A NOVEL PROCEDURE TO DETECT SKIN CANCER

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ABSTRACT

Skin biopsy histopathological analysis is one of the primary methods used for pathologists to assess the presence and deterioration of melanoma in clinical. A comprehensive and reliable pathological analysis is the result of correctly segmented melanoma and its interaction with benign tissues, and therefore providing accurate therapy. In this study, we applied the deep convolution network on the hyper spectral pathology images to perform the segmentation of melanoma. To make the best use of spectral properties of three dimensional hyper spectral data, we proposed a 3D fully convolutional network named Hyper-net to segment melanoma from hyper spectral pathology images. In order to enhance the sensitivity of the model, we made a specific modification to the loss function with caution of false negative in diagnosis. The performance of Hyper-net surpassed the 2D model with the accuracy over 92%. The false negative rate decreased by nearly 66% using Hyper-net with the modified loss function. These findings demonstrated the ability of the Hyper-net for assisting pathologists in diagnosis of melanoma based on hyperspectral pathology images.

Index Terms—Microscopy, segmentation, skin, quantification and estimation, optical imaging.

I. INTRODUCTION

we applied the deep convolution network on the hyperspectral pathology images to perform the segmentation of melanoma. To make the best use of spectral properties of three dimensional hyperspectral data, we proposed a 3D fully convolutional network named Hyper-net to segment melanoma from hyperspectral pathology images. In order to enhance the sensitivity of the model, we made a specific modification to the loss function with caution of false negative in diagnosis. The performance of Hyper-net surpassed the 2D model with the accuracy over 92%A 3D fully convolutional network named Hyper-net to segment melanoma from hyperspectral pathology images. In order to enhance the sensitivity of the model, we made a specific modification to the loss function with caution of false negative in diagnosis. The performance of Hyper-net surpassed the 2D model with the accuracy over 92%. The false negative rate decreased by nearly 66% using Hyper-net with the modified loss function. These findings demonstrated the ability of the Hyper-net for assisting pathologists in diagnosis of melanoma based on hyperspectral pathology images.

In this paper, we focus on the on-going image processing technique implemented in

skin biopsy pathological analysis, in terms of its potential in providing objective standards and improving efficiency for clinical screening. To this end, detecting the unhealthy even malign tissue in epidermis area is of vital importance, lining up with the goal of image segmentation from the perspective of image processing. This is because a comprehensive and reliable pathological analysis is the result of correct segmentation of the malign tissue and its interaction with the benign tissue; moreover, these analysis is the basis of accurate therapy.

II. SYSTEM ANALYSIS

Recently, the advance in deep learning is inspiring and encouraging process in pathology image analysis, which covers a wide range of applications including medical image classification, detection and segmentation for a diversity of diseases. In terms of segmentation, the task requires classification to be performed on each pixel of the image. Long et al. proposed a novel approach which replaced fully connected layers by fully convolutional layers so that the network can output a complete segmentation image in a single forward process. The idea of fully convolutional network (FCN has been applied in melanoma dermoscopic segmentation to generate irregular border.

III. EXISTING SYSTEM

Our previous work has used the object based multiscale detection method to explore on this topic with a small dataset. With the rapidly developing technique, we are able to investigate more challenging task involving larger dataset with different magnitudes. In this paper, we focus on the on-going image processing technique implemented in skin biopsy pathological analysis, in terms of its potential in providing objective standards and improving efficiency for clinical screening. To this end, detecting the unhealthy even malign tissue in epidermis area is of vital importance, lining up with the goal of image segmentation from the perspective of image processing.

2.2.1 Disadvantages:

1.It analysis only small amount of dataset.

2. The loss function with caution of false negative in diagnosis is more.

IV. PROPOSED SYSTEM

In this study, we applied the deep convolution network on the hyperspectral pathology images to perform the segmentation of melanoma. To make the best use of spectral properties of three dimensional hyperspectral data, we proposed a 3D fully convolutional network named Hyper-net to segment melanoma from hyperspectral pathology images. In order to enhance the sensitivity of the model, we made a specific modification to the loss function with caution of false negative in diagnosis. The performance of Hyper-net surpassed the 2D model with the accuracy over 92%. The false negative rate decreased by nearly 66% using Hyper-net with the modified loss function.

ADVANTAGES OF THE PROPOSED

SYSTEM

1. The performance of Hyper-net surpassed the 2D model with the accuracy over 92%.
2. we are able to investigate more challenging task involving larger dataset with different magnitudes.

V. LITERATURE SURVEY

The global burden of melanoma: Results from the global burden of disease study 2015

AUTHORS: Karimkhani et al

ABSTRACT: Despite recent improvements in prevention, diagnosis, and treatment, vast differences in melanoma burden still exist between populations. Comparative data can highlight these differences and lead to focused efforts to reduce the burden of melanoma. Objectives: To assess global, regional, and national melanoma incidence, mortality, and disability-adjusted life year (DALY) estimates from the Global Burden of Disease 2015 study. Methods: Vital registration system and cancer registry data were used for melanoma mortality modeling. Incidence and prevalence were estimated using separately modeled mortality-to-incidence (MI) ratios. Total prevalence was divided into four disease phases and multiplied with disability weights to generate years lived with disability (YLDs). Deaths in each age group were multiplied with the reference life expectancy to generate years of life lost (YLLs). YLDs and YLLs were added to estimate DALYs. Results: The five world regions with the greatest melanoma incidence, DALY, and mortality rates were Australasia, North America, Eastern Europe, Western Europe, and Central Europe. With the exception of regions in sub-Saharan Africa, DALY and mortality rates were greater in males than females. DALY rate by age was highest in those aged 75-79 years, 70-74 years, and 80+ years. Conclusions: The greatest burden from melanoma falls on Australasian, North American, European, elderly, and male populations, consistent with previous investigations. These substantial disparities in melanoma burden worldwide highlight the need for aggressive prevention efforts. GBD results can help shape melanoma research and public policy. This article is protected by copyright. All rights reserved.

Dermatologist-level classification of skin cancer with deep neural networks

AUTHORS: S. W. Menzies et al

ABSTRACT: Skin cancer, the most common human malignancy, is primarily diagnosed visually, beginning with an initial clinical screening and followed potentially by dermoscopic analysis, a biopsy and histopathological examination. Automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of skin lesions. Deep convolutional neural networks (CNNs) show potential for general and highly variable tasks across many fine-grained object categories. Here we demonstrate classification of skin lesions using a single CNN, trained end-to-end from images directly, using only pixels and disease labels as inputs. We train a CNN using a dataset of 129,450 clinical images-two orders of

magnitude larger than previous datasets-consisting of 2,032 different diseases. We test its performance against 21 board-certified dermatologists on biopsy-proven clinical images with two critical binary classification use cases: keratinocyte carcinomas versus benign seborrheic keratoses; and malignant melanomas versus benign nevi. The first case represents the identification of the most common cancers, the second represents the identification of the deadliest skin cancer. The CNN achieves performance on par with all tested experts across both tasks, demonstrating an artificial intelligence capable of classifying skin cancer with a level of competence comparable to dermatologists. Outfitted with deep neural networks, mobile devices can potentially extend the reach of dermatologists outside of the clinic. It is projected that 6.3 billion smartphone subscriptions will exist by the year 2021 (ref. 13) and can therefore potentially provide low-cost universal access to vital diagnostic care.

Learning ECOC Code Matrix for Multiclass Classification with Application to Glaucoma Diagnosis

AUTHORS: X. Bai et al.,

ABSTRACT: Classification of different mechanisms of angle closure glaucoma (ACG) is important for medical diagnosis. Error-correcting output code (ECOC) is an effective approach for multiclass classification. In this study, we propose a new ensemble learning method based on ECOC with application to classification of four ACG mechanisms. The dichotomizers in ECOC are first optimized individually to increase their accuracy and diversity (or interdependence) which is beneficial to the ECOC framework. Specifically, the best feature set is determined for each possible dichotomizer and a wrapper approach is applied to evaluate the classification accuracy of each dichotomizer on the training dataset using cross-validation. The separability of the ECOC codes is maximized by selecting a set of competitive dichotomizers according to a new criterion, in which a regularization term is introduced in consideration of the binary classification performance of each selected dichotomizer. The proposed method is experimentally applied for classifying four ACG mechanisms. The eye images of 152 glaucoma patients are collected by using anterior segment optical coherence tomography (AS-OCT) and then segmented, from which 84 features are extracted. The weighted average classification accuracy of the proposed method is 87.65 % based on the results of leave-one-out cross-validation (LOOCV), which is much better than that of the other existing ECOC methods. The proposed method achieves accurate classification of four ACG mechanisms which is promising to be applied in diagnosis of glaucoma.

Deep learning applications in medical image analysis

AUTHORS: J. Ker, L. Wang, J. Rao, and T. Lim

ABSTRACT: The tremendous success of machine learning algorithms at image recognition tasks in recent years intersects with a time of dramatically increased use of

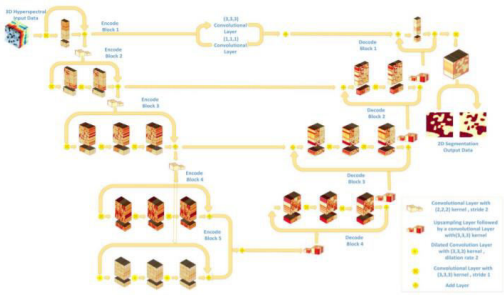
electronic medical records and diagnostic imaging. This review introduces the machine learning algorithms as applied to medical image analysis, focusing on convolutional neural networks, and emphasizing clinical aspects of the field. The advantage of machine learning in an era of medical big data is that significant hierarchal relationships within the data can be discovered algorithmically without laborious hand-crafting of features. We cover key research areas and applications of medical image classification, localization, detection, segmentation, and registration. We conclude by discussing research obstacles, emerging trends, and possible future directions.

Segmentation of Prognostic Tissue Structures in Cutaneous Melanoma Using Whole Slide Images

Author: Adon Phillips,Iris Teo, Jochen Lang

Abstract:Our work applies modern machine learning techniques to melanoma diagnostics. First, we curated a new dataset of 50 patient cases of cutaneous melanoma in whole slide images (WSIs). We applied gold standard annotations for three tissue types (tumour, epidermis, and dermis) which are important for the prognostic measurements known as Breslow thickness and Clark level. Then, we devised a novel multi-stride fully convolutional network (FCN) architecture that outperformed other networks trained and tested using the same data and evaluated on standard metrics. Three pathologists measured the Breslow thickness on the network's output. Their responses were diagnostically equivalent to the ground truth measurements, showing that it is possible to overcome the discriminative challenges of the skin and tumour anatomy for segmentation. Though more work is required to improve the network's performance on dermis segmentation, we have shown it is possible to achieve a level of accuracy required to manually perform the Breslow thickness measurement.

VI. ARCHITECTURE



VII. MODULES DESCRIPTION

Modules

- Upload dataset
  Using this module dataset is uploaded here.
- Read data
  Using this module data set is read.
- Loading the data
  Using this module data is loaded.
- Data analysis
  Using this module data analysis is take place.
- Model training and evaluation
  Using this module model training and evaluation takes place.
- Model interpretation
  Using this module model interpretation is build.
- Predict melanoma

Using this module skin diseases is predicted here.

VIII. ALGORITHMS

CNN

In this paper author describing concept to automate government services with Artificial Intelligence technology such as Deep Learning algorithm called Convolution Neural Networks (CNN). Government can introduce new schemes on internet and peoples can read news and notifications of such schemes and then peoples can write opinion about such schemes and this opinions can help government in taking better decisions. To detect public opinions about schemes automatically we need to have software like human brains which can easily understand the opinion which peoples are writing is in favour of positive or negative.

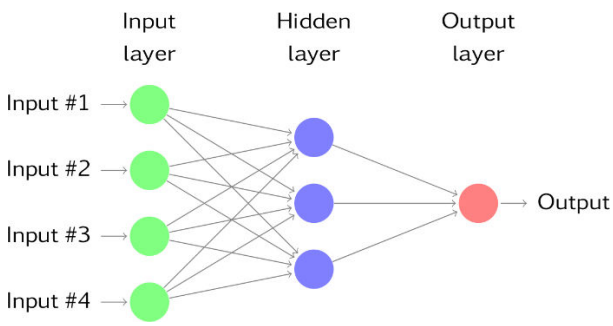
To build such automated opinion detection author is suggesting to build CNN model which can work like human brains. This CNN model can be generated for any services and we can make it to work like automated decision making without any human interactions. To suggest this technique author already describing concept to implement multiple models in which one model can detect or recognize human hand written digits and second model can detect sentiment from text sentences which can be given by human about government schemes. In our extension model we added another model which can detect sentiment from person face image. Person face expressions can describe sentiments better than words or sentences. So our extension work can predict sentiments from person face images.

To demonstrate how to build a convolutional neural network based image classifier, we shall build a 6 layer neural network that will identify and separate one image from other. This network that we shall build is a very small network that we can run on a CPU as well. Traditional neural networks that are very good at doing image classification have many more parameters and take a lot of time if trained on normal CPU. However, our objective is to show how to build a real-world convolutional neural network using TENSORFLOW.

Neural Networks are essentially mathematical models to solve an optimization problem. They are made of neurons, the basic computation unit of neural networks. A neuron takes an input (say x), do some computation on it (say: multiply it with a variable w and adds another variable b) to produce a value (say; z= wx+b). This value is passed to a non-linear function called activation function (f) to produce the final output(activation) of a neuron. There are many kinds of activation functions. One of the popular activation function is Sigmoid. The neuron which uses sigmoid function as an activation function will be called sigmoid neuron. Depending on the activation functions, neurons are named and there are many kinds of them like RELU, TanH.

If you stack neurons in a single line, it's called a layer; which is the next building

block of neural networks. See below image with layers



To predict image class multiple layers operate on each other to get best match layer and this process continues till no more improvement left.

Hyperspectral Pathology Image Pre-Processing

As mentioned, there are some constrains in data acquisition and implementation such as the emission spectra of the illumination sources, the transmission of the optics in the microscope and the detection sensitivity of the charge coupled device (CCD) camera, resulting in redundant and noisy data to some extent. We followed the band selection strategy in [50] using mutual information as the indicator. The Principle Component Analysis (PCA) was first used to select the most informative component as the reference band. The assessment of mutual information between each band and the reference band was defined in equation (1).

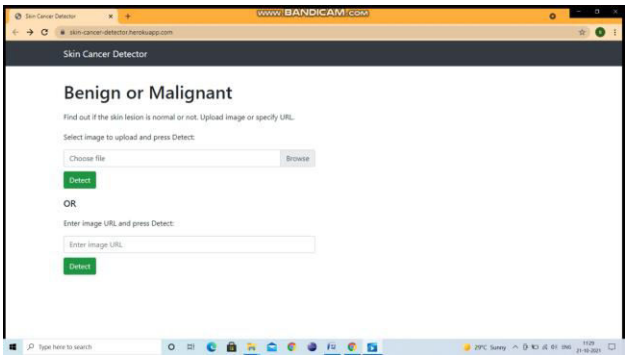
M I n(Hn, R) = H P(Hn, R) ∗ log P(Hn, R) P (Hn) ∗ P(R) (1) where n ∈ [1, 60]

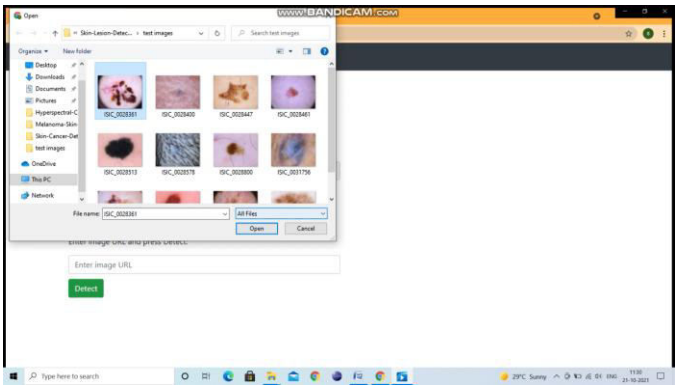
represents the nth band, P() represents the probability distributions of grey scale of the nth band or the reference component R. Moreover, a calibration process is needed beforehand, aimed to eliminate noisy data and obtain the significant characteristic spectra of histopathology tissue. In the spectral imaging microscope under the transmitted illumination system, especially for biomedical applications, the typical method is to use the blank hyperspectral image as the reference image which is acquired at the predetermined wavelengths by imaging a coverslipped slide containing no section. In MHSI system, the blank image is used to characterize the electronic instrument noise. The calibration is calculated by equation (2), where R, B and D represents the raw image, the blank image and the dark image, respectively.

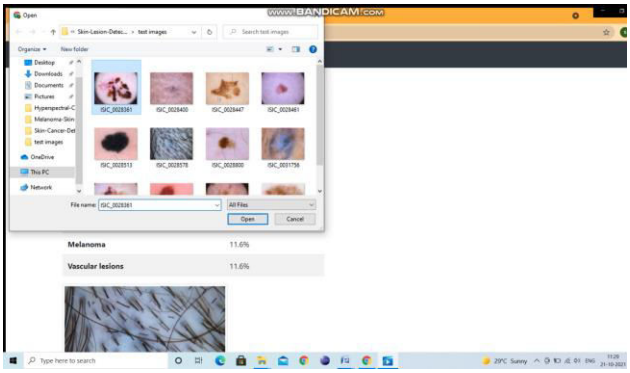
Hn i,j = Rn i,j − Dn i,j Bn i,j − Dn i,j.

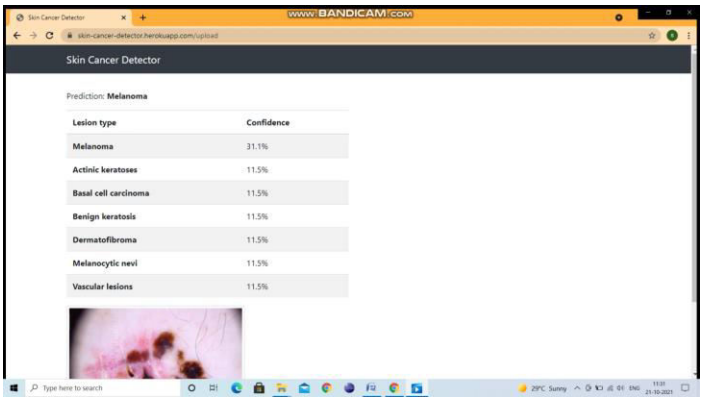
1a illustrates the spectra of melanoma before (red curve) and after (blue curve) calibration. For comparative purpose, the pre-processed spectrum is multiplied by the average spectrum of the blank image. Figure 1b shows values of mutual information obtained from the pre-processed image along the band dimension compared to the reference band generated from PCA. The highest consecutive sixteen bands from 670nm to 783nm (band 16 to band 31) illustrated in Fig were selected and used for the segmentation task whereas the subset of unselected band were also shown in Fig for comparison. These unselected bands were excluded from the original data due to severe damage which may destroy the model's stability.

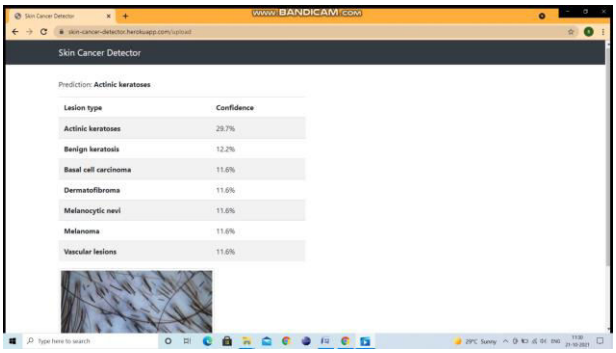
IX. SCREEN SHOTS











X. CONCLUSION

Overall, our work demonstrated that the 3D convolutional neural network can be used to segment melanoma in hyperspectral pathology images, therefore assisting pathologists in determining melanoma deterioration. Melanoma can be identified from healthy tissue under both 10X and 20X magnification with accuracy more than 92%. Also, to improve the sensitivity of diagnosis, we proposed the Hyper-net neural network by making specific modification of loss function, leading to enhanced performance of greatly reduction in false positive and

false negative predictions. By comparing with the 2D CNN model, we demonstrated that hyperspectral pathology images contained rich informative properties of tissues so as to improve the segmentation results and assure diagnosis robustness. Although the accuracy was reasonable, our work only covered limited diversity of tissues in skin pathology. In addition, there are many other complex and rare tissues that may need pathologists' professional knowledge such as cyst, necrosis and inflammation. In terms of our MHSI system, we intend to upgrade the current MHSI system to enlarge the spectra range so as to include spectra between 400 and 750, and to consider more significant features to enhance the quality of these channels. Last but not least, we have to admit that there is a long way before the hyperspectral pathology system could be used in clinical, that's why researchers could not stop exploring various ways of probability. Obviously, deep networks opened a new insight into medical field with carefulness and consideration on clinical situations.

XI. FUTURE ENHANCEMENTS

we have to admit that there is a long way before the hyperspectral pathology system could be used in clinical, that's why researchers could not stop exploring various ways of probability. Obviously, deep networks opened a new insight into medical field with carefulness and consideration on clinical situations.

XII. REFERENCES

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