Classification of Skin Lesion using Unsupervised Convolutional Spiking Neural Network

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Abstract — Automatic diagnostics of skin disease is one of the most challenging problems in medical Image processing. Nowdays, deep learning has become one of the most popular & powerful methods. This paper proposes the classification of Melanoma and benign nevus by using convolutional spiking neural networks With unsupervised Spike Timing Dependency Plasticity learning rule. By applying the Spiking neural networks to the pre-processed image will transform into feature values. Then feature selection method is applied to select more diagnostic feature to increase the performance of our network. SNN with feature selection reaches an average accuracy of about 86%. SNNs not only achieve better classification accuracy but also have better runtime efficiency. Efficient temporal coding, event driven learning rule and WTA mechanism together ensure sparse Spike coding and efficient learning of our networks. This work shows that STDP-based SNNs are very beneficial for the implementation of automated skin lesion classifiers on small portable devices like mobilephones etc.

KeyWords: Deep Learning, STDP Learning rule,WTA mechanism, Skin lesion.

1. INTRODUCTION

Dermatological diseases among human has been a common disease. Especially millions of peoples are suffering from various kinds of skin disease. Usually, these diseases have hidden dangers which lead to human not only lack of self-confidence and psychological depression but also a risk of skin cancer. Diagnosis of these kinds of diseases usually required medical experts with high-level instruments due to a lack of visual resolution in skin disease images.

Moreover, manual diagnosis of skin disease is often subjective, time-consuming, and required more human effort. Thus, there is a need to develop a computer-aided system that automatically diagnoses the skin disease problem. At present, skin diseases are one of the most infectious diseases to see among people. Because of the physical structure affected by the direct exposure to ultraviolet radiation i.e. use of different types of high-frequency wireless equipment for a long time and it can develop skin cancer[1].Malignant melanoma is the deadliest form of skin cancer, which accounting for 79% of skin cancer deaths. Early detection of malignant lesions has great significance for helping the clinicians to improve the chances of survival. The visual similarities of some lesion types, correct diagnosis is a challenging task for clinicians, and is largely dependent on the experience. Early diagnosis is of great importance for treating skin cancer as it can be cured better at early stages [2]. With the increase in medical technology the concept of computer being used for the diagnosis of skin diseases has been around recently. Use of computer technology can make it simpler to detect the diseases just from the images of the infected skin image and could assist the human's ability to analyze complex information. Artificial Intelligence is taking up automation in all fields of application even in the healthcare field. A computer can efficiently and effortlessly interpret a lot of images where it is difficult for the human to interpret such a high number of data and look into the details of the image inside. Therefore Computer-Aided-Detection and Computer-Based-Diagnosis have become desirable and are under development by many research groups [3]. Computer based diagnosis have proven to be very helpful in disease diagnosis.The most prevalent technology which is being used for the prediction is Artificial Intelligence using Machine Learning. Artificial Intelligence uses learning methods to learn about the images to predict the diseases based upon the common patterns. The machine interprets the images and its slices and processes the image and predicts. Machine learning (ML) is that branch of computer studies that gives the potentiality to the methods have shown their advantages in detecting key features and patterns from complex datasets, thus are suitable to perform classification, prediction or estimation tasks [3]. Machine learning is employed in a wide range of computing functions where building and designing specific algorithms with better performances is difficult or impractical. In recent years there is growing trend on

the application of ML methods as an aid to accurate and automated cancer diagnosis and detection [4]. The application of ML techniques has significantly improved the accuracy of cancer prediction by 15%–20% over the past decades. Deep Learning is a part of broader family of machine learning where the learning can be supervised, unsupervised or semi supervised. Deep learning unlike machine learning uses a large dataset for the learning process and the number of classifiers used gets reduced substantially. The training time for the deep learning algorithm increases because of the usage of the very large dataset [5]. Deep learning algorithm chooses its own features unlike the machine leaning making the prediction process easier for the end user as it does not use much of pre-processing. The problem that arises in both data science world and data mining in an unsupervised learning task is locating the hidden structure in an uncharacterized or unlabeled data. Therefore when the learner is given an unlabeled example, no error or reward signal is present for evaluation of an impending solution. SNNs have been emerged as an ideal biologically inspired neuromorphic-computing, paradigm for realizing energy efficient on-chip intelligence hardware. Like in the brain, information in SNNs is encoded not only by spike rates, but also by precise spike times and spike latencies of neurons. Furthermore, SNNs usually apply bio-inspired STDP as unsupervised local learning (synaptic weight modification) rule, which is crucial for brain learning. STDP is observed in different brain areas, in particular in the visual cortex. Weight modification of this synaptic plasticity depends on the temporal order and time difference between pre-synaptic and postsynaptic spikes. Since individual spike events in the networks can be made sparse in time, learning in SNNs in principle is sparse and event-driven, leading to low computational consumption. Moreover, SNNs equipped with unsupervised STDP learning rule have the capability to learn the spatio-temporal patterns of input signals, especially in an online model. SNNs with multiple hidden layers can extract more complex features from input to obtain high classification performance[6]. Recently SNNs have shown very good performance in the task of pattern recongnition such as visual processing and speech recongnition[7].

Discussed about a model using deep CNN with triplet loss function to improve the classification of skin diseases. ResNet152 and InceptionResNet-v2 is used to address the problem of facial images of skin disease. They classify four types of datasets involving blackheads, acne, dark circles and spots. The input images is given to the triplet loss selection and then output of triplet loss selection is feed to deep CNN, embedded to find the L2 distance (hard positive, hard Negative).128-D features are extracted from training samples into Euclidean space and then L-2 computes the distance between the images using learned embeddings 90%of training data &10%of testing data is used.The accuracy of this method may reaches about 87%.[1]
proposed an automated facial skin disease method using a pre-trained deep convolutional neural network (CNN). In CNN they use pretrained VGG-16 network model. The images refer to 10 classes comprising of eight facial skin diseases classes (Acne, Actinic keratosis, Angioedema, Blepharitis, Granuloma facial, pityriasis Alba, Rosacea, and Vitiligo)are taken. The original image of these disease is first resized an image of size 224x224, then the image is processed 10 through the series of convolution layer. They used filter 3*3 and size reduction is handled and max pooling is performed by 2*2 filter. Softmax classifier is used to classify these diseases.[14]

Laplacian based algorithm, filtered image is subtracted from the initial image to remove any removal Wiener filter. Hair strands detection is done using the Laplacian of Gaussian edge detection operator. Laplacian of Gaussian edge detection (LoG) based algorithm, RGB image is separated into the three channels and the Laplacian of Gaussian edge detection method is applied to the red channel. By trial and Error they found that they use a higher threshold in the LoG method to get a less false identified hair pixels in the hair mask. LoGsobel based algorithm, adds the output of the LoG and the Sobel edge detection method is used. Linear Least Square (LLS) based algorithm, the filtered image is subtracted from the grayscale one. The LoG and the Sobel edge detection method are applied to the resulting image. It can be calculated by Mathew correlation coefficient and root mean square error. Linear Least Square algorithm can be effective method for removing the brown hair.[10]

2 METHODOLOGIES

2.1 DATA SET

The analysis of skin database is taken from the ISIC (**International skin imaging collaboration)** challenge on skin lesion analysis towards the melanoma detection. For classification of disease the image is processed using Python. The databases consists of 200 images of Malignant Melanoma and Benign Nevus. The files are saved in the format of training and testing as train.csv and test.csv. The value 0 denotes benign and 1 indicates malignant.

Sequence for Training and Testing

- 75% of training and 25% of testing images,
- 25% of training and 75% of testing images,
- 50% of training and 50% of testing images.

2.2 OVERVIEW OF PROPOSED METHOD

In this proposed system, the convolutional SNNs with unsupervised Spike Timing dependent plasticity (STDP) learning rule for skin lesions classification. It mainly consists of three parts

i. Skin lesion image data pre-processing.
ii. Feature extraction based on spiking neural networks.
iii. Skin lesions classification using SVM classifier.

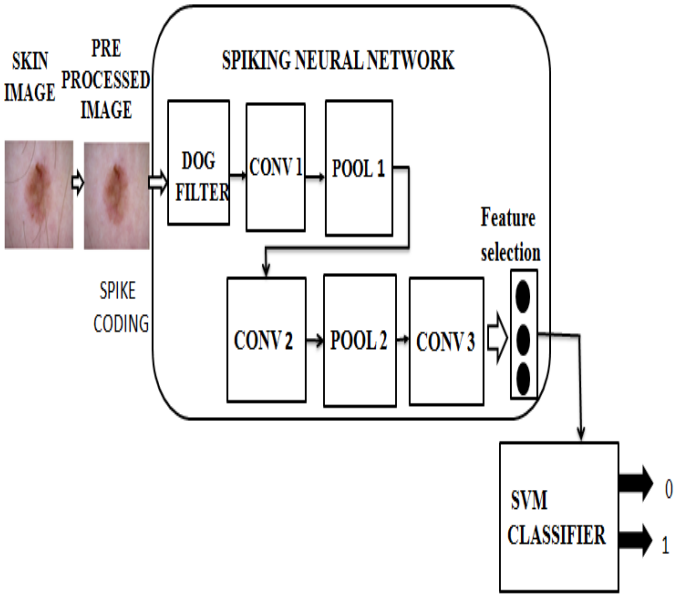

Fig-1 BLOCK DIAGRAM OF SKIN LESION DETECTION.

Our SNNs include a DOG encoding layer, three convolutional layers (Conv1, Conv2 and Conv3), and three pooling layers (Pool1, Pool2 and Pool3). The DOG filter is applied to convert the pre-processed skin images into spikes using the intensity-to-latency coding scheme. Convolutional layers and pooling layers are all consisting of integrate-and-fire (IF) neurons. Each convolutional layer learns features from its input by STDP learning rule, in combination with WTA weight updating strategy and lateral inhibition mechanism. Finally we replace the final global maximum pooling layer (Pool3) with a feature selection layer in order to improve the classification performance of the SNNs. The outputs of feature selection layer are then used to make the skin lesion classification by SVM classifier.

2.3 PREPOCESSING

Data pre-processing is used to remove the hairs or noises in the raw images. We use three pre-processing methods which are hair deleting, media filter and global contrast normalization. Many images in the ISIC dataset have a lot of hairs which affects the classification accuracy. In our work hair deleting is implemented by using an algorithm called Dull Razor. The Dull Razor can remove hairs effectively, and also additional noises by using Fast Median Filtering. Then, a media filter with a window size of 7*7 is used to reduce small pores on the skin and light reflections or shines in the dermoscopic images. Finally, we use global contrast normalization to eliminate the effects of different light conditions on the pixel values of the images.It works by subtracting the mean of the intensities in the image to each pixel.

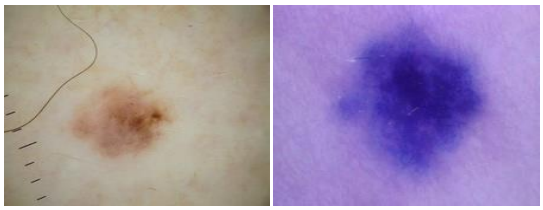

Fig-2(a) Inputimage**(b)**Pre-processed image

2.4 SPIKING NEURAL NETWORKS

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2.5 CONVOLUTIONAL NEURAL LAYER

Each convolutional layer in the networks has several feature maps to learn different features determined by their input synaptic weights. Like CNNs, each visual feature obtained in one convolutional layer is a combination of several simpler features extracted from the previous layer. Each neuron receives input spikes from the neurons located in the same convolutional window of all feature maps of the previous layer. Input synaptic weight sharing is applied to neurons

belonging to the same feature map. At each time step, the membrane potential of an IF neuron is updated. When its membrane potential exceeds its threshold Vthr, the neuron fires a spike, and its value is reset V(t) = 0 and S(t) = 1. Lateral inhibition mechanism is applied to the neurons of all convolutional layers. When a neuron belonging to one feature map fires, it inhibits neurons in that same location but belonging to other feature maps to fire. In addition, each neuron is allowed to fire only once. Each spike of a feature map indicates the detection of a particular feature at that location, and the earlier the spike, the more prominent the detected feature.

2.6 STDP LEARNING RULE

In the networks, the synaptic learning of each convolutional layer is unsupervised and done layer by layer. A simplified STDP rule in combination with a winner-takes-all (WTA) mechanism is used to update the input synaptic weights of neurons in convolutional layers. The synaptic weight from the jth neuron in the input layer (pre-synaptic neuron) to the ith neuron in one convolutional layer (post-synaptic neuron). tj and ti are the firing times of the pre-synaptic neuron and the post-synaptic neuron, respectively. And a+ and a− are the two learning rate parameters of STDP. In a convolutional layer, neurons corresponding to the same feature map detect the same feature but at different locations. They compete with each other to update their shared input synaptic weights. The neuron that fires the earliest is the winner which is then modify their shared weights according to STDP rule, and the other neurons of the same feature map are prevented from doing weights updating. Moreover, in order to encourage different feature maps to learn different and prominent features, there is local lateral inhibition between the feature maps of one convolutional layer. That is, if one neuron is allowed to modify its input synaptic weights, it prevents other neurons at the same location and belonging to other feature maps to update their input synaptic weights. These biological mechanisms make the learning event-driven and the information processing sparse and effective in the networks.

$$\Delta\omega ij = \alpha+\omega ij(1-\omega ij), \text{ if } tj-ti\leq 0, \quad (1)$$

$$\Delta\omega ij = \alpha-\omega ij(1-\omega ij), \text{ if } tj-ti>0, \quad (2)$$

2.7 Polling Layer:

The first two pooling layers in the networks are local pooling. Each local pooling layer performs a nonlinear max pooling operation over its previous convolutional layer. Such an operation helps the networks to gain invariance and also to reduce the dimensionality of the input. A pooling neuron receives input spikes from the neurons in a pooling window located in the corresponding feature map of its previous convolutional layer. Each pooling neuron is allowed to fire at most once, and its input synaptic weights and threshold are all set to one. After the last convolutional layer, there can be a global pooling layer whose outputs are used to classify the input prototypes. This layer performs global maximum pooling over their corresponding feature maps in the last convolutional layer. That is, a global pooling neuron receives input spikes from all the neurons located in the corresponding feature map of its previous convolutional layer. The thresholds of the global pooling neurons are set to infinity. Therefore, the output of each global pooling neuron is the maximum neural membrane potential of its corresponding neural map and it is also the maximum membrane potential value of all the time steps of this neural map. So, there is only one output value for each feature map, which indicates the presence of that feature in the input image. These output values are used to classify the input prototypes by SVM classifier.

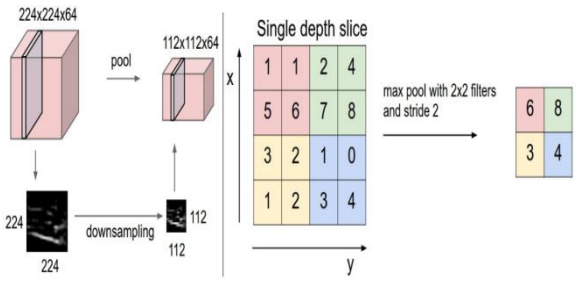


Fig-3(a) Visualization of down sampling of an image using non-overlapping max pooling.

(b) Illustrative example of non-overlapping max pooling

2.8 FEATURE SELECTION

The features extracted by the convolutional layers in the convolutional SNNs are to some extent redundant (including irrelevant features). A global maximum pooling is used to compress input information and remove the redundancy. After the global pooling, there is only one output value for each feature map, which represents the most prominent feature of this feature map.These output values are then used to classify the input prototypes by SVM classifier. However, when classifying images with very high similarity, it is very likely that the global maximum pooling might filter some diagnostic but not the most prominent features, which will affect the classification result of the classifier. Therefore, to improve classification accuracy we use univariate feature selection based on chi-square test to replace the global maximum pooling in order to select more diagnostic features, while reducing redundancy. After the learning of all convolutional layers have finished, we use each training

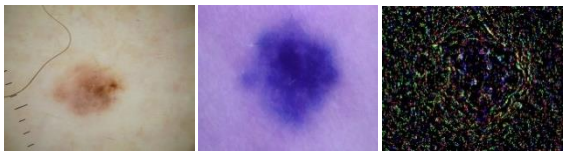
sample as the input of the SNNs, and then the output of Conv3 (extracted features) is flattened and input to the feature selection layer. The chi-square test is used to measure the relationship coefficient between each extracted feature and input category, and these relationship coefficients are sorted by value.

2.9 SUPPORT VECTOR MACHINE (SVM) CLASSIFIER

SVM is a supervised machine learning algorithm which can be used for both classification and regression challenges. SVM classifier to classify input prototypes. In the skin lesion diagnosis, it is more important to correctly predict melanoma lesion which has high mortality than to incorrectly predict benign melanocytic nevi lesion.It is a discriminative classifier. The EvalutionMetrices are calculated.

RESULT AND DISCUSSION

The input skin lesion images are pre-processed and given to the spiking neural networks. The difference of Gaussian filter is applied to encode the images in to dicrete spikes. Then the feature values are learned from the convolutional layers. And classify the diseases using svm classifier.

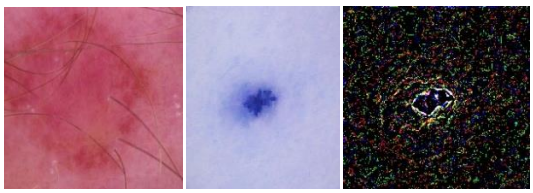


(a) (b) (c)

Fig-4 (a) INPUT IMAGE OF MELANOMA

(b) PREPROCESSED IMAGE OF MELANOMA

(c)DOG FILTER OUTPUT



(a) (b) (c)

Fig-5 (a) INPUT IMAGE OF NEVUS

(b) PREPROCESSED IMAGE OF NEVUS

(c)DOG FILTER OUTPUT

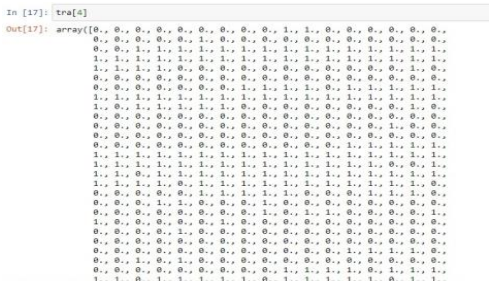


Fig-6 FEATURE VALUES OF SNN

Table-1CLASSIFICATION PERFORMANCES OF SNNS

Total Images	Train	Test	Accur-acy	Sensiti-vity	Specif icity	Precis ion
200	150	50	86%	91%	25%	93%
200	50	150	78%	89%	9%	86%
200	100	50	79%	85%	33%	90%

CONCLUSION

In this work the skin lesion images are taken from the ISIC 2018.The images are given to the pre-processing layer. In this layer dog filter is used to remove the hair, noise and light condition of the images. The output of the pre-processing is given to spiking neural networks with STDP learning rule & WTA mechanism to extract the feature values. The accuracy is improved at 86% by using feature selection of chi square test. The svm classifier is used to distinguish melanoma from melanocytic nevi. This classification results shows the efficient temporal coding &winner take all mechanism of our SNN network and performance of the network is measured.

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