

Unsupervised Deep Neural Scheme for Mobile Phone Based Unlabelled Medical Image Classification

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Abstract: *The ever-increasing size of medical datasets combined with increasing numbers of missing data has made unsupervised learning one of the strong focus of significant practical importance in the real world. There has been much interest in applying unsupervised techniques that incorporate information from unlabeled data for higher representation. Accurate identification of diseases within a short span is of great importance due to the global increase in new disease cases. Medical diagnosis by using automated computer-aided procedure is more effective compared to the manual pathological methods. This study presents an automatic identification of infected erythrocytes parasites and intestinal parasites using a new deep learning method. This new deep neural network architecture consists of autoencoder followed by support vector machine. The entire network consists of two phases: in the first phase the autoencoder takes the network weights with their initial values by unsupervised greedy layer-wise technique, and the support vector machine in the second phase are fine-tuned by the backpropagation algorithm. Our extensive experimental results demonstrate that the proposed deep neural network can obtain better performance in terms of accuracy and time than other broadly used deep learning techniques.*

Index Terms: *Proposed Deep Neural Network; Unsupervised Learning; Unlabelled; Deep Learning; Detection Time.*

I. INTRODUCTION

A large amount of data being digitally collected and stored could be an enabling resource for useful information and knowledge for improving health care and reduce waste. Medical data contains a large volume of unlabelled information in an unstructured format and is too difficult to understand. The enormity and complexity of these medical datasets state great challenges in identifying diseases and solving this tedious task in a short span. The risk burden of being infected and developing the disease is still accounted for due to lack of clinical and research expertizes, widespread of fake and substandard medicines, erroneous manual enumeration of malaria diagnosis, time-consuming visual diagnosis, handling of huge unlabelled data, lack of advanced machine learning tools and many more. One of the major issues in the area of the content-based image is image classification. It requires a group of samples labeled or tagged with their correct meaningful categories for better classification. Accurate labeling of samples is costly and time-consuming, as it requires human effort. The comprehensive analysis of image datasets promises to reveal many aspects of the complexity and density of cellular functions. The portable mobile phone datasets are ubiquitous

and transformative in nature. Mobile phone provides easy and cost-effectiveness for collecting image datasets with less time, but the image quality of scanning the blood smear slides is quite low compared with the digital camera. The volume of cases and low-resolution images degrade the performance of manual interpretation and are difficult to identify the disease through normal machine learning techniques. These issues can be handled by many fast preprocessing deep learning techniques by automatic estimation of useful features for malaria identification and grading. The enormous density of data and a huge amount of medical images can be addressed simultaneously in one platform by deep learning. Figure 1. illustrates the infected intestinal and erythrocyte parasites captured through a mobile phone. The intestine is infected and needs proper diagnosis if it contains taenia egg in oval shape caused by hookworm. Figure 1(b) represents the infected erythrocytes present in microscopic blood smear image and is caused by female Anopheles mosquito.

Considering, the above issues and approaches, we have proposed a quantitative new deep neural network architecture for the diagnosis of malaria and intestinal parasite cell samples using their microscopic high magnification images. The main task of our work are mentioned below,

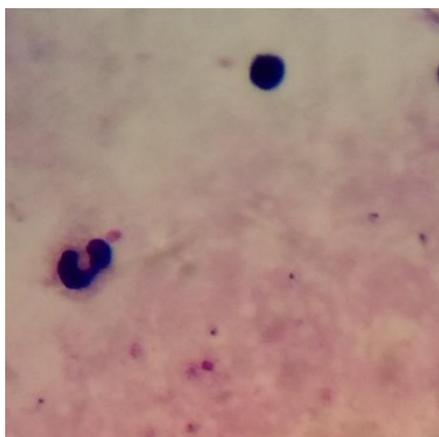
- i. To solve the muddle of ineffective classification and complexity found in cell objects of low-resolution phone images due to inadequate labeled training samples.
- ii. To address the issue of insufficiency of training data caused by the difficulty of obtaining unlabeled medical images.
- iii. Using the proposed deep neural network enables a faster convergence rate and less computational load with superior performance than other broadly used deep learning methods.
- iv. The proposed method incorporates to classify the different parasites present in the phone images as shown in Figure 1.

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(a)



(b)

Figure 1. Illustrates the infected parasites captured through the phone.

Figure 2 states the contribution of this paper where we present the latest systematic proposed deep neural network technique for parasite identification. The remainder of this paper is organized as follows. Section 2 briefly introduces the prior art, Section 3 presents the proposed deep neural network. Section 4 illustrates dataset, experimental details, and the produced classification results. Conclusion for the study is presented in Section 5.

II. REVIEW WORK

In recent years, several machine learning techniques with multiple layers have been proposed for a variety of health diagnosis using phone images. Feature extraction techniques have become an evident need in many medical imaging applications [1][2]. A large variety of techniques, including machine learning techniques, have been applied to medical data to find relevant or informative cells. Besides this popular method, there is a huge range of lossless compression techniques that are fully mathematical optimized frameworks for different [3], [4], [5] and [6] overviewed comprehensive comparison of feature selection based machine learning techniques for automated optimization of parasite cell recognition in detail. These machine learning techniques yet need good improvisation for feature extraction because it still

requires trained skilled experts to handle data and smart techniques for calculating the prognosis of the disease. Recent advances in deep learning, coupled with the onslaught of unlabelled medical data have drawn ever-increasing research interests by discovering multiple levels of distributed representations and solving complex medical related problems. Deep neural network provide quite competitive outcomes by improving the prediction performance and automatic estimation of functional features producing a high-level representation of the in-terms data. Deep neural network have many success stories for health diagnosis tasks as they solve many tedious problems reducing the burden that they can calculate accurate output parameter. The deep neural network (DNN) architecture carries many multiple hidden layers and so the network is called deep, not only in classification tasks but also in regression. DNN is an emerging approach to excellent performance in various variants, such as dimensionality reduction, object segmentation, modeling textures, modeling motion, information retrieval, robotics, natural language processing, collaborative filtering, so on [7][8]. The deep learning model analysis and extensive empirical evaluation help to design high performance with good accuracy architectures for medical image tasks. Z. Zhang et al. [9] demonstrate apart based deep learning representation using sparse auto-encoders to gain high reconstructed quality decompose data as compared with the traditional autoencoder. It also demonstrates how to get a useful representation from unlabelled data that perceive the hidden layer of high-dimensional human brain data based on autoencoders.

The next section describes the proposed deep neural network been used in detail below.

III. PROPOSED DEEP NEURAL NETWORK

In this proposed deep neural network architecture, the whole network is of two phases. In the first phase, the autoencoder takes the network weights with their initial values by unsupervised greedy layer-wise technique, and the support vector machine in the second phase are fine-tuned by backpropagation algorithm. Images are captured in real time, comprising a ZTE Blade low-cost Android smartphone to a Brunel SP150 microscope with a 1000× magnification [10]. The more direct the image and higher its resolution, higher is the chances for better result and accurate analysis. The comprehensive analysis of image datasets promises to reveal many aspects of the complexity and density of cellular functions. The portable smartphones datasets are ubiquitous and transformative in nature. Smartphones provide easy and cost-effectiveness for collecting image datasets with less time [10]. Each color image is converted into a grayscale image through thresholding method and denoising is followed to improve the image quality. The pre-processing is a process of preparing clear features of phone images to ensure a fast and accurate processing. Here, we have used the spatial domain filtering method to remove salt and pepper noise by preserving the edge details of the original image.

The spatial domain

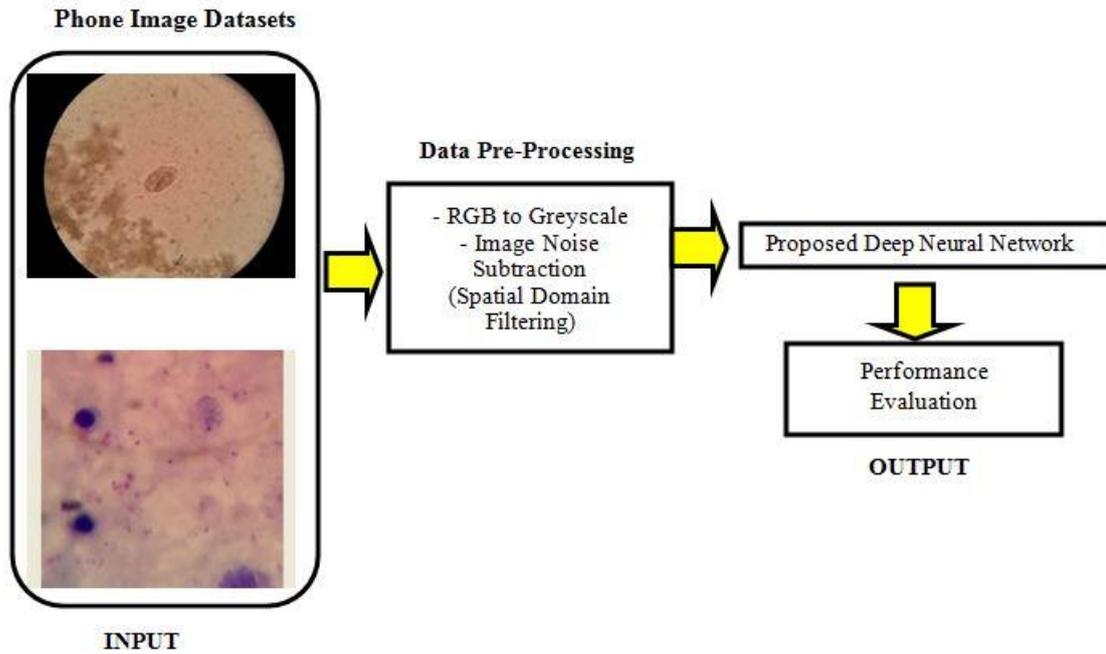


Figure 2. The proposed deep neural network representation in order to identify infected parasites captured through a mobile phone.

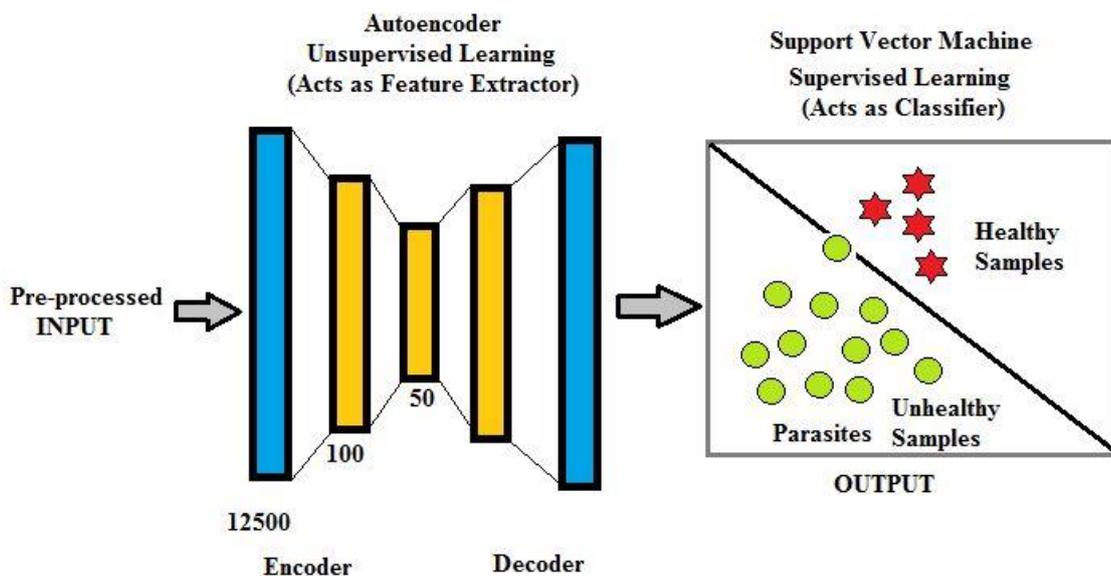


Figure 3. Work flow of Proposed Deep Neural Network.

filtering method aims to use the middle value of every pixel in the neighbor instead of considering to the current pixel [11]. These are the data pre-processing steps to be carried followed by the two neural network techniques. The entire proposed network was trained over 1000 epochs with a learning rate of 1×10^{-3} and decay rate of 0.1 per epoch. After the procedure of pre-processing, the phone image datasets are feeding into autoencoder in order to extract useful information for identifying the infected samples. In this work, the image size is defined as $750 \times 750 = 5,62,500$ pixels which are huge enough to contain parasite under low magnification resolution images. To enhance training of the proposed deep neural network and to extract useful features, cropped each image of 50×50 pixels. The input to the proposed deep neural network is a mat file of 1182 images of

pixel intensities, which further gets converted to vector input layers after layers. As shown in Figure 2, 12500 is the dimension of the input layer of autoencoder with two hidden layers of 100 and 50 respectively.

IV. EXPERIMENTS

We demonstrate the applicability of proposed deep neural network, all focussing on the aspect of identifying infected parasites and extensively compare it with competing for broadly used methods.

A. Dataset

This section presents an experimental estimation of the proposed model using publicly available from AI research group at Makerere University¹ [10], as part of the collaborative research on automated malaria infection diagnosis. The blood cell images are RGB color images with a 750×750 pixel resolution [10]. The Field-stained malaria blood smear slides are scanned and captured into 3D-printed phone adapters, at 1000× optical magnification. All simulations in this section were performed on a workstation with Intel Core i5 CPU and 16 GB of memory.

B. Evaluation Metrics

For performance evaluation, we have considered two evaluation metrics namely:

- i. **K-Fold cross-validation:** The proposed deep neural network performance is validated using K-Fold cross-validation.
- ii. **Class Performance:** Effectiveness of the proposed network is measured in terms of mean square error level for 1000 epochs.
- iii. **Baselines for Comparisons:** The proposed deep neural network is compared with well-known deep learning techniques in terms of accuracy and detection time.

K-Fold cross-validation: The malaria images are split using K-Fold cross-validation into two subgroups for K subset as testing and the other is K-1 subsets as training.



Deep Learning Techniques	Precision (%)	Recall (%)	F-measure (%)	AveP (%)	Total Detection Time (in seconds)
Proposed Deep Neural Network	88.84	90.02	91.22	80.67	41
AE + SMC	83.51	77.40	79.85	68.09	45
SAE + SMC	84.52	77.93	80.68	70.51	45
STAE + SMC	83.71	82.98	83.12	78.29	45
TSAE + SMC	88.35	77.15	82.26	73.48	45

classifier together. SAE + SMC is a two hidden layered based deep learning technique of sparse auto encoder of two hidden layers followed by softmax classifier. STAE + SMC method

Figure 4. Graphical representation of 10 fold cross-validation.

Class Performance: The figure demonstrates the observable trend of the best training performance of error rate 0.00342383 at 1000 epochs.

The error rate goes on decreasing as per the increasing number of epochs.

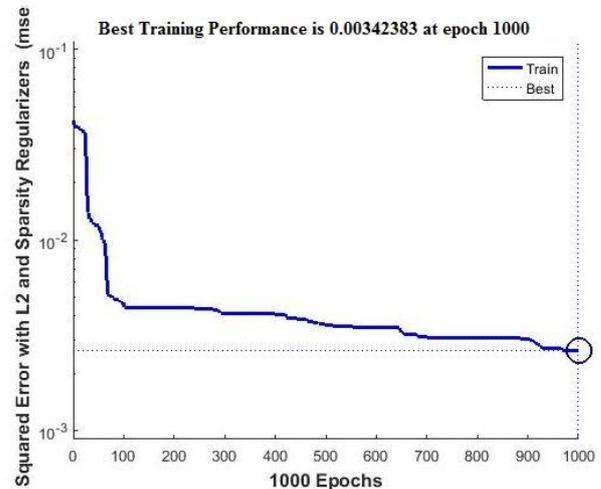


Figure 5. Graphical representation of the training performance of bandwidth at epochs 1000 to achieve mean square error level of the proposed deep neural network.

Baselines for Comparisons: In this section, we have shown that the proposed deep neural network is compared with well-known deep learning techniques in terms of accuracy and detection time. From Table 1, we conclude that the proposed deep neural network delivers a better F-measure 91.22 % with least detection time of 41 seconds than other benchmark deep learning techniques in identifying parasites. In Table 1, AE + SMC is one of the most widely used deep learning method which combines auto encoder and softmax

<http://air.ug/microscopy/>¹

Table1. Accuracies and defection time of broadly used deep learning techniques like AE+SMC, SAE+SMC, STAE+SMC, TSAE+SMC, and Proposed Deep Neural Network

delivers a F-measure of 83.12 % forming three hidden layer sparse auto encoder with softmax classifier. It can be



noted that there is a significant difference in order of the statistical metrics between the proposed deep neural network and deep learning based benchmarked algorithms in terms of precision, recall, F-measure and detection time.

V. CONCLUSION

In this paper, we adopted a novel deep neural network, to identify the parasites present in intestine and blood smear images captured through a mobile phone, respectively. The effectiveness of the proposed deep neural network is demonstrated by using intestine and microscopic blood smear datasets, in terms, of k fold cross-validation, error rate, precision, recall, F-measure and detection time. The experimental results show that the proposed network achieves promising results of F-measure of 91.22% with 41 seconds of detection time. For further studies, this proposed deep neural network is worth investigating for other types of diseases and also can be used in different medical areas.

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