as they are light and efficient. Pruning has become the most successful network compression algorithm. Hence pruning technique is also explored in this work.

The dataset considered in this study are of three classes: Nevus, seborrheic keratosis and Melanoma. This problem is tackled by releasing the Human Against Machine with 10000 training data sets. From the dataset, 2000 images are considered for training the model, of which 374 are related to melanoma, 1372 are related to nevus and 254 images are related to seborrheic keratosis. There is clearly a class imbalance. 150 images are considered for and 600 images for testing the model. The ratios of training, testing and validations are 70:20:10. Jupyter notebook is the tool used and python 3 is the version.

![Figure 1: Proposed Flowchart.](image-url)
Proposed Methodology
The input image is initially processed by applying the pre-processing techniques (refer Figure 1). The preprocessing involves resizing the images and increasing the number of images for both training and validation on melanoma and seborrheic keratosis. Next stage is the modified InceptionV3 model through its paces with the redesigned VGG16 model (refer Figure 1).

Data Augmentation
In this research, data augmentation is carried out as the number of training dataset is small. Statistical development processes such as zooming, shifting, rotating, flipping, and transformation are performed to increase the dataset. The numbers of images available in the category “Nevus” are 1372, as determined by the "Keras conceit Data Generator". In this research records expansion technique is used to increase the number of images for both "Melanoma" and "seborrheic keratosis" in order to balance thenumber of images for all three categories. For the purpose of statistics augmentation, selected a 45-degree circle, a straight flip, and a vertical flip in that work. We got 1372 pictures for each class as a result.

Skin Cancer Classification Using a Modified VGG16 Model
The flowchart in Figure 2, depicts the proposed method applied for detection of skin cancers using the modified VGG16 model. Modified VGG16 has five blocks (refer Figure 2). The first pair blocks contain a couple of convolution layers and a Relu activation function, followed by three blocks for Max Pooling. Each barrier is surrounded by three convolution layers that include Max Pooling and a Relu activation function.

Figure 2: Flowchart of the modified VGG16 for skin cancer detection.
fundamental symmetric or uneven elements. The model makes extensive use of batch normalization, but activation inputs are applied after it. Through 3 blocks of BasicConv2d, Modified InceptionV3 begins. Each capture incorporates a convolution crease or a group standardization base followed via 3 modules A, module B, 4 modules C, and module D, yet 2 modules E followed by average pooling, Dropout, Straight layer, ReLu, Dropout edge yet Direct layer.

**Results and Discussion**
The proposed classifier’s overall performance is analyzed using the accuracy, precision, recall and F1-score metrics. Modified VGG16 model and the modified InceptionV3 model performance is compared using the aforementioned metrics.

\[
accuracy = \frac{TP + TN}{TP + TN + FP + FN}
\]

\[
precision = \frac{TP}{TP + FP}
\]

\[
recall = \frac{TP}{FN + TP}
\]

\[
F1\text{-}score = 2 \times \frac{precision \times recall}{precision + recall}
\]

Where, TP is True Positive, TN is True Negative, FP is False Positive, and FN is False Negative.

Using the dataset, experiments are conducted on modified VGG16 and modified InceptionV3 algorithms. The advanced alignment scan is performed with every class of melanoma, nevus, and seborrheic keratosis from the dataset. The second alignment experiment is conducted with only two classes: Nevus and melanoma. Confusion matrix and ROC curve for modified VGG16 model are given in Figure 4 and 5 respectively. Figure 6 shows the confusion matrix for the ModifiedInceptionV3 model.

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy</th>
</tr>
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<tbody>
<tr>
<td>Modified VGG16</td>
<td>73.33%</td>
</tr>
<tr>
<td>Modified InceptionV3</td>
<td>42.00%</td>
</tr>
</tbody>
</table>

Table 1: Accuracy metric for Modified VGG16 and InceptionV3.

![Figure 4: Confusion matrix for modified VGG16 model.](image-url)
It can be observed from Table 2, the proposed method delivers better performance for the “Nevus” class dataset. With both modified VGG16 and modified InceptionV3 models, Nevus class achieved an accuracy rate of over 54%. However, the "Seborrheic keratosis" class dataset gives significantly reduced performances with both the proposed methods (refer Table 2). With the modified VGG16 and modified InceptionV3 models, precision values are limited to 47% and 24%, respectively.

Table 3 shows the recall, precision and F1-score metrics computed for the proposed modified VGG16 and modified InceptionV3 models. The classification results in Table 3 demonstrates that the proposed modified VGG16 model achieves better results than the modified InceptionV3 model. It can be observed (refer Table 3) that the F1-score recall values for the proposed modified VGG16 model and for the modified InceptionV3 model are almost similar. Whereas, the modified VGG16 model achieved better
precision value than the modified InceptionV3 model.

Table 4: Comparison for uniform classification.

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
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<tr>
<td>KNN (Daghrir et al., 2020)</td>
<td>57.3%</td>
</tr>
<tr>
<td>SVM (Daghrir et al., 2020)</td>
<td>71.8%</td>
</tr>
<tr>
<td>AlexNet (Sasikala et al., 2020)</td>
<td>65.3%</td>
</tr>
<tr>
<td>Proposed method on modified VGG16</td>
<td>73.33%</td>
</tr>
</tbody>
</table>

Determined that our modified VGG16 approach outperforms K-Nearest Neighbor (KNN), SVM, and Alex Net methods by comparing the truth values listed in Table IV for the various viewed methods. In point of fact, our proposed VGG16 method led to a proprietary level of 73.33 percent. The KNN method is able to identify skin lesions despite the fact that the truth is only 57.3% because it is sensitive to outliers.

On the other hand, the SVM outperforms the KNN and Alex Net techniques due to its adaptability and effectiveness. In point of fact, the SVM method achieves accuracy of 71.8 percent, while the KNN and Alex Net techniques, on the other hand, achieve accuracy of only 57.3 percent and 65.3 percent, respectively. Despite Alex Net's quiet performance, the SVM is still regarded as an effective skin cancer detection tool.

**Conclusion**

For skin cancer detection, Nevus, seborrheic keratosis and Melanoma are the three classes of dataset considered in this paper. This dataset is preprocessed preprocessed by applying class imbalance handling technique from the literature. The data is heavily imbalanced so the data augmentation technique is used to balance the classes. The models built in this paper are the Modified Inception V3 and the VGG16. The modified VGG16 model detects skin cancer with better accuracy compared to the Inception V3 and existing models (KNN, SVM and AlexNet). The metrics like precision, recall and F-1 score are used to evaluate the performance of the proposed model. The proposed model has given better results than the existing KNN, SVM and AlexNet models.

**References**


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