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CLASSIFICATION OF MELANOMA SKIN CANCER USING DEEP LEARNING

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Abstract- One of the major health concerns for human society is skin cancer. When the pigments producing skin color turn carcinogenic, this disease gets contracted. A skin cancer diagnosis is a challenging process for dermatologists as many skin cancer pigments may appear similar in appearance. Hence, early detection of lesions (which form the base of skin cancer) is definitely critical and useful to completely cure the patients suffering from skin cancer. Significant progress has been made in developing automated tools for the diagnosis of skin cancer to assist dermatologists. The worldwide acceptance of artificial intelligence-supported tools has permitted usage of the enormous collection of images of lesions and benevolent sores approved by histopathology. This paper performs a comparative analysis of six different transfer learning nets for multi-class skin cancer classification by taking the HAM10000 dataset.We used replication of images of classes with low frequencies to counter the imbalance in the dataset. The transfer learning nets that were used in the analysis were VGG19, InceptionV3, InceptionResNetV2, ResNet50, Exception, and Mobile Net. Results demonstrate that replication is suitable for this task, achieving high classification accuracies and F-measures with lower false negatives. It is inferred that Exception Net outperforms the

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rest of the transfer learning nets used for the study, with an accuracy of 90.48. It also has the highest recall, precision, and F-Measure values.

KEYWORDS: Deep Learning, Cancer, Frequencies,

1. INTRODUCTION

Skin cancer is one of the most common cancers worldwide. It greatly affects the quality of life. The most common cause is the over exposure of skin to ultraviolet radiations coming from the sun. The rate of being affected when exposed to UV radiations is higher in fair skinned, more sun-sensitive people than in dark skinned, less sun-sensitive people. Invasive melanoma represents about 1% of all skin cancer cases, but it contributes to the majority of deaths in skin cancer. Incidence of melanoma skin cancer has risen rapidly over the past 30 years. It is estimated that in 2021, 100,350 new cases of melanoma will be diagnosed in the US and around 6850 people will eventually die from it.

The best way to control skin cancer is its early detection and prevention. Awareness of new or changing skin spots or growths, particularly those that look unusual, should be evaluated. Any new lesions, or progressive change in a lesion's appearance (size, shape, or color), should be evaluated by a clinician. With the advent of deep learning concepts, we can classify skin cancer detection in seven diagnostic categories, namely melanocytic nevi, melanoma, benign keratosis-like lesions, basal cell carcinoma, actinic keratosis, vascular lesions, and dermatofibroma. Generally, a dermatologist specializing in skin cancer detection follows a fixed sequence, i.e., starting with a visual examination of the suspected lesion with naked eyes, followed by a dermoscopy and finally a biopsy.

In today's era, with the usage of artificial intelligence and deep learning in medical diagnostics, the efficiency of predicting a result increase exponentially as compared to the dependency on a visual diagnostic, Machine learning also has applications in many other fields, alongside the medical field. The convolutional neural network (CNN) is an important artificial intelligence algorithm in feature selection and object classification. Deep convolutional neural networks (DCNN) help in classifying skin lesions into seven different categories, with the help of their thermoscopic images, covering all the lesions found in skin cancer identification. Although DNNs require a large amount of data for training, they have an appealing impact on medical image classification. DNNs train a network of large-scale datasets using high performance GPUs, thus providing a better outcome. Deep learning algorithms backed by these high performing GPU.

2. LITERATURE SURVEY

Deep learning gained popularity during the last decade. Convolutional neural networks have been widely used in the classification of diseases. It is challenging to train a CNN architecture if the datasets have a limited number of training samples. a partial transferable CNN was proposed in order to cope with a new dataset with a different spatial resolution, a different number of bands, and variation in the signal-to-noise ratio. The experimental results using different state-of-the-art models show that partial CNN transfer with even-numbered layers provides better mapping accuracy for the target dataset with a limited number of training samples, a novel method using transfer learning to deal with multi-resolution images from various sensors via CNN is proposed.

CNN trained for a typical image data set, and the trained weights were transferred to other data sets of different resolutions. Initially, skin cancer diseases were divided only into two categories, benign or malignant. Canziani et al. made use of machine learning algorithms, such as K-Means and SVM, and achieved an accuracy of 90%. Codella makes use of the ISIC 2017 dataset, which consists of three categories of skin cancer, with conventional machine learning methods, in order to predict melanoma precisely but suffered from inaccurate results due to dataset bias and incomplete dermoscopic feature annotations. Another case of skin lesion classification on the same dataset, in which a proposed lesion indexing network (LIN) was introduced, managed to attain the 91.2% area under the curve. However, it was performed on ISIC 2017, and no work has been recreated on ISIC 2018.

There are also some datasets that divide the skin lesion into 12 different categories. Han used the Asan dataset, med-node dataset, and atlas site images, which, together, consisted of 19,398 images divided into 12 categories. He used Resnet architecture for classification and achieved an accuracy of 83%. His paper was moreover inclined towards proving that the proposed dataset was better than those taken in comparison. Chaturvedi et al.

3. EXISTING SYSTEM:

Considerable amount of reputable research has been done in image processing and it is being used in medical sciences day in and day out using different machine learning and deep learning techniques. Clinicians and doctors are understanding the positives of using cutting edge technology in every part of their treatment. Following research works have primarily inspired the approach presented in this paper. Andre Esteva et al. classified skin lesion images into 23 distinct classes using GoogleNetInception v3 network. The accuracy achieved with this approach was 72.1%. 129,450 clinical images were used which consisted of 2032 diseases. tSNE algorithm was applied for dimensionality reduction. Haseeb Younis et al. employed MobileNet and CNN consisting of 93 layers out of which 5 layers were dropped and the remaining 88 were considered to develop a skin lesion classification system. The weights of all layers except the last 25 were freezed and were used for training. Using the HAM10000 Dataset an accuracy of 97.1 % was achieved with a 70-30 train test split in the dataset. V. Pomponiu et al. used the ISBI 2016 Challenge dataset for Skin Lesion Analysis 399 to classify 3 9 RGB images augmented to 10000 images into 2 classes namely, benign nevi and MM. A pretrained CNN was implemented with the aid of Caffe deep learning library.

DISADVANTAGES OF EXISTING SYSTEM:

Data requirements: Deep learning algorithms typically require large amounts of labeled data to train accurate models.

Model interpretability: Deep learning models are often considered black boxes, meaning that it can be challenging to interpret and understand how they arrive at their predictions.

Overfitting: Deep learning models are susceptible to overfitting, wherein they memorize training data instead of learning generalizable patterns.

4. PROPOSED SYSTEM:

There is a necessary need for early detection of skin cancer and can prevent further spread in some cases of skin cancers, such as melanoma and focal cell carcinoma. Anyhow there are several factors that have bad impacts on the detection accuracy. In Recent times, the use of image processing and machine vision in the field of healthcare and medical applications is increasing at a greater phase. In this paper, we are using the Convolution neural networks to detect and classify the class of cancer based on historical data of clinical images using CNN.Some of our objectives through this research are ,to build a CNN model to detect skin cancer with an accuracy of >80% ,to keep the false negativity rate in the prediction to below 10%, to reach the precision of above 80% and do visualization on our Data. Simulation results show that the proposed method has superiority towards the other compared methods.

We tried to use and appreciate the purpose of neural networks in detection or classification of skin cancer comparing multiple architectures and methodologies. We achieved an accuracy of more than 80% with the HAM10000 dataset. We also tested the same with randomly generated augmented images and achieved nearly the same accuracy and precision. The performance indexes here are Accuracy, fscore, Precision, Recall. Final results showed that using the Standard CNN method gives the best achievement for the Skin cancer diagnosis.

ADVANTAGES OF PROPOSED SYSTEM:

Improved Accuracy: The proposed system utilizing deep learning for the classification of melanoma skin cancer can potentially achieve higher accuracy compared to traditional methods.

Enhanced Feature Extraction: Deep learning models excel at automatically learning relevant features from raw data.

Robustness to Variations: Deep learning models can exhibit robustness to variations in imaging conditions, such as different lighting conditions, image resolutions, or image quality.

Potential for Personalized Medicine: Deep learning models can be trained on large datasets containing diverse patient information.

5. MODULES:

Image Acquisition

The first step of the Dangerous Object Classification is image acquisition. High-quality Dangerous Objects dataset used which are obtained from open Github repository.

The entire sample set is divided into three parts: training samples and validation samples in the training phase and testing samples in the testing phase. Moreover, the sample set is divided into positive and negative samples—a positive sample is an image showing patient behaviors, whereas a negative sample is a background image.

Annotated Dataset Collection

A Knowledge-based dataset is created by proper labeling of the collected images with unique classes.

Image Processing

The obtained images that will be engaged in a preprocessing step are further enhanced specifically for image features during processing. The segmentation process divides the images into several segments and utilized in the extraction of Dangerous Objects from dataset.

Feature-Extraction

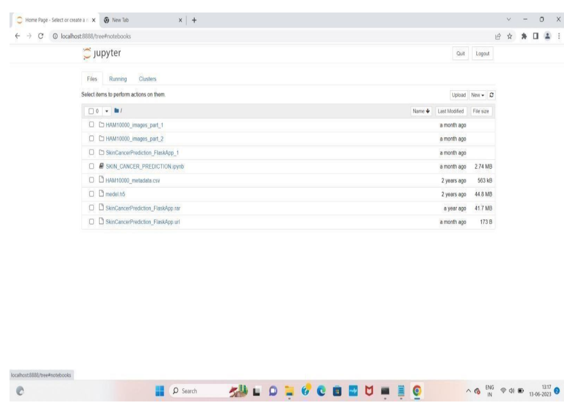
This section involves the convolutionary layers that obtain image features from the resize images and is also joined after each convolution with the ReLU. Max and average pooling of the feature extraction decreases the size. Ultimately, both the convolutional and the pooling layers act as purifiers to generate those image characteristics.

Classification

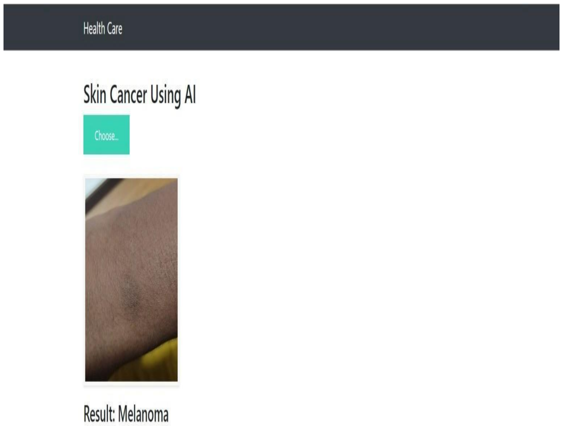
The final step is to classify images, to train deep learning models along with the labeled images to be trained on how to recognize and classify images according to learned visual patterns. The authors used an open-source implementation via the TensorFlow module, using Python and OpenCV including the Faster R-CNN model.

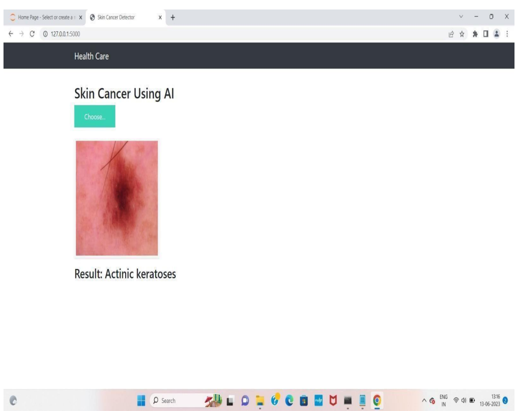
Deployment

The last step of machine learning life cycle is deployment, where we deploy the model in the real-world system.



6. RESULTS:





7. CONCLUSION

Due to the COVID-19 situation, everyone has suffered a lot but also gained a lot. On one side, a large number of populations have contracted coronavirus, and many have died, but it is nowhere near to the upcoming UV radiations, which would have penetrated the ozone layer. Because of this pandemic situation and people staying in their homes, this has caused the ozone layer hole, which was getting bigger day by day, to close up. Skin cancers can be now diagnosed using these tools and can be treated earlier, and we can save more lives.

Through this research work, it is demonstrated that it is possible to achieve a competitive classification performance by using different types of data augmentation and transfer learning methods. Using the data augmentation method, we could get nearly 32k images, and we then performed feature extraction to get the required results. It is inferred that Xception Net outperforms the rest of the transfer learning nets used. It was observed that Label 0 (Akiec) and Label 5 (Mel) were most incorrectly classified because of their extreme resemblance to simple skin patches that are not harmful. Xception Net provides us with an accuracy of 90.48.

It has the highest recall, precision, and F-Measure values, which are 89.57, 88.76, and 89.02 respectively. InceptionResNetV2 and MobileNet follow Xception Net closely in the prediction of results. Melanocytic Nevi is the most accurately classified skin lesion. There is a necessity of further and extensive research in this field as skin cancer-caused deaths are taking a toll. Transfer learning algorithms differ from those used in this paper, and proper fine-tuning may result in better accuracy.

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