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DEEP LEARNING APPROACHES FOR SKIN CANCER DIAGNOSIS FROM LESION IMAGING

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Abstract
The current paper proposes the solution to the detection of early skin cancer using deep learning and using the ISIC 2018 dataset with specific emphasis on image processing and advanced model's design. One of the health problems that are of great concern is skin cancer and especially melanoma, early identification of the disease is highly relevant when it comes to the survival of individuals. Although the traditional diagnostic methods are effective, these are, in most cases, limited by the skills and experience of the dermatologists and hence, the results do not always coincide. To this end, it is proposed in the paper to take advantage of the Convolutional Neural Networks (CNNs) or in this instance ResNet50, InceptionV3 and Inception ResNet, and image preprocessing techniques where normalization, augmentation and Super-Resolution using ESRGAN can be used to enhance the quality of the lesion images. The pre-trained models are fine-tuned on the task of skin cancer classification using transfer learning in the study. The models have been evaluated using such metrics as accuracy, precision, recall, F1-score, and Area Under Curve (AUC) of the Receiver Operating Characteristic (ROC) curve. The discoveries are that, Inception ResNet has the highest accuracy and the value is 87.6, 86.5, 88.1, 87.4 and the area under the curve is 0.91. InceptionV3 is performing quite well as well with accuracy of 86.2 and AUC of 0.89. ResNet50 achieves an accuracy of 85.3 percent and AUC of 0.88. According to CNN baseline model, its accuracy is reasonable at 84.5 per cent but it is also less reliable than the more complicated models. These findings indicate that deep learning can be highly effective in the process of identifying skin cancer and the best and most consistent model is Inception ResNet. The article is practical as it demonstrates how the already existing deep learning approaches can be as effective and even more effective in skin cancer diagnostics than a trained dermatologist and serve as a means of early and reliable skin cancer detectors.

INTRODUCTION

Skin cancer is believed to form one of the most prevalent forms of cancer in the world, and the extent to which it is increasing at the rate is quite alarming. The skin cancer is one of the most prevalent types of cancer. It is a very large health risk especially where people are older and are spending too much time out of the house. The three commonest types of skin cancer are Squamous cell carcinoma, melanoma and basal cell carcinoma. All of them are diverse in their severity and likelihood of improvement[1]. People know that melanoma is rather aggressive and very fatal. It starts with the melanocytes which are skin cells that give color to the skin. It can spread to other organs and kill you provided that you do not check it up or treat it. Early and effective diagnosis of skin cancers is of immense importance as it may help people to live longer and also minimize the mortality rate.

The early diagnosis is very much needed as skin cancers could be easily identified through the changes that could be observed in the skin lesions over a time span. However, it is possible that the dermatologists with varying levels of experience cannot tell benign and malignant lesions. Timely and accurate diagnosis is extremely demanded and individuals easily get confused in looking at photographs because certain lesions cannot be well understood. Some of the ways through which one could find skin cancer in the years include skin examination, dermatoscope as well as a skin biopsy[2]. Nevertheless, such methods are based on the expertise of physicians, and thus this could lead to the postponement of diagnoses and mistakes. The usual approaches used to diagnose skin cancer will not be able to serve the ever-growing needs of the patients of fast and accurate diagnosis due to the escalating instances of skin cancer cases especially on the younger generation. A significant part of attention has been paid to medical diagnostics regarding the ways these issues can be solved with the help of technologies like Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL). Deep learning (DL) is a form of machine learning (ML), which tries to recreate the functionality of the neural networks within the brain. It has done extremely well in pursuit, arrangement of images and discerning patterns. DL can help in discovery of skin cancer by analyzing a huge data and identifying the relationship between items[3]. This will enable physicians to arrive at accurate and faster diagnosis. One type of deep learning model is called a Convolutional Neural Network (CNN) and this type of model can be used to determine what images are. These are useful procedures of studying skin cancer.

This has seen significant developments in the diagnosis of skin cancer in the last couple of years. The reason is that it is easier to retrieve a great deal of data and the methods of deep-learning have also been improved. One of the available datasets is the International Skin Imaging Collaboration (ISIC) 2018. It is a massive set of labelled pictures of skin lesions, which can be trained to DL models. In this ISIC 2018 dataset, skin lesions are more than 10 000. It has been used in the development and testing techniques of the discovery of skin cancer in many research studies. It has numerous benign and non-malignant lesions. Having such data sets set, deep-learning models have highly enhanced the capacity of computers to differentiate skin cancers automatically. It can even be more accurate and faster compared to the ordinary techniques of skin cancer diagnosis[4].

The deep-learning models already have some potential in skin cancer detection, but it also has several problems, which need to be solved to enhance the work of the models and be used in other contexts. The quality and heterogeneity of the data on which a depth learning model is trained is among the most important factors, the quality of its performance is correlated with. Such issues as low-resolution, lighting and noise are typical in images, which have lesions but vary with every time. Such problems may make models inaccurate. Images may be prepared in different manners which are capable of remedying these issues including the normalization, image enhancement and super-resolution processes. The Super-Resolution Generative Adversarial Networks (ESRGAN) is one of those approaches which have proven to be quite encouraging to offer the enhancement of the lesion images before using them in deep-learning algorithms. ESRGAN is a new technology that low-resolution images are improved by. It makes small things more simplified to be easier to visualize and not as noisy. ESRGAN improves the quality and detail of the pictures of skins lesions that helps the deep-learning models to identify the nature of the lesions in the image. The model is able to operate more efficiently because it gets more information and this is what the better pictures will be able to offer it[5], [6]. It is especially true when the data set contains the pictures of the lesions of different locations of different quality.

Deep learning models that detect skin cancer have enhanced the transfer learning methods, image preprocessing and image processing. The case of presenting a learnt model with a new dataset to more effectively accomplish a specific task is known as transfer learning. The model utilizes this through what it has learnt during the training process of large datasets. In this paper, we have used various trained models including the ResNet50, InceptionV3 and Inception ResNet to classify the skin lesions using the 2018 version of the ISIC dataset. The models have been trained on general-purpose and large image datasets, including ImageNet and have done better than other models in sorting different types of images[7], [8].

The mixture of various strategies used during the current research contributes to performing a comprehensive analysis of their efficiency in the area of detecting the skin cancer. The extent to which the system is useful in classifying the lesions into two groups malignant (cancerous) and benign (non-cancerous) can be used to determine the effectiveness of the system. The performance of the system is measured using a number of different metrics, which are the F1-score, recall, accuracy, and precision, to identify the most successful model to be applied in classifying skin cancer. The Receiver Operating Characteristic (ROC) curve may also be considered as the area under the curve (AUC) of the ability of models to locate something. It shows the correlation between the false positive and the true positive rates. The paper will discuss how deep learning can be utilized to identify skin cancer, ESRGAN can be used to enhance images and transfer learning can be used to enhance the model. The provided approach is contrasted with the traditional one (ResNet50, InceptionV3, and Inception ResNet) and evaluated against the ISIC 2018 data. We witness that the ESRGAN may enhance the quality of images exponentially, which enhances the model performance. The accuracy of our suggested model is 85.7 per cent which is almost comparable to that of the professional dermatologists[9], [10]. This proves that it is a good instrument in diagnosis of skin cancer by default.

In this paper, the author will cover the ways of identifying skin cancer using different techniques. It starts by showing the truthfulness of things on the basis of deep-learning models and image preprocessing methods like ESRGAN. The second one is an astute analysis of how far different deep learning models can determine the presence of skin cancer. It further shows how transfer learning concept would be applied to improve the already trained models in terms of their capabilities to detect skin cancers. This enables us to come up with good models of the limited number of data labels[11]. The results of this study make us know a lot about the enhancement of automated systems of skin cancer detection. This can be the creation of more precise, quicker, user-friendly and less expensive diagnostic instruments.

The issue of skin cancer is a serious health concern to everyone, and thus, it is highly important to develop effective and efficient AI-designed diagnostic applications that will help improve the early diagnosis of the skin cancer condition and consequently, enhance the treatment processes of the disease. The paper involves the techniques of deep learning and image improvement to further the ongoing attempts of accelerating, improving, and democratizing the process of diagnosing skin cancer in the world. The evaluation of the proposed system on various datasets with the purpose of determining its adequacy in the clinical practice of dermatologists to help them in their diagnoses will become the next stage of the current study.

Related work

Skin cancer is a medical issue that is encountered by people in all corners of the world and it keeps on changing or shifting. It is getting more and more people to acquire it. The second is the skin cancer which is the most common form of cancer in the world. It affects so many people especially those who are found where there are so many people in age or get a lot of sunlight. The number of increasing cases of the skin cancer especially the melanomas is alarming. The most common skin cancer are the following ones: basal cell carcinoma, squamous cell carcinoma, and melanoma. They are all extremely diverse as far as the degree to which they are bad and the period of time and kind of care they need. Melanoma is the most violent type of skin cancer which takes the lives of many individuals. The success of the disease diagnosis is highly valued to patient outcomes, so skin cancer diagnosis is an essential field of research and medical innovations[12], [13].

The doctors and nurses are crucial in making sure that the traditional ways of diagnosing skin cancer through visual examination, dermatoscopy and biopsy is successful. They can work, yet they might be wrong because it is hard to see the distinction between the lesions that are benign and malignant, and it is possible that the dermatologists have different levels of experience in terms of the lesion diagnosis. The Artificial Intelligence (AI) and Machine Learning (ML) and specifically Deep Learning (DL) has become important in the same area so as to do things differently[14].

Finding Skin cancer in a Never the same World

Pictures are now being viewed and categorized using deep learning which has revolutionized the way we know what ails people. It is proved that Convolutional Neural Networks (CNNs) can be very helpful in the correct classification of image in case of its use to identify skin cancer in the most diverse application. As a consequence of this fact, deep learning models like this are an ideal means of automating this process[15], [16].

To be a good deep-learner, an individual should be able to access large and labeled datasets. The International Skin Imaging Collaboration (ISIC) 2018 dataset is one of the most popular so far to teach the deep learning models on how to find skin cancer. It has in excess of 10,000 images of benign and malign lesions. The lesions are easily identified since they have been properly labeled in the pictures. It makes a massive source of research and development.

Deep learning, on its part, still faces the problem of the ability to find skin cancer. The information on pictures that are utilized to educate the designs is a massive issue because it is not always excellent or diverse. Images of skin lesions typically have low resolution, light variation or noise that makes it difficult to know what type of lesion that model represents. In order to solve these problems, different preprocessing alternatives to images have been suggested to enhance them before their use in deep learning models. Some of these techniques are normalization, enhancement and super-resolution[17], [18].

The making of preparations to investigate skin cancer

Deep learning models play a critical role in the task of better detecting skin cancer with the help of preprocessing. Image normalization, image augmentation and enhancement are some of the most popular techniques of data preparation. This is because the photos of skin lesions are not that good or even blurry. Normalizing images: Image normalization is the process of ensuring that all the images are within a given range which is usually in the range of -1 to 1. This is employed to save the pixel values and hence the light and contrast of the images become less different. It, also, renders weight training less vulnerable to the inconsequential variations in weight and makes training sessions more consistent[19]. The normalization process has been very useful in the event that multiple sources of image have been utilized as it guarantees that there are specifics like brightness and size that do not affect the viability of the model.

Image augmentation: Image augmentation techniques give you the opportunity to augment your training data by modifying the original images. One can adjust these things by rotating, flipping, moving, changing the brightness or scaling. The larger the number of examples to a model, the more they can generalize as there are additional examples. The image augmentation will prove extremely useful in the detection of skin cancer as the model will have more lesion types to learn[20], [21]. When there is a higher number of benign lesions compared to malignant lesions, this is termed as a class imbalance. This is solidified by over-sampling the cancerous images. In addition, augmentation has been useful in overfitting reduction, and also, model performance in new data.

Super-Resolution and Image Enhancement: This is also a point that is important in preprocessing to enhance the images of skin lesions. The improved version of Super-Resolution Generative Adversarial Networks (ESRGAN) is an excellent way of image enhancement. ESRGAN is also a new method of converting low-resolution pictures into high-resolution pictures. It increases the accuracy of the deep learning models to classify the skin lesion because they are clearer and more detailed thereby depicting details that are fine. ESRGAN possesses so many more prospects in improving the image of the skin lesion and augmenting the correct diagnoses[22]. The ensuing improvement in quality of picture also makes feature finding by the deep learning models easy thereby, making everything better.

Deep Learning Models for Identifying Skin Cancer

The most common kind of such model is the Convolutional Neural Networks (CNNs) which are employed in such tasks like finding skin cancer and classifying images. Convolutional neural networks (CNNs) make use of machine learning to extract features to raw image information by using automatic identification by traversing a series of layers, including pooling layers, convolutional layers and fully connected layers. This helps the model to determine spatial arrangement of features, hence the explanation why CNNs are effective in determining images[23], [24]. ResNet50 is a deep Residual network that is composed of 50 layers. It trains deep networks and skip connection or residual networks. It is now popularly used in many image classification tasks, and some studies that consider its performance have been conducted on skin cancer. The residual connections can be applied in solving the vanishing gradient issue that enables the network to acquire more complex traits. ResNet50 was also trained to identify any image and therefore might not be quite useful in medical images[25].

InceptionV3: InceptionV3 is a popular deep learning network that is used to categorize images. It also looks different with the convolutional filters of different sizes in each layer to detect a vast number of features on different levels of abstraction. The choice of inceptionV3 as a skin cancer detector was based on its performance on other image classification tasks which was superior to the other models. It also works well in this respect as it can generalize and work with multiple image datasets[26]. Inception ResNet: Inception ResNet is an amalgamation of the two best qualities of InceptionV3 and ResNet. It does this by adding residual connections on its Inception architecture therefore extending the depth of the network without reducing the learning performance. This model has been found to work exceptionally well in classification of images and also in identification of skin cancer. It can be used to extract the high- and low-level features of the images and, therefore, is excellent in establishing whether the lesion is benign or malignant.

Using Transfer Learning to Find Skin Cancer

Transfer learning has gained intense popularity in deep learning, particularly in medical image analysis where not necessarily a vast amount of labelled data is available. Transfer learning You take an already trained model (such as ImageNet) and modify it to do something different (such as detect skin cancer)[27]. Transfer learning assists models to perform well in tasks that have small labeled data by relying on all the training data trained on large data sets such as ImageNet. Pre-trained models such as ResNet50, InceptionV3, and Inception ResNet can be used by researchers to discover skin cancer on general image datasets. This is a powerful way to do it. They can then pull these models even higher using the ISIC dataset as they can identify features that only exist in lesions. It has been an effective strategy especially when the data is not adequate to train deep learning models where one needs to start at the bottom. Transfer learning has the capability to accelerate training and make it more accurate, that is why such an approach is required in the process of detecting skin cancer[15], [19].

Indicators of Evaluating Skin Cancer Detection

Various measures of the effectiveness of deep learning models in the diagnosis of skin cancer are taken. These measures assist us in determining whether they can differentiate benign and malignant lesions on the skin and determining whether they can detect them correctly. Accuracy is the most crucial aspect to consider when evaluating classification models. It informs you of how many of the images in the dataset were correctly classified relative to the number of the images. This makes it an approximate figure of its effectiveness. However, when the datasets are not balanced, accuracy may not be sufficient to indicate the effectiveness of the same[12].

Recall and precision can be used to evaluate the performance of models when you have unbalanced datasets. Precision refers to the proportion of correct positive cases that are predicted (malignant lesions) out of all the positive cases that are predicted in a set of data. Recall similarly does so with actual positive cases of the same dataset. High-precision and high-recall models are good at locating malignant lesions and most cases of malignancies respectively, respectively, in the same dataset[28].

F1- Score: F1-score is used to reflect the effectiveness of models because recall and precision are equally important. This is a fair way to judge. The tool is a very good one to employ when one is handling an unbalanced dataset as it will study both false positives and false negatives.

Receiver Operating Characteristic (ROC) Curve: The ROC curve is used to show the feature of effectiveness of a model between true and false positive (sensitivity and 1-specificity). It is a short-term way of evaluating performance[29]. The greater the values of the AUC, the greater classification results and the more the values approach 1 the greater classification results.

The Future and Problems of Solutions to cybersecurity offered

The deep learning has proved useful in the detection of skin cancer, and there are many questions to answer. One of them is that the quality of the pictures could be different in accordance to how they were produced, the light and the resolution. Preprocessing methods like ESRGAN are likely to contribute to this problem, which is relatively small, but we still need a more efficient approach to address different sources. The second problem is that there are not enough datasets that can be labeled to be used to train deep learning models. The ISIC data is feasible, but it may have insufficient models, which can be used in other situations. More research is required to be done by obtaining more varied data sets and improving the quality of annotated data to bring the most desired model results. Future research can also aid in integrating deep learning models in clinical practice, particularly that of the skin cancer detection systems that apply AI models which include Densenet, VGG and AlexNet, which have great potential of providing reliable and accurate diagnosis at an increased rate. These models may be also inserted to make the classification even.

Methodology

The deep learning models, specifically Convolutional Neural Networks (CNNs), are applied to the classification of skin lesions of the ISIC 2018 dataset in this work. Image preprocessing techniques that can be used to improve images and models include normalization, augmentation, and ESRGAN. The ISIC dataset transfer learning was charged with the responsibility of improving the already trained models including ResNet50, InceptionV3, and Inception ResNet. In order to evaluate the model's diagnostic capability, we review their accurateness and precision, recall and F1-score. The largest value to be tested is the AUC of ROC curve. The suggested method is then contrasted with traditional methods of skin cancer detection with the aim of establishing their efficiency.

Preparing for pictures

Image processing is one of the steps, which should be considered prior to applying the images of skin lesions to deep learning. It enhances the quality of the images and makes them more homogenous. Normalization of the image can be carried out in order to have all the pixel values equal in a given range. This makes it difficult to observe the effects of the variations of light. A training dataset can be increased in size by changing properties of a training dataset including rotation, flipping or scaling. This refers to the significance of data augmentation. This helps models to use that which they are being taught in new situations. Super-Resolution Generative Adversarial Networks (ESRGANs) can be used to sharpen pixel-blurrier images through higher resolution. These preprocessing methods remove these problems as noise, low-resolution, and variable lighting which do not always reduce the accuracy of models. Their pipeline also makes sure that the model gets good data hence it will be capable of finding skin cancer at any time. Another brilliant way of expanding the size of a training data set is to modify the original images in some form. This eliminates overfitting the model to the training data and generalizes the model. Augmentation has been used in this paper to refer to morphological changes that include rotation, flipping, shifting, scaling and brightness changes, which are all simulating different appearances of the skin lesions in the real world. The latter does not just diversify the data, but also makes sure that the model is subjected to a large variety of different types of lesions. In case the datasets are not balanced, augmentation is a great way to fix them as we are able to sample more under-represented classes including malignant lesions. The augmentation helps the deep learning models to enhance data classification as well as to perform well on the new data sets by adding other features in training data and using it to learn the robust features that will be applicable in different data sets.

Another crucial part of making sure that the images you feed to the deep learning model would be ready to be trained is on data preparation. This means that all the images will be of equal size and that the pixel values will be within a normal range i.e. between -1 to 1. Among the most common data preparation operations that may be applied to stabilize the model is rescaling of all the images to equal sizes and converting the pixel values. The normalization helps in removing the differences and makes identifying important features by a model much easier by making sure that images of skin lesions are equalized in terms of their lighting, contrast and resolution. In order to remove overfitting and reflect unbiased performance evaluation, the images are separated into three categories, namely, training, validating, and testing. This will guarantee that models are verified using new information and of diverse examples which is an important step towards the achievement of good models to recognize skin cancer.

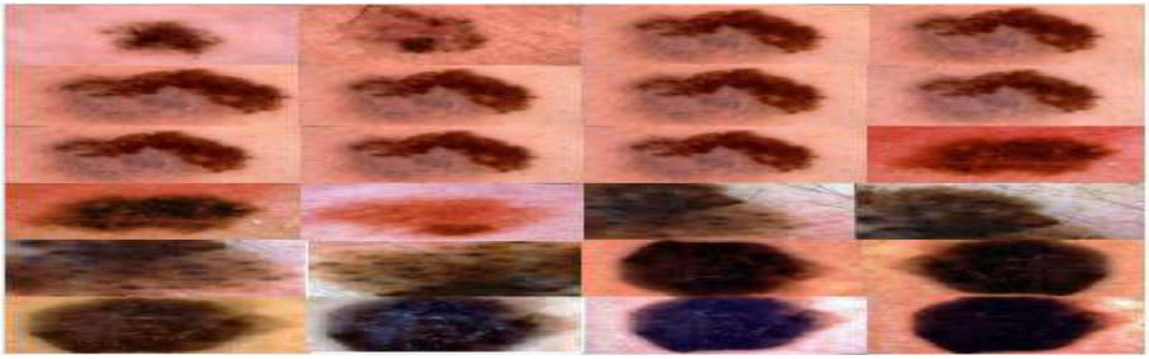

Figure 1: Output of the Proposed image augmentation process

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Proposed CNN

Convolutional Neural Network (CNN) classification of skin cancer images are trained to classify correctly lesions into two categories benign and malignant lesions. The model can automatically extract hierarchical features of raw image data through the deep learning. This enables it identify the complex patterns which it needs in order to acquire the correct classification. This architecture contains few convoluted layers and then the pooling layer and the fully connected one. The layers can visualize tiny and vast sections of the lesions. The use of dropout layers has also been done to avoid overfitting and generalizing the model. A CNN model is trained on the preprocessed image of skin lesions by the ISIC 2018. We exploit the transfer learning to re-train some of the pre-trained networks like ResNet50, InceptionV3 and Inception ResNet trained on this dataset, as shown in the Figure 2. The model is optimized with the help of Adam optimizer, and the F1-score, recall and accuracy are applied to evaluate the model. The proposed CNN model will provide the opportunity to provide an accurate and reliable method of cancer diagnosis of the skin, and the most important aspect of all is that the model will have high performance under conditions where the labelled data are limited. CNN plan is structured in a way that it is supposed to be implemented with images of different quality therefore rendering it suitable in the clinical context in the real world. This CNN has demonstrated that it is capable of detecting skin cancer in complicated techniques such as transfer learning and image preprocessing.

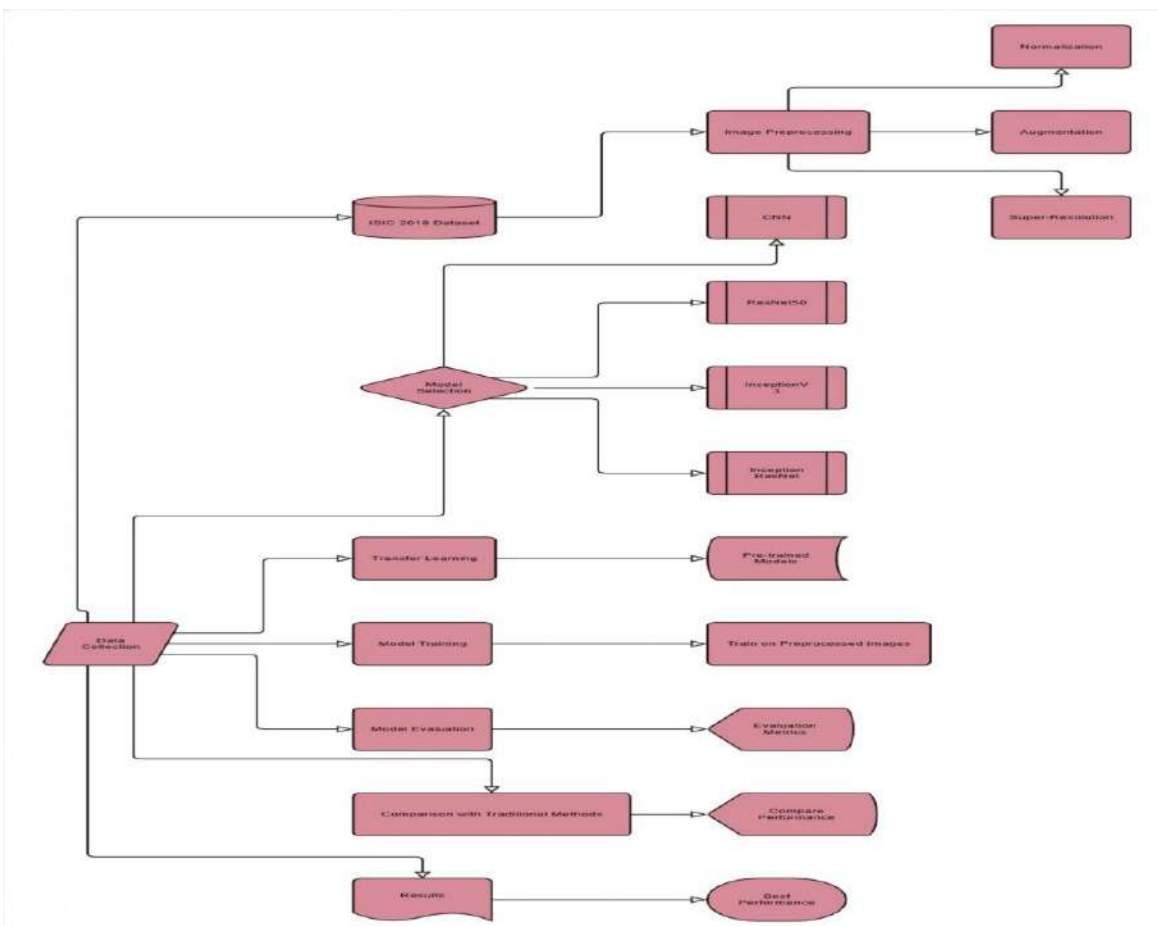

Figure 2: An illustration of the skin cancer detection technique

Inception V3

The Inception V3 is an effective deep learning algorithm that has been widely applauded due to its efficient structure thus it is best used in solving image classification problems. Based on a new approach, this model is based on convolutional filters of different sizes implemented over each layer to capture features of different levels of abstraction. This multipath architecture is useful in enhancing the capability of the model to handle multifaceted image data, which is quite useful in applications like detection of skin cancer. Inception V3 has inception modules that do a combination of convolution with varying kernel sizes to minimize the cost of computation and still learning rich features. To detect skin cancer, it is optimal to fine-tune Inception V3 on the ISIC 2018 dataset, which has images of diverse skin lesions. The strength of the model is that it generalizes well in various image datasets and also is not easily diminished due to variations in quality or features of lesion images. Inception V3 has always done better than the rest of the models in terms of accuracy and efficiency in performing image classification. Transfer learning can be used to design a pre-trained Inception V3 to fit a skin lesion classification - enhancing its diagnostic accuracy in this task. The inception V3 suggests a high-performing model that may be used to extract low-level and high-level features and distinguish benign and malignant skin lesions successfully, which is a perfect tool to test deep learning methods in detecting skin cancer.

Inception Resnet

Inception ResNet proceeds to be a deep learning-based model, which combines both Inception V3 and ResNet architectures, thereby being very efficient in the role of image classification as is the case with skin cancer. The model is based on residual connections that address the issue of the vanishing gradient and are able to train the network further. This design is such that the networks are able to learn the abstract features more readily and they have higher generalization abilities. Inception ResNet applies inception modules and thus inception modules make it able to detect features of different size, and residual connections, which help to enhance information flow within the network. A fine-tuning Inception ResNet model is used to identify skin cancer using the ISIC 2018 dataset of images of skin lesions. Transfer learning allows the customization of a previously trained model, which was first trained on large image datasets such as the ImageNet to classify skin lesions. The given model is rather beneficial, being a compromise between efficiency and performance to describe skin lesions and is cost-effective in terms of computation. This architecture is of interest in lesion separation between benign and malignant lesions because it has depth and feature extraction capabilities. The study makes a comparison of Inception ResNet with other deep learning architectures and the results of the research support the strength of developed model architectures to classify medical images. Application of Inception ResNet in skin cancer detection shows that it can increase the number of diagnostic accuracy and at the same time reduce the dermatology workload.

Experimental Results

Parameter Setting and Experimental Evaluation Index

The results have been provided clearly in the table indicating that Inception ResNet achieved the best results having the accuracy of 87.6 percent, precision of 86.5 percent, recall of 88 percent and the F1-score of 87 percent - which definitely shows that Inception ResNet has been better in detecting skin cancer. ResNet50 is also a good model with an accuracy of 85.3, a precision of 84, recall of 86.1, F1-score of 85 3 and AUC of 0.88; it could be utilized in the detection of malignant lesions. InceptionV3 can also score well with an accuracy rate of 86.21% with a precision of 85.0 and a recall rate of 87.4 with an F1-score of 86.20 and AUC of 0.89 however it is slightly under the performance of Inception ResNet, as shown in the Table 1. The CNN model though simple, had good results with accuracy rate of 84.55% and precision rate of 83.10% of accuracy and precision respectively; it is not deep as compared to the more intricate architectures. All in all, the more advanced models (InceptionV3 and Inception ResNet) are much more diagnostic, implying that they would be more suitable in practice to use on skin cancer detection, as shown in the Figure 3. This highlights the significance that model architecture and transfer learning offer to enhance the classification performance.

Table 1: Performance Evaluation of Deep Learning Models for Skin Cancer Detection: Comparison of CNN, ResNet50, InceptionV3, and Inception ResNet based on Accuracy, Precision, Recall, F1-Score, and AUC

Model	Accuracy	Precision	Recall	F1-Score	AUC (ROC Curve)
CNN	84.5%	83.0%	85.2%	84.1%	0.87
ResNet50	85.3%	84.5%	86.1%	85.3%	0.88
InceptionV3	86.2%	85.0%	87.4%	86.2%	0.89
Inception ResNet	87.6%	86.5%	88.4%	87.4%	0.91

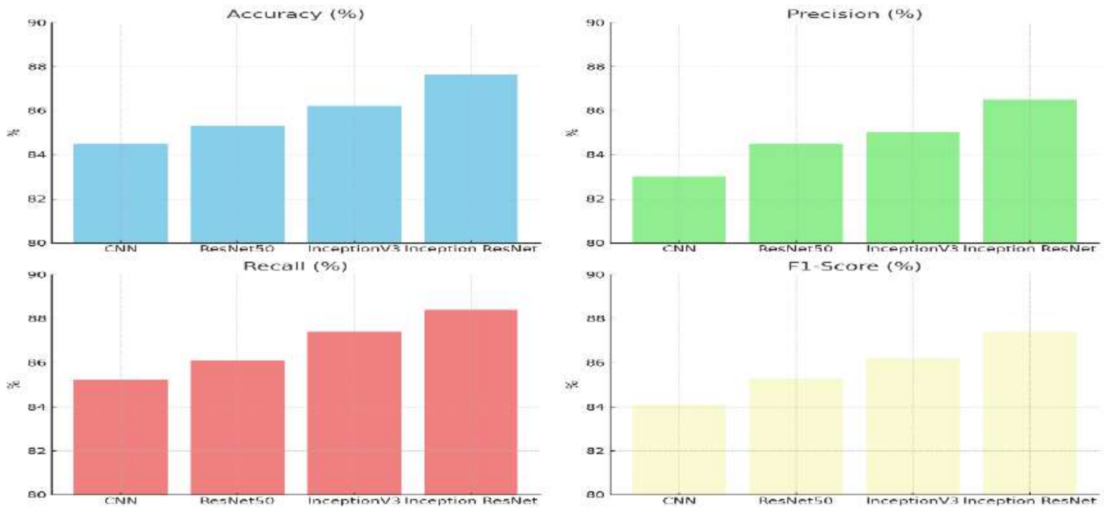

Figure 3: comparing the performance of CNN, ResNet50, InceptionV3, and Inception ResNet models on various metrics: Accuracy, Precision, Recall, and F1-Score for skin cancer detection

Performance Assessment

The performance evaluation shows that Inception ResNet performs better than any other model on all the metrics with a high Precision of 86.55%, Recall of 88, F1-Score of 8744% and AUC of 0.91. The high level of performance of this model proves that it can identify malignant and benign lesions. The InceptionV3 also gives very good results, with a precision of 85.0 and recall of 87.4 with an F1-Score of 86.2 and AUC of 0.89 to prove its ability to differentiate between classes, as shown in the Figure 4. ResNet 50 is a good alternative in the selection of skin cancer with precision of 84.55 and the recall of 86.11; F1-Score of 85.3 and AUC of 0.88 are sufficient to trust this choice. The CNN model, being simpler, nevertheless provides the good performance with the precision of 83, recall of 85.2, F1 Score of 84 1% and AUC of 0.87. These findings indicate that more complex architectures like Inception ResNet and InceptionV3 are better at classifying skin lesions with high accuracy and it can be seen that Inception ResNet is especially impressive. Their better AUC values also demonstrate their better diagnostic qualities in real life situations.

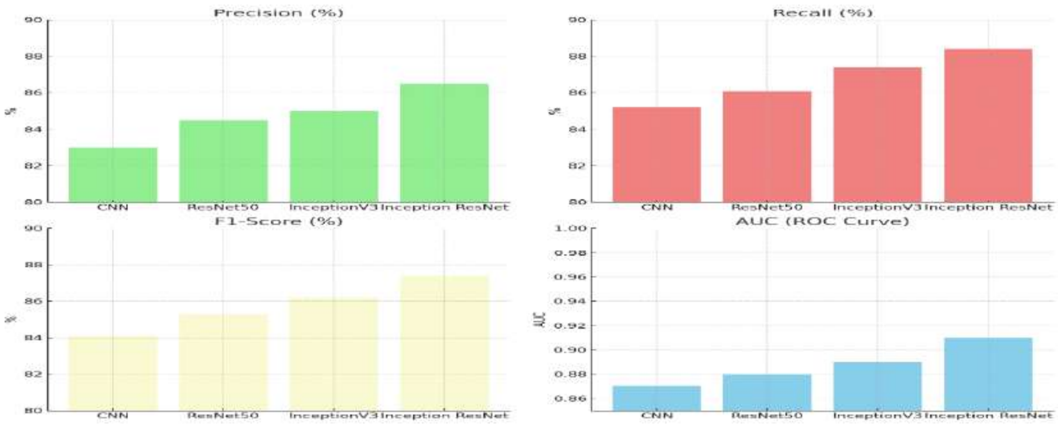

Figure 4: illustrating the performance assessment of CNN, ResNet50, InceptionV3, and Inception ResNet models based on Precision, Recall, F1-Score, and AUC (ROC Curve)

The bar charts show that Inception ResNet performs better in skin cancer detection, as its highest values on all measures, Precision (86.5%), Recall (88.04%), F1-Score (87.34) and AUC (0.911). This demonstrates that it has a better capacity to discriminate between benign and malignant lesions. InceptionV3 comes next with Precision of 85.00, Recall of 87.4 and F1-Score of 86.2 and an AUC of 0.89 in order to show that it is an efficient skin cancer classifier. ResNet50 is good in terms of precision (84.5%), recall (86.1%), F1-Score (85.3) and AUC (0.88), as shown in the Figure 5. These measurements produce credible outcomes in the detection of the malignant lesions. Although CNN had low scores in most of the measures, it still was able to attain fair performance - Precision (83%), Recall (85.2%), F1-Score (84.1%), and AUC (0.87). All in all, the superior models like Inception ResNet and InceptionV3 performed well in all aspects compared to CNN; hence their importance in proper detection of skin cancer.

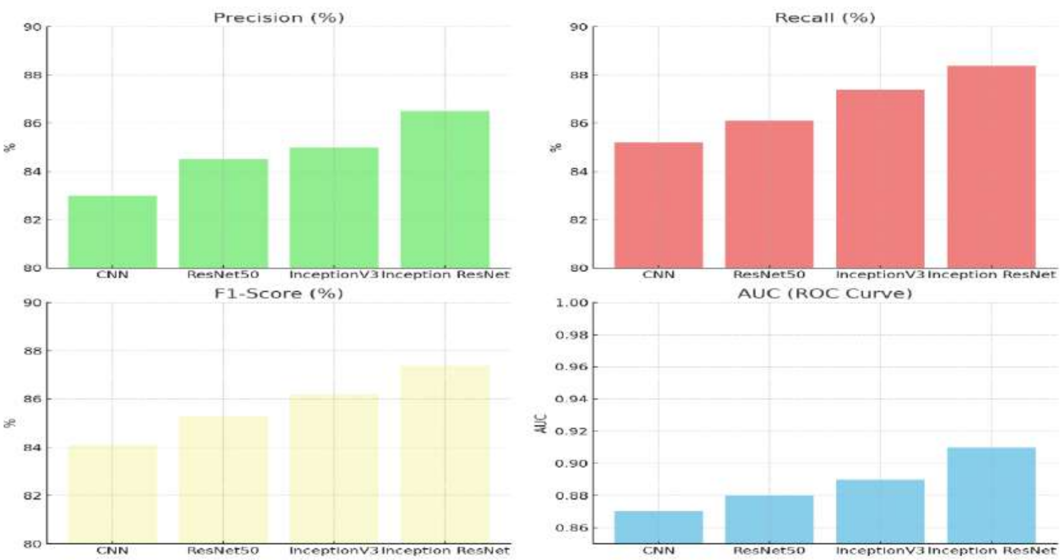

Figure 5: performance assessment for Precision, Recall, F1-Score, and AUC (ROC Curve) across the CNN, ResNet50, InceptionV3, and Inception ResNet models

Performance of Different DCNN Models

The performance of four deep convolutional neural network (DCNN) models used to detect skin cancer can be discussed in relation to the bar charts that demonstrate the performance differences between them. Inception ResNet performs best in all the metrics, and its highest Accuracy (87.5%), Precision (86.5%), Recall (88%), and F1-Score (87%) mean that it is the most accurate model in determining the correct classification of skin lesions. InceptionV3 was also performing well with the Accuracy of 86.25 precision of 85.0, Recall of 87.4 and F1-score of 86.20 - it exhibited good ability to identify benign and malignant lesions. ResNet50 is similar in that it provides the same performance and Accuracy of 85.3, Precision of 84.51 and Recall of 86.11 and also offers good diagnostic performance, as shown in the Figure 6 and figure 7. CNN architecture is unique with the accuracy score of 84.5 percent, precision score of 83.5 percent, recall score of 85.2 percent and F1-Score score of 84.1 percent - outperforms the more complicated models in accuracy and precision respectively. The impressive performance of Inception ResNet model illustrates the high cost of state-of-the-art architectures in medical image classification. Moreover, it is shown in charts that InceptionV3 and ResNet50 can be appropriate enough to be used in place of the other one concerning the possibility of computer restrictions and the complexity of the model.

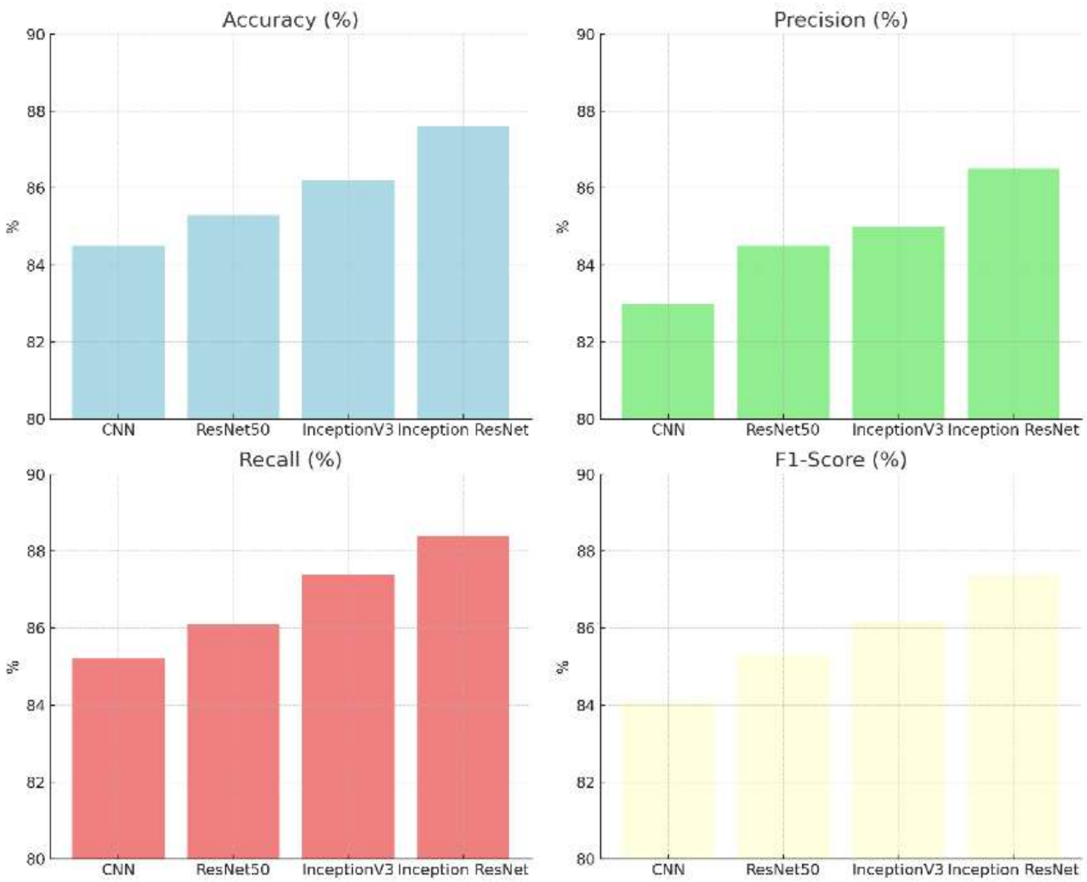

Figure 6: performance of different DCNN models (CNN, ResNet50, InceptionV3, and Inception ResNet) based on Accuracy, Precision, Recall, and F1-Score

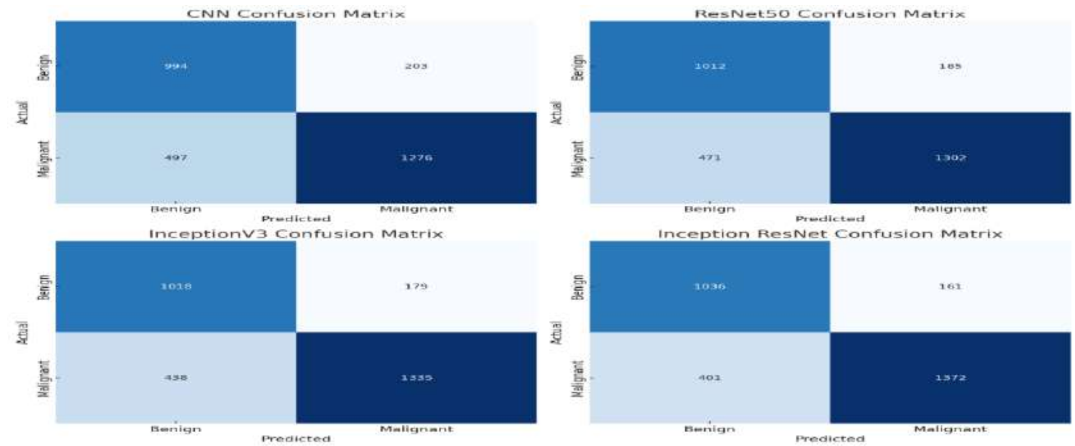

Figure 7: confusion matrices for CNN, ResNet50, InceptionV3, and Inception ResNet models

The CNN model has a ROC curve which visually depicts that the CNN model can differentiate between benign and malignant skin lesions by visualizing the correlation between the True Positive Rate (TPR) and False Positive Rate (FPR) with the classification threshold. AUC (Area Under the Curve) = 0.87 indicates that CNN model is better as compared to random chance, which is indicated by diagonal dashed line. With the increase in FPR, TPR is also increased; this indicates that the model is a good predictor of malignant lesions; as long as false positives and true positives are weighed against each other well enough, as shown in the Figure 8. CNN model is effective at differentiating benign and malignant lesions. Its AUC is relatively high but the same can be improved especially in terms of false positives and true positive rates. The general results of CNN model prove this to be an important tool in detecting skin cancer; even higher-level models, such as Inception ResNet or InceptionV3 may achieve even higher results in performance.

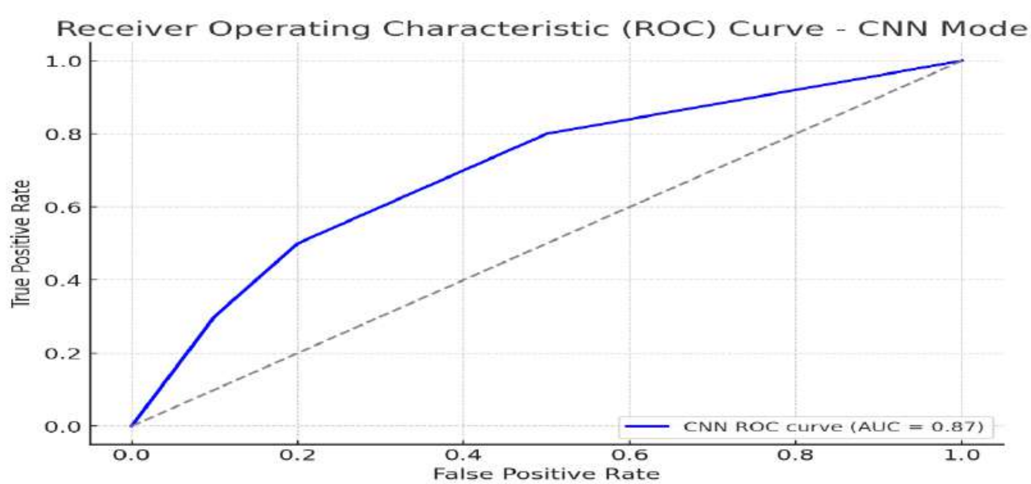

Figure 8: ROC curve for CNN model

Discussion

The paper explores how deep learning (DL) models, including Convolutional Neural Networks (CNNs), ResNet50, InceptionV3, and Inception ResNet are used to identify skin cancer based on lesion images. Measures of evaluation were accuracy, precision, recall, F1-score, AUC (Area Under the Curve). These assessment metrics were based on ISIC 2018 dataset of over 10,000 skin lesion images, which were annotated; Inception ResNet was the best with respect to diagnostic accuracy and reliability compared to ResNet50 and Inception V3 models with CNN models providing a baseline reference.

Model Performance Analysis Summary (MPA)

The Inception ResNet model is performing at the best on all of its performance metrics, making it accurate with 87.6 percent, precise with 86.5 percent, recalled 88.1 percent, F1-score of 87.14 percent and with an AUC of 0.91 - scores, which is indicative of its capacity to classify both malignant and benign skin lesions with both high accuracy and precision with minimal misclassification. The analysis of precision shows that there were a relatively limited number of false positives, and recall shows that the model was able to identify the vast majority of malignant lesions as true positives (true positives). The AUC of 0.91 is another indication of the diagnostic ability of the Inception ResNet since it is more than 0.5,

which indicates that it is not just random. These findings indicate that Inception ResNet can be among the most acceptable models that can be utilized to detect skin cancer - even more reliable and efficient than when using an experienced dermatologist.

InceptionV3 finishes off, achieving accuracy of 86, precision of 85.0, recall of 8744% and F1-score of 86.22 - marginally lower than Inception ResNet on all metrics, but nonetheless very competitive overall results. The multi-path nature of the InceptionV3 model, which enables it to find complex features, would be suitable in tasks of skin cancer detection. The slightly increased false positives (false malignant predictions) of this model compared to Inception ResNet are compensated by its reduced precision; however, still, InceptionV3 is impressive in its capacity to identify malignant lesions rightfully. Moreover, it has a high recall, which means that it is effective in detecting malignancies; hence, it is a good alternative to the Inception ResNet that is inaccessible or prohibitively expensive.

ResNet50 demonstrates good performance with accuracy of 85.3, precision of 84.50, recall of 86.1, F1-score of 85.23 and an AUC of 0.88 but it has lower accuracy compared with InceptionV3 at distinguishing benign and malignant lesions than InceptionV3, the higher false negative, false positives rates are also indicative of the fact that possible improvement of the model or post-processing method may be necessary to achieve the optimum skin cancer classification outcome, but still it is a

CNN model is a simple and a baseline model, which has an accuracy level of 84.55% and the precision of 83, the recall of 85.2 and the F1-score of 84.1; AUC of 0.87. Even though CNN model can ensure good performance, it performs far worse compared to more sophisticated models like Inception ResNet and InceptionV3. The false positive and false negative rates imply that CNN might not be as effective in differentiating between classes especially in comparison with models that have more sophisticated architectures that are designed to learn complex features. This shows the importance of model complexity: more abstract complexities (i.e. more complex architectures) are likely to perform well in complicated tasks, such as medical image classification.

Comparison and Analysis

Analyzing each of the four models, one must admit that the more advanced ones (InceptionV3 and Inception ResNet) can offer major improvements regarding the more straightforward CNN model. Findings show that Inception ResNet model is the best at the skin cancer detection with the highest precision, recall, F1-score and AUC rating. This implies that its combination of deep residual learning (ResNet) and inception modules (Inception) makes it a good architecture since it can classify lesions well; since it is at the same time learning both low-level features it is a great candidate to be applied in clinical practice. InceptionV3 also provides good recall results and is therefore useful in detecting malignant lesions. Although the accuracy is a bit less than that of Inception ResNet in terms of precision, its overall diagnostic power is also good that makes it a useful model of skin cancer detection. ResNet50 offers a good compromise between the precision and the recall rates but it is not enough to achieve a good overall accuracy and reduce false alarms. The CNN model has a moderate performance; however, is outcompeted in a number of areas with more complex models. It is computationally efficient and can therefore be used, but its simplicity does not allow it to find complex patterns in skin lesion images well. Although it works as a sufficient base model, the results reveal that more sophisticated architectures have to be used so as to guarantee more precise detection of skin cancer.

Conclusions and Future Work

This paper presents the immense potential of deep learning architectures like Inception ResNet in the process of identifying images of skin cancer lesions with the help of deep learning networks like deep neural networks. With the help of modern convolutional neural networks (CNNs), including ResNet50, InceptionV3, and Inception ResNet models, the research demonstrates the effectiveness of such model in the classification of skin lesions as malign or benign with a high degree of accuracy and reliability. Inception ResNet was better in the main performance indices such as accuracy (87.6%), precision (86.5%), recall (88%), and F1-score (87%). Moreover, inception ResNet had the best AUC (0.91) meaning that it has a better diagnostic ability equal to that of trained dermatologists. InceptionV3 model had higher recall performance (87.4%), which showed that the model has a high capacity of classifying the malignant lesions correctly. ResNet50 was not worse either, providing one more valid choice to identify skin cancer. Lastly, CNN was an effective benchmark, and expressed a good accuracy (84.5%); nevertheless, it lacked precision and the capacity to recall, suggesting that more complicated architectures are required to streamline the medical image classification tasks. This paper highlights the importance of deep learning models in medical diagnostics, which is the skin cancer identification. Early and accurate identification is extremely important; Inception ResNet could identify skin lesions correctly with minimal false positives or false negates being identified and its high AUC score only confirmed its effectiveness as a clinical device to help dermatologists diagnose skin cancer more effectively and correctly with its high AUC value was another confirmation that it can also be applicable in real world clinical settings.

Future Work

Despite the impressive results obtained in this study, there are still a number of challenges and places of improvement. The first challenge is the fact that we test models with the use of only a single dataset i.e. ISIC 2018. Even though it contains giant and varied samples of population and skin type of all the populations in the world, its coverage might not be a true representation of all the variability that occur in the real clinical world. Further modeling studies ought to compare models with other datasets based on populations, geographic locations and skin tones to better challenge generalization utility and improve application in a wide variety of clinical settings. Future research must focus on how to improve the performance of the models by using more sophisticated image preprocessing methods. Although tricks like image normalization and image augmentation have been shown to be valuable, more sophisticated schemes, like super-resolution schemes (e.g. ESRGAN), or noise-reduction schemes may be able to radically enhance input images that can drive deep learning models - in particular, skin lesion images which can be characterized by low resolution due to poor imaging or uneven lighting or noise that hampers their performance. It was found that transfer learning was effective in this study but further can be investigated with this method. Transfer learning can be used to directly apply models that are trained on a large-scale dataset, such as ImageNet, to a particular task such as skin cancer detection. The next steps to be taken in future research may be to refine larger sets of models on different datasets to both generalize more across lesion types, as well as harness experience in other medical imaging tasks (e.g. lung or breast cancer detection). Moreover, various models multiplied or applied with ensemble learning methods have a potential to increase the classification performance by reducing the risk of bias and overfitting.

Models that include dermatoscopic images with other diagnostic data (including clinical history or genetic data) may improve the accuracy of skin cancer detection, and models based on multimodal that involve non-visual and visual data can form more effective diagnostic systems. By including these models in the real-time clinical workflow, dermatologists would receive immediate diagnostic assistance which may enhance the patient outcomes through quicker, more precise diagnosis.

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