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DEEP LEARNING MELANOMA DETECTION USING CNN

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ABSTRACT:
Skin cancer is a typical common cancer. Melanoma, also known as malignant melanoma, is the most lethal form of skin cancer and responsible for 75% of skin cancer deaths, despite being the least common skin cancer. The best way to combat that is trying to identify it as early as possible and treat it with minor surgery. In this paper, I systematically study melanoma and notice that using deeper, wider and higher resolution convolutional neural networks can obtain better performance. Based on these observations, I propose an automated melanoma detection model by analysis of skin lesion images using EfficientNet-B6, which can capture more finegrained features. The experimental evaluations on a large publicly available dataset ISIC 2020 Challenge Dataset, which is generated by the International Skin Imaging Collaboration and images of it are from several primary medical sources, have demonstrated state-of-the-art classification performance compared with prior popular melanoma classifiers on the same dataset.

Keywords-skin cancer, melanoma, convolutional neural network, classification..

INTRODUCTION:

Melanoma, also known as malignant melanoma, is a type of skin cancer that develops from the pigment producing cells known as melanocytes. Melanomas typically occur in the skin but may rarely occur in the mouth, intestine or eye. Unfortunately, it is the most dangerous type of skin cancer. Based on the analysis report from 2015, there were 3.1 million people with active disease, which resulted in 59800 deaths. From point of diagnosis, currently, dermatologists evaluate every one of a patient's moles by door to door to identify outlier lesions or "ugly ducklings" that are possible to develop into melanoma. As you can image, this is very tedious and laborious work. Some efforts based on deep learning have been done to develop algorithms to help dermatologists diagnose the disease in recent years. Intuitively, the diagnosis of melanoma can be treated as classification problem of whether a captured dermoscopic image of skin lesion contains a malignant melanoma or benign one. Some samples of skin lesion images are shown in Figure 1. From the samples, it is easy to notice that melanoma lesions show many different features, which are helpful for diagnosis using deep learning model. However, existing deep learning approaches have not

adequately considered this clinical frame of reference. Models based deep learning could enhance their diagnostic accuracy by taking into account "contextual" images within the same patient to determine which image represent a melanoma. In this way, classifiers would be more accurate and could better support dermatological clinic work. According to above points, I present a novel melanoma detection model, the core of which is the application of more powerful EfficientNet network. Unlike popular VGG , ResNet, EfficientNet uses a baseline network created by neural architecture search to scale all dimensions of depth, width, image resolution using a simple yet highly effective method called compound coefficient. This greatly enhances the ability to capture richer and much more complex features for melanoma recognition. I demonstrate that by conducting a variety of experiments to evaluate the proposed network performance with that of prior networks on a large publicly available dataset ISIC 2020 Challenge Dataset , which comes from the larger ISIC Archive that contains the largest publicly available collection of quality-controlled dermoscopic images of skin lesions generated by the International Skin Imaging Collaboration (ISIC) and some medical research institutes. The experimental results show my proposed model has achieved 0.917 of AUC-ROC score, 3% higher than 0.819 of VGG-based model. These results demonstrate the effectiveness of my network to produce significant improvements in the melanoma detection of skin cancer. The proposed network can better support dermatological clinic work and further promotes computer-aided diagnosis system for cancer detection. To sum up, my contributions differ from the previous works in two points.To my best knowledge, I am the first to apply Efficient Net for melanoma detection. I rethink feature extraction of previous networks and elaborately design the novel architecture to achieve better detection accuracy and efficiency.To go even further, transfer learning allows me to better deal with training. I transfer the existing pretrained model weights learning from much larger ImageNet dataset to melanoma classification domain. With transfer learning, not only accelerates my training but also helps model find better model weights for inference.

The reset of the paper is organized as follows. In section 2, I provide a survey on the current skin cancer detection work and popular classification models. Section 3 gives an overview of the proposed convolutional deep learning model and a detailed explanation of why my architecture can obtain better precision. Section 4 shows the experimental evaluations of the proposed model compared to previous models. Final section is for conclusions of my work and some

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points that may be improved in the future.

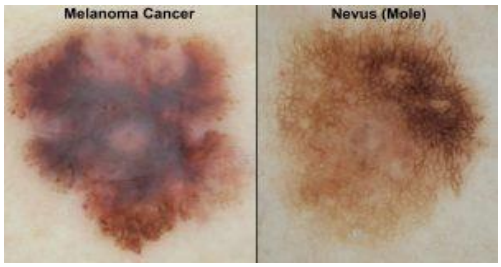

Figure 1. Samples of skin lesion images

On the left side from top to bottom shows:

(a) slight mole of a patient
(b) early stage of malignant inrlanoina lesion
(c) slight melanoma lesion
(d) malignant melanoma lesion.

Patients are nowadays considered consumers of health services, and the assessment of their perspective has become a priority in medical management .Furthermore, the shift to a biopsychosocial model of healthcare and patient-centered care has emphasized the patient's part in medical decision making, and promoted more shared-decision making. When patients participate in medical decision-making evidence suggests that they are more satisfied with their care, which can result in higher compliance to health regimens and better health outcomes. Patient satisfaction is therefore a common indicator for quality healthcare. Other important aspects of quality healthcare may be diagnostic accuracy and length of consultations in order to achieve clinical effectiveness and patient safety . To this end, support tools for better differential diagnoses may be helpful.A visual clinical decision support system (CDSS) may improve diagnostic accuracy of skin conditions and reduce misdiagnosis-related harms. A CDSS is a computer-assisted differential diagnosis tool with content and potentially images of medical conditions.Often it can be accessed using computers, tablets and smartphones (via websites and applications). Unlike textbooks indexed by disease, CDSS allows doctors to enter patient demographics like age, sex, and objective and subjective symptoms, including lab-findings. Based on this information the CDSS may suggest the GP a diagnosis that matches the entered criteria, enabling doctors to "rule in or out" by comparing a patient's skin condition with the information and potentially images given to match the condition. Often for each differential the CDSS also provides concise content on disease-specific information as well as information on management, therapy, and handouts for patients which may be used to improve the patient-doctor communication.

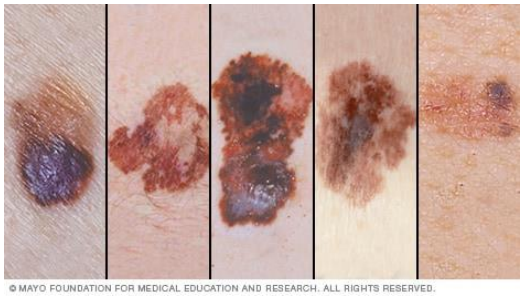

Fig 2.Mayo Foundation for Medical Education and Research

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LITERATURE SURVEY

The need to use learning techniques in any area for performance improvement requires consideration of knowledge in the related field. Computer-aided skin cancer diagnosis is a big challenge given the relative lack of labeled lesion data and consequently the low-quality data for training. Throughout time, several methods have proposed to improve the detection accuracy. Pomponiu et al. present an algorithm for skin cancer classification by applying a pre-trained AlexNet to generate high level feature representations of dermoscopic skin images. The extracted features are fed to train nearest neighbor classifier for skin cancer identification.Followed by, Esteva et al. propose a pre-trained Convolutional Neural Network (CNN) for skin cancer detection and a big dataset used for their training. In Mahbod et al. study, a fully automatic computerized method for skin lesion classification which employs optimized deep features from a number of well-established CNNs. In addition to use the pre-trained CNNs, Masood et al. design a novel semi supervised, self-advised learning model for automated detection of skin cancer using dermoscopic images . Deep belief architecture is constructed using labeled data together with unlabeled data and fine-tuning model by an exponential loss function in order to maximize separation of labeled data. Next, Majtner et al. propose a model based on deep learning method combined with so called hand crafted RSurf features and Local Binary Patterns.Although higher detection accuracy is obtained in skin cancer by these methods, it still remains an open question of how to achieve further performance while keeping better efficiency.Many researchers have been working on the Computer vision approach for skin cancer detection. For segmentation of skin lesion in the input image, existing systems either use manual, semi-automatic or fully automatic border detection methods. The features to perform skin lesion segmentation used in various papers are: shape, colour, texture, and luminance. Many border detection methods are reported in the literature.Some of the methods include histogram thresholding, global thresholding on optimised colour channels followed by morphological operations,Hybrid thresholding.In this study,we have applied Automatic thresholding and border detection method. Different image processing techniques have been used to extract such features.In ,author has introduced an automated Global border-detection method in dermo-scope images based on colour-space analysis and global histogram thresholding which exhibits high performance in detecting the borders of melanoma lesions. In the authors have used the technique of dividing the input image into various clinically significant regions using the Euclidean distance transform for the extraction of color and texture features. The ABCD rule of dermoscopy suggest that,many researchers have been working on the computer vision approach for skin cancer detection. For segmentation of skin lesion in the input image, existing systems either use manual, semi-automatic or fully

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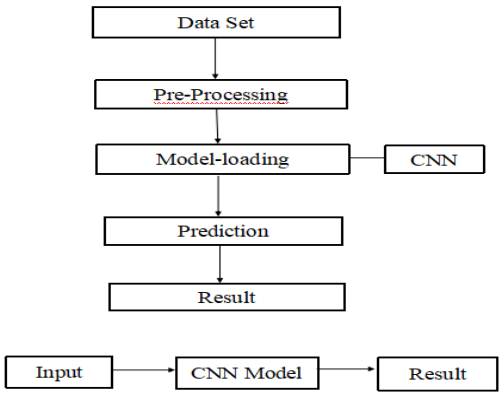
ARCHITECHURE: -



EXISTING SYSTEM

Managing the balance between accurately identifying early stage melanomas while avoiding obtaining biopsy specimens of benign lesions (ie, overbiopsy) is the major challenge of melanoma detection. Decision making can be especially difficult in patients with extensive atypical nevi. Recognizing that the primary screening modality for melanoma is subjective examination, studies have shown a tendency toward overbiopsy. Even low-risk routine surgical procedures are associated with morbidity, mounting health care costs, and patient anxiety. Recent advancements in noninvasive diagnostic modalities have helped improve diagnostic accuracy, especially when managing melanocytic lesions of uncertain diagnosis. Breakthroughs in artificial intelligence have also shown exciting potential in changing the landscape of melanoma detection. In the first article in this continuing medical education series, we review novel diagnostic technologies, such as

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automated 2- and 3-dimensional total body imaging with sequential digital demo-scopic imaging, reflectance confocal microscopy, and electrical impedance spectroscopy, and we explore the logistics and implications of potentially integrating artificial intelligence into existing melanoma management paradigms.

DISADVANTAGES: -

- Relatively time consuming.
- High cost,trained personel.
- Complexity, high cost.
- Complexity , not suitable for current practice.

PROPOSED SYSTEM:-

The system was developed in this study could identify skin cancer and benign tumor lesions automatically using the Convolutional Neural Network (CNN). The proposed model consists of three hidden layers with an output channel of 16,32, and 64 for each layer respectively. The paper presents a novel method of melanoma recognition on the basis of dermoscopic images. We use color images of skin lesions, advanced image processing, and different classifiers to distinguish melanoma from the other non-melanoma lesions.

ADVANTAGES: -

- Low cost,Easy operation
- Low cost,Easy execution
- Possibility to work with large amounts of data

Exploration of the epidermis and dermis via 2D images

METHODOLOGY: -

At the core of my network is a pre-trained convolutional neural network EfficientNet, used for feature extracting for my melanoma dataset. The motivation behind this network instead of other popular CNN network is activated by several factors including excellent feature extraction power and efficiency of EfficientNet. Meanwhile, I transfer the knowledge of pre-trained EfficientNet on ImageNet to a new skin lesion image classification domain. A. The EfficientNet Architecture Unlike regular CNN designs that mostly focus on finding the best layer architecture, EfficientNet tries to expand the network depth, width, input resolution in the baseline network. Inspired by MnasNet , baseline network of EfficientNet-B0 is developed by leveraging a multi-objective neural architecture search that optimizes both accuracy and limited computation resources. Starting from the baseline network, the EfficientNet-B6 is generated by applying the compound scaling method, which uses a compound coefficient 0 to uniformly scales network depth d, width w, resolution r in a principled way:

Depth: d=a0
Width: w=ff0
Resolution: r=y0
s.ta f 2y 2 ~ 2 a > 1 , f > 1,y > 1

Where a, p, y are constants that can be set by a grid search. Intuitively, 0 is a user-specified coefficient that is subject to how many computation resources are available for model. To be more specific, fix 0 = 1 first, assuming twice more resources available, and do a small grid search of a, p,Y. The best values found are applied to construct EfficientNet-B0. Next, fix a, p,Y as constants and scale up

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EfficientNet-B0 with different 0 based on Equation 1. Of these various models, EfficientNet-B6 outperforms others and requires fewer computations. The reason why EfficientNet-B6 is better than others can be attributed to three factors. The first is deeper network, which can capture richer and more complex feature, and generalize well on new tasks. The second is wider network tends to be able to extract more fine-grained features and is easier to train. The last is higher resolution of input images, that means more pixels are fed. With higher resolution, my model can potentially catch more fine-grained patterns. Therefore, EfficientNet-B6 , scaling up these dimensions of EfficientNet-B0, obtains superior performance. Transfer Learning As I can see from the overview of the proposed network illustrated in Figure 2, the classifier I choose to build on the top of features extracted from the last layer of EfficientNet contains four fully connected layers. Just as I already mentioned, EfficientNet-B6 network is used to capture high-level feature representations of input skin lesion images. Then these features are fed into the classifierTransfer learning, which can accelerate training and help model find better convergence state for inference, is studied and proved successful in many applications. I employ it to transfer the knowledge of pre-trained EfficientNet to effectively extract fine-grained feature of given dermoscopic skin image since CNN generally contains enormous parameters and costs expensive resources. On the other hand, the weights of four much less fully connected layers are initialized by Xavier method and trained from scratch.

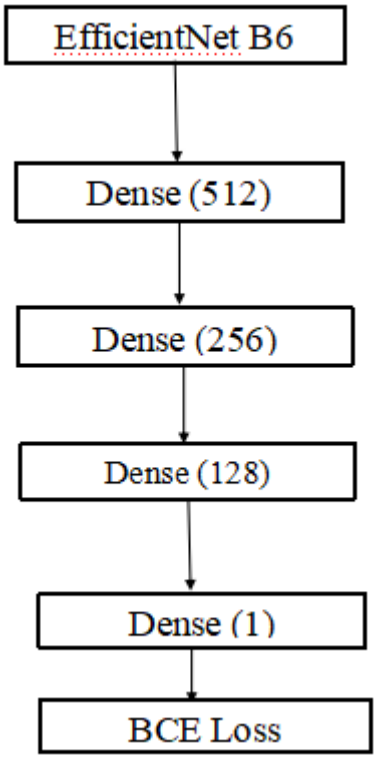
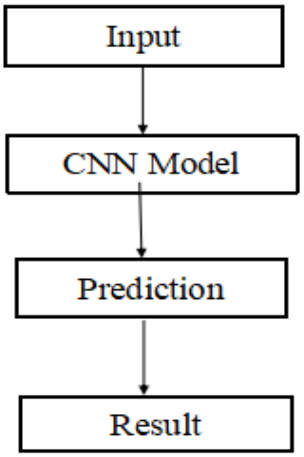


Figure 2. An illustration of the proposed network for melanoma lesion detection.

The first part is EfficientNet B6 network, which used to capture high-level feature representations of dermoscopic skin lesion images. These features are fed into fully connected layers of the second part to generate final prediction.

FLOW CHART:



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V. IMPLEMENTATION

In this section, I evaluate my proposed approach and previous approaches previous on a large publicly available dataset ISIC 2020 Challenge Dataset , which comes from the larger ISIC Archive that contains the largest publicly available collection of quality-controlled dermoscopic images of skin lesions generated by the International Skin Imaging Collaboration (ISIC). All images with corresponding diagnosis information label are collected in some medical research institutes. To better measure model performance, I split the whole dataset as training, validation and test sub dataset with the proportion of 7:2:1. All experimental results are reported on the same test dataset. I train my model using setting as: Adam optimizer with initial learning rate 1e-3, batch size 32. The final trained model is generated after 22 epochs. The metrics that could be considered for melanoma classification evaluation is AUC-ROC score, which stands for "Area under the ROC curve". ROC curve plots True Positive Rate (TPR) versus False Positive Rate (FPR). Intuitively, AUC-ROC score of 0.0 means a model predicts extremely terrible, while AUCROC of 1.0 indicates a model predicts 100% correct.

As the size of the input images increases, the number of layers of the convolutional neural network needs to increase. The size of input image's was set to 256 × 256. Since the training dataset is limited the network could overfit. To avoid over-fitting and to make sure that the network converges, the size of the convolutional neural network is adjusted so that there are adequate number of layers in the network. The network is adjusted by changing the filter size of the convolutional layer, the stride and the pooling layers. In addition to manual network's adjustment, dropout layers are added after the pooling layers. The network is constructed using 17 layers organized in 5 blocks as mentioned in the previous section. The hyperparameters of the network are set according to the dataset's size and computer's capabilities. The success of the proposed architecture depends on correct setting of network hyperparameters. Examples of our network hyperparameters include: batch size which is the number of training images in one forward pass or backward pass, number of epochs which is one forward and backward pass of all the training examples, and learning rate which is the amount the weights are updated in the network [24]. The batch size is set to 5, as there are only 900 training images. Increasing the batch size requires a large memory. The number of epochs computed is dependent on the training data. Early stopping terminates the algorithm when the training error goes below 15%. The learning rate is set to $1 \times e{-}2 = 0.1353$. The weight decay parameter in the Adagrad algorithm is set to $1{\times}e{-}2 = 0.1353$ as well. Hyperparameter values are summarized in table I.

DATA SET

The dataset used for melanoma detection is from the International Symposium on Biomedical Imaging (ISBI) 2016 challenge: Skin Lesion Analysis

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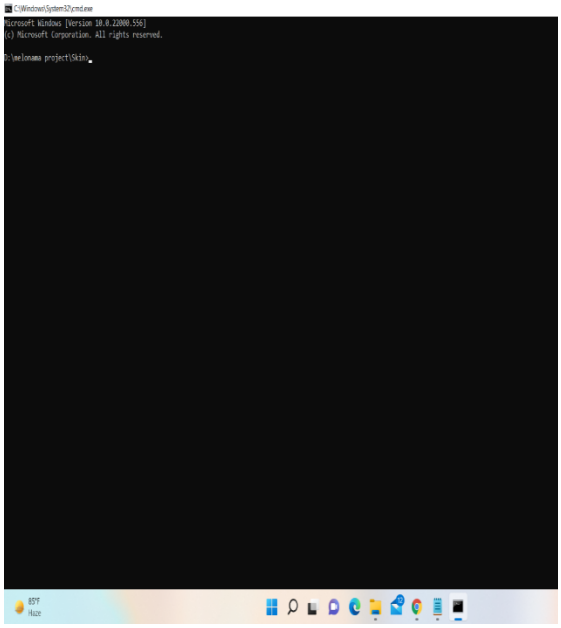
Towards Melanoma Detection. The images are provided by the International Skin Imaging Collaboration (ISIC) [7]. The ISIC has one of the largest collections of skin dermoscopy images. The dataset for lesion classification consists of 900 training and 379 testing dermoscopic images with labels of benign and malignant. This dataset has 727 benign images and 173 melanoma images in the training subset, as for the testing subset there are 304 benign images and 75 melanoma images. The images' original sizes vary from 1022 × 767 to 4288 × 2848 pixels. Each image has a label of either melanoma or non-melanoma (1 for melanoma and 0 for non-melanoma). The program used for classification is Matlab on HP elitebook laptop without using GPU, using a 2.60 GHz CPU and a memory of 8 GB.

RESULT :

Step 1:



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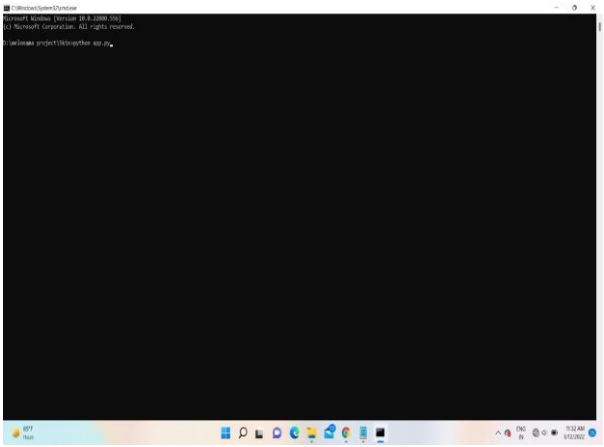

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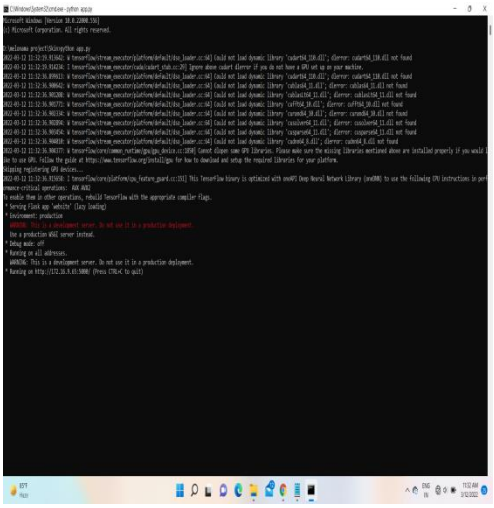

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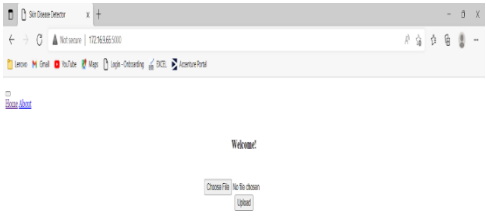

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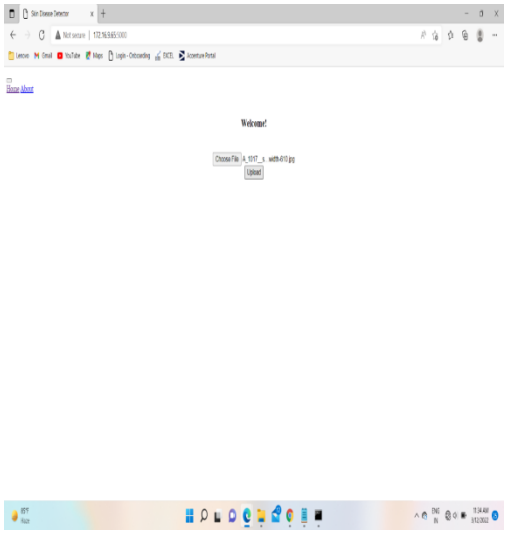
Step 5:



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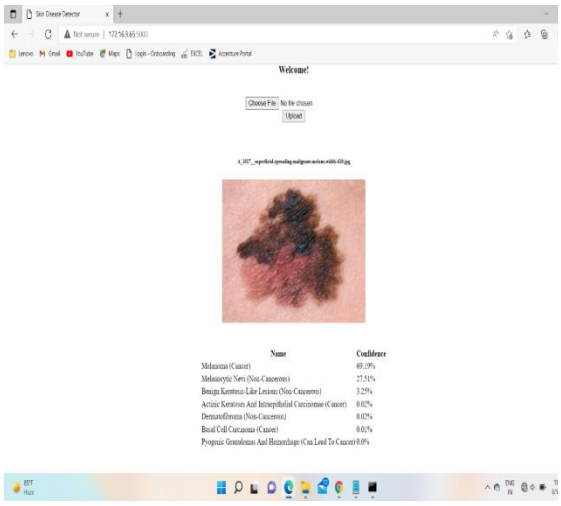

VI. CONCLUSION

CONCLUSION

In this work, a method for melanoma classification based on Convolutional Neural Networks is proposed. The method proposed uses a deep learning framework LightNet to classify melanoma images into benign and malignant. The convolutional neural network architecture in LightNet is modified to work with the ISBI skin challenge data set. Melanoma classification is performed without applying lesion segmentation or complex image pre-processing. Our results are comparable to state-of-the-art results while using a significantly lower number of parameters. In this paper I systematically study the background and status quo of melanoma detection. Based on my observations, I investigate the Efficient-B6 capability of capturing more complex and more fine-grained features from clinic dermoscopic images of skin lesion. The experimental results show that the proposed network tends to focus on more relevant regions with melanoma details thanks to deeper, wider and higher resolution network. Therefore, I achieve better classification accuracy than previous popular methods. In the future, I plan to investigate two directions: the first aims to further study the certain relationship between skin cancer and melanoma, which makes it possible to generalize my proposed network on more types of skin cancer. The second directions I would like to explore is the more profound reason for causing melanoma and various signs of melanoma in hope to design a more powerful network, in which I consider more medical knowledge from the "contextual" images

FUTURESCOPE

In the future, we plan to improve the proposed method by employing parts of the ABCD rule to extract useful input features. A neural network that takes these features as input can be implemented to enhance detection accuracy. The dataset involved in this work

has a class imbalance problem because there are more benign class samples than malignant. A simple way to handle this problem is to perform oversampling of

the data in which the minority class examples are duplicated. Another way is to use cost-sensitive learning which incorporates the misclassification costs between classes. For example, one of the techniques of this learning method is the application of misclassification costs as a form of data weighting to the imbalanced dataset. Since the data set is limited and there are few training examples, data augmentation can be applied to the data set to increase the number of training samples can be implemented to enhance detection accuracy. The dataset involved in this work has a class imbalance problem because there are more benign class samples than malignant. A simple way to handle this problem is to perform oversampling of the data in which the minority class examples are duplicated. An- other way is to use cost-sensitive learning which incorporates the misclassification costs between classes. For example, one of the techniques of this learning method is the application of misclassification costs as a form of data weighting to the imbalanced dataset. Since the data set is limited and there are few training examples, data augmentation can be applied to the data set to increase the number of training samples

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