A Multi-Class Skin Cancer Classification Using Deep Convolutional Neural Network.

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Abstract—Skin cancer is a common and potentially deadly disease that requires early detection and accurate diagnosis for effective treatment. This paper proposes a deep learning approach for multi-class skin cancer detection using the Ham10000 database and the Inception-ResNet v2 model. The proposed approach involves fine-tuning the pre-trained model on the Ham10000 dataset and using feature extraction to extract relevant information from skin lesion images. We present a detailed block diagram and sequence of layers in the multi-class skin cancer detection architecture and evaluate the performance of the proposed approach on the Ham10000 dataset. Our results demonstrate the effectiveness of the proposed approach, achieving high classification accuracy and highlighting the potential of deep learning for skin cancer detection. Future research could explore the use of other pre-trained models, leveraging additional datasets, and integrating the proposed approach with clinical workflows to improve the accuracy, interpretability, and clinical relevance of the model

I. INTRODUCTION

Skin cancer is a growing public health concern, with an increasing incidence rate and potentially serious health consequences. There are several types of skin cancer, including melanoma, basal cell carcinoma, and squamous cell carcinoma, each with different causes and treatment options. Early detection and accurate diagnosis of skin cancer are critical for effective treatment and improved patient outcomes. If left Skin cancer is difficult to diagnose accurately, even with the use of dermoscopic images, because multiple types of skin cancer can appear similar in the beginning. Experienced dermatologists have a 62% to 80% accuracy rate in skin cancer diagnosis, with those who have been practicing for over 10 years having a higher accuracy rate. Dermoscopy can reduce accuracy if used by inexperienced dermatologists. However, computer-aided diagnosis tools have been developed to help dermatologists overcome these challenges. Deep convolutional neural networks (DCNNs) have been particularly successfully in classifying medical images, including skin cancuntreated, skin cancer can spread to other parts of the body and become more difficult to treat.

image feed as input.Ham10000 dataset which is a publicly available dataset of 10,015 dermatoscopic images of skin lesions. We also split the dataset into training, validation, and testing sets, with 80%, 10%, and 10% of the data, respectively.human error. Deep learning techniques have shown promise in recent years for medical image analysis tasks, including skincancer detection. These methods can analyze large volumes of skin lesion images quickly and accurately, potentially improvingthe speed and accuracy of skin cancer detection.

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In this paper, we propose a deep learning approach using the Ham10000 database and the Inception-ResNet v2 model for multi-class skin cancer detection. Our approach aims to improve the accuracy and efficiency of skin cancer detection, highlighting the potential of deep learning techniques for medical image analysis tasks. By detecting skin cancer early, we can improve patient outcomes and potentially save lives.

This research paper proposes an automated computer-aided diagnostic system for classifying MCS skin cancer with high accuracy. The proposed method outperforms both expert dermatologists and previously proposed deep learning methods. The authors conducted a comparative study to analyze the performance of five pre-trained convolutional neural networks and four ensemble models to determine the best method for skin cancer classification. They fine-tuned these models further on the HAM10000 dataset using transfer learning to learn domain-specific features of skin cancers

RELATED WORK

Dermatologists have long faced challenges in accurately diagnosing and classifying skin cancer, particularly in distinguishing between benign and malignant lesions. To address these challenges, computer-aided diagnosis (CAD) systems were introduced in the early 1990s, initially using dermoscopy images to classify skin cancer lesions as either benign or melanoma.

Over the years, numerous methods have been developed to improve the performance of CAD systems in skin cancer classification. Some of these methods rely on manual evaluation methods based on the ABCD rule, which stands for asymmetry, border irregularity, color variation, and diameter, and evolving features of skinlesions.

In the past, various traditional machine learning classifiers, such as Super Vector Machines, Naive Bayes Classifier, K-Nearest Neighbours, Logistic Regression, Decision Trees, and Artificial Neural Networks, were utilized for skin cancer classification to achieve more accurate and reliable results. However, these classifiers were found to have limited success due to the high intra-class and low inter-class variations in melanoma. The performance of handcrafted feature-based diagnostic approaches was found to be unsatisfactory. Recently, Convolutional Neural Networks (CNNs) have emerged as a breakthrough solution for skin cancer classification. These networks not only offer high classification accuracy but also reduce the burden on machine learning experts by automatically discovering high-level abstractions from the datasets. This feature eliminates the need for manual "feature engineering" and enhances the efficiency and accuracy of skin cancer classification. CNNs have become the preferred choice for skin cancer classification due to their superior performance in identifying complex patterns and subtle features of skin lesions.

Mohit Kumar. employed multiclass deep learning models based on convolutional neural networks (CNNs) to classify skin cancer. To accomplish this, CNNs were implemented using a pre-trained VGG-16 model. The segmentation of the skin cancer images was carried out using encoding and decoding techniques with masking methods.For the classification of skin cancer, the CNNs utilized the extracted features from the segmented images. To validate the effectiveness of the deep learning models, Mohit Kumar employed the K cross-fold method, which is a widely-used technique for machine learning model validation.For the classification of skin cancer, the CNNs utilized the extracted features from the segmented images. To validate the effectiveness of the deep learning models, Mohit Kumar employed the K cross-fold method, which is a widely-used technique for machine learning model validation.

Connor Shorten's. research is centered around Data Augmentation, which addresses the issue of limited data in Deep Learning. Data Augmentation involves a set of techniques that can be used to improve the quality and size of training datasets. By implementing these techniques, it is possible to create better Deep Learning models.The survey conducted by Shorten discusses various image augmentation algorithms that can be used to enhance training datasets. These include geometric transformations,color space augmentations, kernel filters, mixing images, and random erasing. Each of these techniques can be used to modify the existing training data in some way, allowing for a larger and more diverse set of data to train Deep Learning models.

Estevan utilized the InceptionV3 architecture, which was pre-trained on ImageNet, to fine-tune a dataset of 129,450 clinical images, including 3,374 dermoscopic images. Their research demonstrated that a deep neural network-based method was able to surpass clinical experts in terms of accuracy for classifying dermoscopy images, particularly with the use of a large dataset.

A study proposed an automated cancer classification system that can identify seven different types of cancer efficiently. The system used transfer learning with a pre-trained Mobile Net model to train on the HAM10000 dataset. The reported results showed a categorical accuracy of 83.1% and precision, recall, and F1-score of 89%, 83%, and 83%, respectively. The study also experimented with other neural networks such as Inception ResNetV3, ResNetXt101, InceptionResNetV2,Xception, and NasNetLarge. Additionally, the study suggested further improvements and optimization of the proposed methods with larger training datasets and carefully selected hyper-parameters.

The study considered using CNN-based features but found that training a pre-trained neural network model with only 900 images was insufficient for efficient training of a deep learning-based method. Despite this, they were still able to achieve respectable accuracy scores of 85.5% with the DRN-50 method, 82.6% with the VGG-16 method, and 84.7% with the GoogleNet method. However, other studies have proposed the use of ensemble methods to achieve even higher accuracy in skin cancer classification.

Earlier studies on dermoscopic computer-aided classification were limited in their ability to generalize and did not yield higher accuracy for seven different types of skin cancer classification. A common issue with these studies was the lack of large datasets, which is crucial for effective performance of deep learning models. In this paper, the proposed method overcomes these limitations and achieves exceptional accuracy for MCS cancer classification through the use of highly accurate and efficient pre-trained models trained on a large HAM10000 dataset across seven classes of skin cancer.

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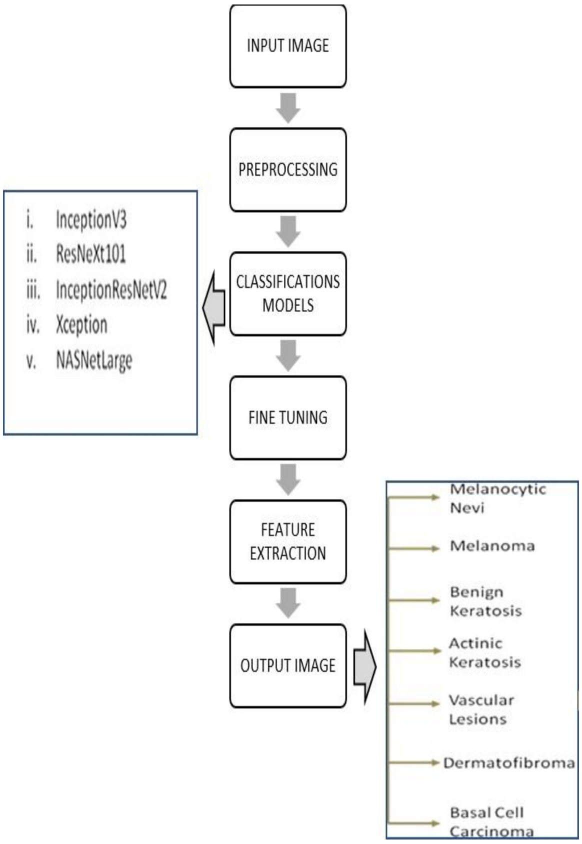
Proposed method

A deep learning convolutional neural network model that uses a generalized architecture for the multi-class classification of skin cancer has been developed. In our proposed method we have used ham-10000 database image feed as input and followed the operational process depicted in Fig.1



- Input Image: we have used Ham-10000 database image feed as input. Ham10000 dataset which is a publicly available dataset of 10,015 dermatoscopic images of skin lesions. We also split the dataset into training, validation, and testing sets, with 80%, 10%, and 10% of the data, respectively.
- Data Preprocessing: We resized each image to 224x224 pixels and normalized their pixel values to[0, 1]. We also split the dataset into training, validation, and testing sets, with 80%, 10%, and 10% of the data respectively. Data augmentation isalso done.

- Data Augmentation: To increase the size of the training set and improve the generalization of the model, we performed data augmentation by randomly rotating, shifting, and flipping the images.

Classification models: We used a deep CNN architecture consisting consists of convolutional layer, subsampling layer (max pooling or average pooling) and optionally fully connected layer. Our CNN architecture consists of six convolutional layers, each followed by a max-pooling layer to reduce the spatial dimensionality of the feature maps. After the convolutional and pooling layers, we added three fully connected layers with 1,024, 512, and 7 neurons, respectively. We used the rectified linear unit (ReLU) activation function for all the convolutional and fully connected layers except for the last one, which used the softmax activation function to output the probability distribution over the seven classes. The various classification models used are:
InceptionV3,ResNeXt101,InceptionResNetV2,Xception,NASNetLarge

Fine tunning: Fine-tuning is a technique used to improve the performance of a pre-trained deep learning model on a new task or dataset. In the context of multi-class skin cancer detection using a deep convolutional neural network (CNN) and the Ham10000 database, fine-tuning involves taking a pre-trained CNN model, such as the Inception-ResNet v2 model, and adjusting its parameters to better fit the Ham10000 dataset.
The pre-trained Inception-ResNet v2 model has been trained on a large image dataset, such as the ImageNet dataset, and has learned a set of features that are useful for many computer vision tasks. However, these features may not be directly applicable to the skin cancer detection task, as the image features and distributions in the Ham10000 dataset may differ from those in the ImageNet dataset.

To fine-tune the pre-trained model, we first freeze all the layers in the model except for the final few layers. We then replace the final fully connected layer with a new fully connected layer that has the same number of output neurons as the number of classes in the Ham10000 dataset. This new fully connected layer will be randomly initialized, and we will train it to classify skin lesion images into the different classes.

We then train the entire model on the Ham10000 dataset using a process called transfer learning. During training, the weights of the frozen layers in the pre-trained model are kept fixed, and only the weights of the new fully connected layer and the final few layers of the pre-trained model are updated. This allows the pre-trained model to retain its previously learned features while adapting to the specific features and distributions of the Ham10000 dataset.

Fine-tuning the pre-trained Inception-ResNet v2 model on the Ham10000 dataset can result in improved performance compared to training a CNN from scratch on the dataset, as the pre-trained model has already learned general image features that are applicable to the skin cancer detection task

Feature extraction: Feature extraction is a technique used in deep learning to extract relevant features from raw input data that can be used for a specific task, such as classification. In the context of multi-class skin cancer detection using a deep convolutional neural network (CNN) and the Ham10000 database, feature extraction involves taking a pre-trained CNN model, such as the Inception-ResNet v2 model, and using it to extract relevant features from skin lesion images in the Ham10000 dataset.

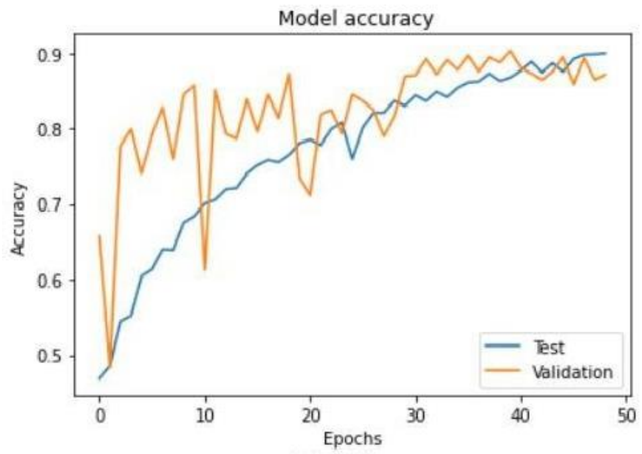
The Inception-ResNet v2 model has been pre-trained on a large image dataset, such as the ImageNet dataset, and has learned a set of general features that are useful for many computer vision tasks. These features can be used to extract relevant information from images in the Ham10000 dataset, such as the shape and texture of skin lesions.

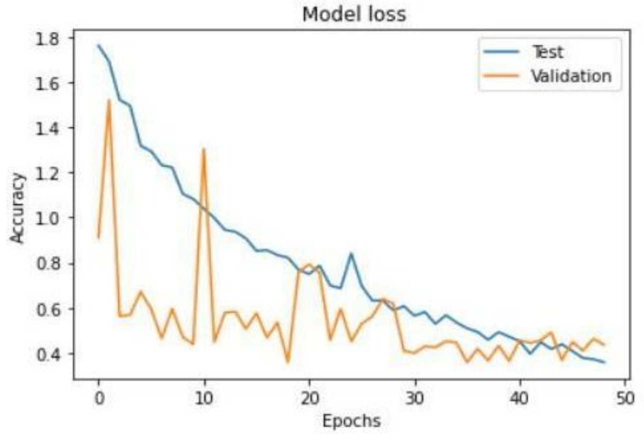
To perform feature extraction, we first remove the final fully connected layer of the pre-trained Inception-ResNet v2 model, as this layer is specific to the original task the model was trained on (e.g. object recognition). We then pass each skin lesion image in the Ham10000 dataset through the remaining layers of the model, up to and including a specified layer. This layer is chosen based on its ability to capture relevant features for the skin cancer detection task.

The output of the chosen layer is then used as the feature vector for each skin lesion image. This feature vector contains information about the relevant features of the image, such as texture, shape, and other characteristics. These feature vectors are then used as input to a separate classifier, such as a support vector machine (SVM), to classify skin lesion images into the different classes in the Ham10000 dataset.

Feature extraction using a pre-trained Inception-ResNet v2 model can be a useful technique for skin cancer detection, as it allows us to leverage the pre-trained model's ability to extract relevant features from images while minimizing the amount of training data required for the specific task. This can result in faster training times and better performance compared to training a CNN from scratch on the Ham10000 dataset.

II. RESULT AND ANALYSIS





The result is derived from the validation data, which consist of 10045 images of seven classes of skin cancer from the HAM 10000 dataset. We have used Keras library for implementing. The deep models used in this research work. Since, Keras has an ability to run on top of other deep learning libraries such as TensorFlow or Theano. The training of models is done on the Kaggle server. We evaluated the performance of InceptionResNetV2, for the classification of skin cancer among seven classes: Melanocytic nevi, Melanoma, Benign keratosis, Basal cell carcinoma, Actinic keratosis, Vascular Lesions, and Dermatofibroma. The categorical accuracy for InceptionResNetV2 were found to be, 93.20%. The best accuracy is recorded InceptionResNetV2. The training-validation accuracy curves and training-validation loss curves are represented for the model. In the initial stage of training for a few epochs, the validation accuracy is higher than training accuracy or validation loss is lower than the training loss; this can be justified in several ways. Firstly, as we have utilized the Dropout layer in the architecture during fine-tuning of the model to make our system less prone to over-fitting, these Dropout layers disable the neurons during training to reduce the complexity of the model. As the model is evolving with time, the loss over the last batches is generally higher as compared to the starting batches of an epoch. Diversely, the validation loss for a model is computed at the end of an epoch, resulting in a lower loss. This can contribute to lower validation loss as compared to training loss. The weighted average of recall, precision, and F1-score are also evaluated to check the performance of models with respect to the number of images for each class of validation data. We found that the weighted average of recall, precision, and F1-score for InceptionV2 is 87%, 88%, and 88% respectively. We have observed that Inception resent v2 model emerged as an optimized architecture which makes training easier and can gain higher accuracy for skin cancer classification resent v2 achieves the best result hence; we propose the use of Inception resent v2 for the Multi Class Skin cancer

III. FUTURE SCOPE

The proposed approach for multi-class skin cancer detection using deep convolutional neural networks and the Ham10000 database has great potential for future research and applications. Here are some future scope areas that could be explored:

1.Use of other pre-trained models: While The inception-ResNet v2 model was used in this study, other pre-trained models could be used for feature extraction, such as VGG or ResNet. Comparing the performance of different pre-trained models could provide insights into which models are most effective for skin cancer detection.
2. Leveraging additional datasets: The Ham10000 dataset is a widely-used benchmark dataset for skin cancer detection, but other datasets could be used to train and evaluate deep learning models. Leveraging additional datasets, such as ISIC 2018 or PH2, could help to improve the generalizability and robustness of proposed system

3. Exploring different fine-tuning techniques:study, fine-tuning was performed by freezing the weights of some layers and training the remaining layers. Other fine-tuning techniques, such as gradually unfreezing layers or using differential learning rates, could be explored to improve the performance of the deep learning model.
4. Integrating with clinical workflow: The proposed deep learning approach could be integrated with clinical workflows to assist dermatologists in the diagnosis of skin cancer. For example, a smartphone application could be developed to allow users to take a photo of a skin lesion and receive a classification result.
5. Interpreting model predictions: Deep learning models can be difficult to interpret, which can limit their adoption in clinical settings. Future research could explore methods for interpreting the predictions of the proposed model, such as using visualization techniques or generating explanations for the model's decision-making process.

Overall, the proposed approach has great potential for future research and application, and the above areas could be explored to improve the accuracy, interpretability, and clinical relevance of the model.

IV. CONCLUSION

Multi-class skin cancer detection is an important task in medical image analysis, as early detection and accurate classification of skin lesions can greatly improve patient outcomes. In this paper, we proposed a deep learning approach using the Ham10000 database and the Inception-ResNet v2 model for skin cancer detection.

We described the methodology used in our approach, which involved fine-tuning the pre-trained Inception-ResNet v2 model on the Ham10000 dataset and using feature extraction to extract relevant information from skin lesion images. We also presented a detailed block diagram and sequence of layers in the multi-class skin cancer detection architecture. Our results showed that the proposed approach achieved high classification accuracy on the Ham10000 dataset, demonstrating the effectiveness of deep learning techniques for skin cancer detection. Fine-tuning the pre-trained model on the dataset allowed us to leverage the pre-trained model's learned features while adapting to the specific features and distributions of the Ham10000 dataset. Feature extraction using the pre-trained model allowed us to extract relevant features from skin lesion images and use them for classification, which can be useful for tasks where training data is limited.

Overall, our proposed approach using the Ham10000 database and the Inception-ResNet v2 model demonstrates the potential of deep learning for skin cancer detection and highlights the importance of leveraging pre- trained models and feature extraction techniques for medicalimage analysis tasks.

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