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Skin Cancer Detection Using Deep Learning

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Abstract - **Melanoma is a type of skin cancer which detected in early stages can be highly curable. Melanoma is a from a skin cancer that begins in the skin cells (melanocytes) that control the pigment in your skin. Spread of pigment from the border of a spot into surrounding skin. Redness or a new swelling beyond the border of the mole. Change in sensation, such as itchiness, tenderness, or pain. Change in the surface of a mole scaliness, oozing, bleeding, or the appearance of a lump or bump. Its detection to naked human eye is hardly possible, so the algorithms like CNN are used by computers for melanoma detection. The non-invasive medical computer vision or medical image processing plays increasingly significant role in clinical diagnosis of different diseases. Such techniques provide an automatic image analysis tool for an accurate and fast evaluation of the lesion.**

Melanoma the deadliest form of skin cancer, is considered as the less common form of skin cancers but it is the most fatal. As mentioned above, it can quickly spread to other parts of the body. Melanoma arises through malignant transformation of melanocytes which are derived from the neural crest neoplasia. Melanoma causes 55 500 cancer deaths annually which is 0.7%.

Keywords—**SVM, Android internet, malicious application, Skin Cancer, Image Processing)**

I. INTRODUCTION

In the past few years many researches investigated algorithms to diagnose skin cancer lesions where melanoma is the deadliest type of skin cancer.Melanoma the deadliest form of skin cancer, is considered as the less common form of skin cancers but it is the most fatal. As mentioned above, it can quickly spread to other parts of the body. Melanoma arises through malignant transformation of melanocytes which are derived from the neural crest neoplasia [7]. Melanoma causes 55 500 cancer deaths annually which is 0.7% of all cancer deaths.

Skin cancer is a deadly disease. Skin has three (3) basic layers. Skin cancer begins in outermost layer, which is made up of first layer squamous cells, second layer basal cells, and innermost or third layer melanocytes cell

Squamous cell and basal cell are sometimes called non-melanoma cancers. Non-melanoma skin cancer always responds to treatment and rarely spreads to other skin tissues. Melanoma is more dangerous than most other types of skin cancer .if it is not detected at beginning stage, it is quickly invade nearby tissues and spread to other parts of the body. Formal diagnosis method to skin cancer detection is Biopsy method. A biopsy is a method to remove a piece of tissue or a sample of cells from patient body so that it can be analysed in a laboratory. It is uncomfortable method.

II.RELATED WORK

The experiments were conducted using a public dataset which is collected from the ISIC (International Skin Imaging Collaboration) archive, it contains more than 23000 images of melanoma. We chose to work with only 640 skin lesion images, containing benign and malignant lesions. They were collected from a dermatoscopy tool. 512 of these images will be used as a training set, the rest as a testing set. Fig. 7 shows some examples of the skin lesion images. The CNN was trained using 640 images of size 124 × 124 using the 3 different methods. The CNN was trained for 10 epochs. It is shown that the CNN has the highest performance over the other two methods, although, classical machine learning and image processing techniques has a few advantages and could also detect melanoma when a CNN can not. In this matter, a result aggregation of the different method is used in order to ameliorate the performance of the melanoma detection system. Actually, the fusion of multiple model prediction has appeared as an accurate strategy to ameliorate the performance of many pattern recognition systems, rather than relying on one single model prediction. In this paper, we use the majority voting approach which is one of the basic and intuitive approaches.

III.SYSTEM ARCHITECTURE

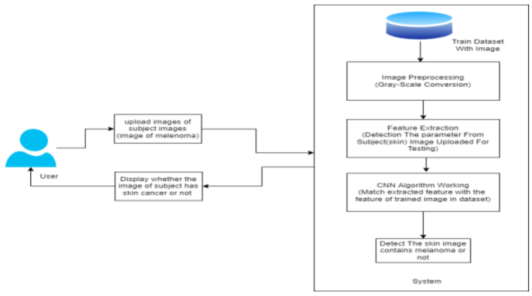

Fig 1 - System Architecture

In Data Flow Diagram,we Show that flow of data in our system in DFD0 we show that base DFD in which rectangle present input as well as output and circle show our system,In DFD1 we show actual input and actual output of system input of our system is text or image and output is rumor detected like wise in DFD 2 we present operation of user as well as admin.

III.A)Methodology

A. Data

The data is provided by the International Skin Imaging Collaboration (ISIC). It includes a training dataset of 2,000 dermoscopic images and their corresponding lesion masks labelled by clinical specialists. In addition, the organizers provided a validation dataset with a corresponding set of masks that includes 150 images and 600 images as hold out test data. Our predicted segmentation masks generated will be evaluated against these segmentation masks provided by ISIC.

B. Data Augmentation

Training images and masks were resized to 128×128, which allows shorter training time. In addition, we used online image augmentation, with horizontal and vertical flips, with zooms up to 20%, and with rotations up to 270 degrees.

C. Implementation Framework

The proposed solution is implemented using Python 3.6 libraries and packages related to deep learning. These packages include Keras with Tensorflow, H5PY, OpenCV and ScikitLearn.

1) Segmentation Network Architecture

1. U-Net: In general, a U-Net consists of an encoding path to capture context and of a symmetrically decoding path that enables precise localization . The encoding path consists of alternating convolution blocks followed by a maxpool down sampling to encode the input image into feature representations at multiple different levels. The decoding part of the network consists of up-sample and concatenation followed by regular convolution operations.
2. U-Net with VGG-16 Encoder: Typically, neural network initialized with weights from a network pre-trained on a large data set like ImageNet shows better performance than those trained from scratch on a small dataset.
3. As an improvement over U-Net, we use similar networks with pre-trained encoders. The encoder consisted of the VGG16 layers up to the last convolutional layer, but without the last max-pooling layer and fully-connected layers. In other words, the encoder consists of thirteen convolutional layers, each followed by a ReLU activation function, and five maxpooling operations, while the decoder consists of four upsampling operations and eight convolutional layers.

2) Segmentation Training

a. Loss Function: We chose Dice coefficient as our loss function. Dice coefficient compares the similarity between the target mask, X, and predicted mask, Y , which is defined as following: DSC = 2|X ∩ Y | |X| + |Y |

b. Ensemble: Once the models were trained, we applied the individual models test set to generate predicted segmentation masks. With our ensemble scoring strategy, we will then perform image arithmetic by blending the masks together based on the formula. $g(x) = (1 - \alpha)f1(x) + \alpha f2(x)$ where $\alpha = 0.5$.

c. Segmentation Results

3) Evaluation Metric

We chose Jaccard index[6] (Intersection Over Union) as our evaluation metric. It is defined as the intersection of the surface of the predictions with the true labels that should be predicted, divided by their union. Jaccard index quantifies the percent overlap between the target mask, A, and predicted mask, B, which is defined as following:

$$J(A, B) = |A \cap B|\ |A \cup B|$$

$$= |A \cap B|\ |A| + |B| - |A \cap B|$$

The evaluation is done on the test set segmentation mask of 600 images provided by ISIC.

In this paper, we have used an approach which is aimed at uncovering the already known malware families and also the unknown malware to reduce chances of malware in the android community from escaping detection from scanners. For this we created a dataset using multiple Android .apk samples downloaded from both google play and VirusShare and other trusted sites providing malware samples.

Ensemble Model :We investigated further as to why the U-Net ensemble model has better generalisation characteristics. We compared the predicted segmentation mask generated by the U-Net model, U-Net with VGG-16 encoder model and the combined output mask. This is followed by a cross reference check with the ground truth test image. We found some interesting examples showing the benefits of combining hypothesis generated by different models. As illustrated in Figure 2, we observe that for the Ground Truth Image, ISC 0012265. There are 3 sections demarcated in red with lesions. The U-Net Model managed to segment out section 1 and 2 only. Whereas the U-Net with VGG-16 encoder model managed to segment out section 1 and 3 only. However if we were to overlay both masks, we will have an output that covers sections 1, 2 and 3 of the Ground Truth Image

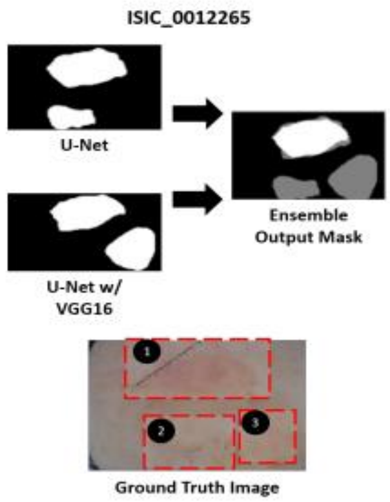

Fig 2 - Sample Images

IV.CONCLUSION

In this project, different phases of image processing were applied on skin Nodules. From these different image processing techniques, the fuzzy filter will provide the efficient de noising. Segmentation done by marker based watershed algorithm, gives various region of image. GLCM is used to extract the different features of image and which takes less time for generating the result. This results are passed through CNN Classifier, which classifies the nodules as benign or malignant. CNN classifier provides 92.5 percentage accuracy.

V.EXPERIMENTS AND RESULTS

The experiments were conducted using a public dataset which is collected from the ISIC(International Skin Imaging Collaboration) archive, it contains more than 23000 images of melanoma. We chose to work with only 640 skin lesion images, containing benign and malignant lesions. They were collected from a dermatoscopy tool. 512 of these images will be used as a training set, the rest as a testing set. Fig. 7 shows some examples of the skin lesion images. The CNN was trained using 640 images of size 124 × 124 using the 3 different methods. The CNN was trained for 10 epochs. It is shown that the CNN has the highest performance over the other two methods, although, classical machine learning and image processing techniques has a few advantages and could also detect melanoma when a CNN can not. In this matter, a result aggregation of the different method is used in order to ameliorate the performance of the melanoma detection system. Actually, the fusion of multiple model prediction has appeared as an accurate strategy to ameliorate the performance of many pattern recognition systems, rather than relying on one single model prediction. In this paper, we use the majority voting approach which is one of the basic and intuitive approaches. It assigns a sample based on the most frequent class assignment [4]. Table. I summarizes the results of the three proposed method as well as the result of fusing them. Using the KNN classifier, Fig. 7. Image samples of melanoma skin cancer from the ISIC dataset. TABLE I THE ACCURACY VALUES OF USING THE DIFFERENT METHODS Methods KNN SVM CNN Majority voting Accuracy 57.3% 71.8% 85.5% 88.4% we obtained the lowest accuracy considering the 5 nearest neighbors only. KNN barely can identify malignant skin lesions since it is sensitive to outliers. However, SVM classifier performs better than KNN due to its efficiency and adaptability. Although an SVM classifier achieved a quiet performance, still the CNN is considered as a more powerful and robust tools for identifying melanoma skin cancer. Yet, fusing the decision of all these systems obviously can ameliorate their performance, the idea is to take the decision not based on one single result

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