Detection of Cervical Cancer Using Machine Learning Techniques

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Abstract

Accurate and efficient detection of cervical cancer at an early stage can be crucial for the survival of a patient. Manual intervention in the process results in costly and time consuming procedures and introduces the risk of manual errors. An effective solution to these drawbacks is automation of the process using machine learning techniques to train neural networks. In this paper, we have presented a survey of the research conducted in the area. The use of convolutional neural networks (CNN) can be frequently observed as they are proven to be effective for images. These networks are based on transfer learning models which have given good results. Other than these, the use of support vector machines (SVM) can frequently be observed. Various pre-processing methods like segmentation and feature extraction plays an important role in all of the papers surveyed.

Keywords:-*CNN,Transfer learning,Resnet, Inception V3.*

I. INTRODUCTION

This paper includes usage of different architectures like Resnet 50, Resnet 101, InceptionV3 and VGG16 and fine tuning them exhaustively. The study consisted of almost 215 different trials.

The determination of cancerous cervix takes into consideration three categories that are red indicating cancerous cervix, amber indicating moderate levels and finally green indicating safe levels. The data was segregated based on the classification classes and trained models to differentiate red, red not red, gng, cnc, milky not milky, etc.

VGG16 turned out to have the best performance out of all of them..Creating an ensemble model from the best models obtained during this procedure (which were all from VGG16) gave a model with accuracy 85.52%.

II. DATASET

Dataset consisting of medical images of cervix were collected from three renowned hospitals. The images dataset consisted of medical cervix images distinguished by three different classes as red, amber, green each class representing severity of cancerous nature of the cervix.

The images in dataset had resolution 256*256 pixels. The class wise distribution of images were as follows: red class consisting of about 1800 images, 600 images of amber class and 300 images of green class.

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III. METHODS

A. Pre-processing

For training models , the dataset containing images of cervix into respective categories of classification is segregated and noisy data from the dataset is removed . Preprocessing method is carried out by cropping the images of the dataset containing homogenous images into a desired ratio.

Image scaling was used for transformation of the dataset so that all the features are within a specific range. In pre-processing it is mandatory to do the data normalization ,since the range of values of data may vary widely. So normalization is used to standardize the range of features of data into one particular range.

Some datasets were also converted to gray scale images to effectively make use of median filters. In some cases, augmentation of images was carried out by flipping and rotating the images.

B. Feature Extraction

White lesions and abnormal area detection is a major contributing factor in determining if a cervix is having cancer or not.

Hence in the feature extraction phase ,extracting white lesions feature is important and calculating the distance from the centre of the cervix. As closer the white lesions to the centre of the cervix then it is more cancerous.

C. Segmentation

The main objective of image segmentation is to convert the image into significant items and thus effectively breaking down the irregular bits. The input image is isolated into leveled structures through segmentation.

The input cervix image containing cells and core is divided using free level sets. The medical cervix image has white lesions which plays a crucial role in determining it's cancerous nature thus needs proper segmentation procedure to increase accuracy.

The cervix image is segmented and thus results into proper data of the image regarding its shape, surface and size.

D. Classification

The data obtained from fragmented areas is used to group the medical cervix image into generous groups. Thus surface and geometric areas are identified in order to arrange cancerous and noncancerous cells. Using KNN strategy the patches occurring on cervical tissues are resolved. Characterization of the input medical image is done using ANN and SVM techniques. The main aim of classification phase is to classify the image based on its cancerous nature.

E. VGG 16

It is a convolution neural network trained on millions of image datasets. VGG16 has 16 layers and thus is able to classify images in 1000 object categories. The network has learned rich feature representations for a large range of images. VGG16 has good performance on image dataset. VGG16 has only 3*3 convolution and 2*2 pooling throughout the network. The depth of the network in VGG plays an important role. Deeper the network is more accurate. This network can be considered a pretty large network as it has about 138 million(approx) parameters.

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IV. Our Methodology / Algorithms

Resnet 50, Resnet 101, InceptionV3 and VGG16 were the neural network architectures used while using the method of transfer learning, out of which VGG16 gave better overall results as compared to other architectures. After rigorous training and fine tuning for each version of the models being trained, four models with features considerable for creating an ensemble model together with each other were selected in order to develop a single model with optimum accuracy. Each of these models were based on VGG16 and they all used a callback.

A. Models

The ensemble model comprises these four models mentioned above. The image to be predicted first goes into the Model 1. Based on it's prediction here, it is consequently sent to other models for further confirmation. If Model 1 predicts that the image belongs to the red class, it is sent to Model 2 for further confirmation.

If Model 2 predicts the class of the image to be amber, then the final result is tentatively considered to be amber, else it is considered red. Alternatively, if Model 1 predicts the class amber or green for the image, the final result is tentatively considered to be amber or green respectively.

The image is further passed on to Model 2 and Model 4. If both these modes predict that the image belongs to the green class, then the earlier result is discarded and the final result is considered to be green. Else, the earlier result is considered. After this, the result of Model 2 alone is considered for the image.

If Model 2 predicts amber, the final result is considered to be amber. However, during this procedure, an image belonging to the green class is at a high risk of being misclassified as red or amber. In order to avoid this, only if the final result is red, it is once again passed through Model 2 to check it's correctness. Here, if Model 2 predicts that the image belongs to the class green, then the final result is considered to be green. Else, the pertaining final result is considered.

B. Model 1

The first model selected was trained to classify between three classes – red, amber and green. Out of these,the model was sensitive for classification of the class red and had an accuracy of 78.32% for identification of images belonging to the red class.

C. Model 2

The second model selected was trained to classify the same three classes as Model 1. However, this model has an accuracy of 79.45% with a clear distinction for all three classes and the number of misclassified images were less here as compared to most other models. Evidently, using this model as a part of this ensemble model has led to an increase in the overall resultant accuracy.

D. Model 3

This model too was trained to classify images into three classes as red, amber and green. This model showed a sensitivity for the amber class, as a result of which, it could be used to confirm whether an image was from the amber class and was misclassified from another model in the ensemble model as belonging to some other class. Model has accuracy of 77.33%.

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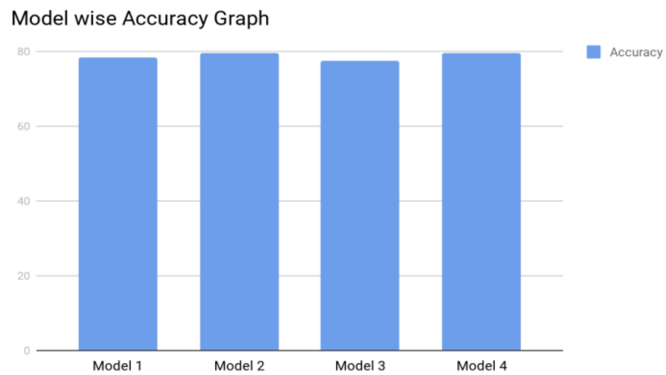
E. Model 4

This model is a binary model as it was trained to identify whether the image belongs to the green class or not. It’s performance was better than the rest of the models trained to make similar classifications and hence, was useful in order to ensure the class of an image belonging to the green class. Accuracy of the model is 79.65%.
Following table summarizes the accuracies of all the models used.

Model Number	Description	Properties	Accuracy
Model 1	The image first goes in model 1. If model 1 predicts that image belongs to red class, it is sent to model 2 for confirmation.	Trained to classify between 3 classes - red, amber and green. Sensitive to red class.	Model sensitive for classification of red class Accuracy of 78.32%.
Model 2	Here the model predicts the image to be amber, the final result is taken tentatively else considered as red. If model 1 predicts red or amber result is taken tentatively as amber or green	Trained to classify between 3 classes - red, amber and green.	Model has accuracy of 79.45% with a clear distinction for all three classes.
Model 3	The final decision about amber class image prediction is carried out by model 3.	Trained to classify between 3 classes - red, amber and green. Sensitive to amber class.	Accuracy is 77.33%.
Model 4	The prediction of the image to be of green class is carried out by model 4.	Trained to identify whether the image belongs to green class or not,	Increased accuracy compared to other models. Accuracy is 79.65%.



V. Conclusion

In this paper, we applied an ensemble model of various transfer learning based convolution neural networks, to accurately diagnose malignancy in cervices and the possibility of the cervix in question having cancer in a time and cost effective manner and also in order to spread awareness in rural areas and help them take effective action at the earliest. All the models used in the ensemble model were based on the VGG16 architecture and were chosen after rigorous trials and fine tuning of 215 different versions of CNNs made using the transfer learning method. Our final accuracy for the model was 85.52%.

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