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Survey on Deep Learning Analysis Of Spectrophotometric Data

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Abstract— **Deep learning-based study of visual datasets plays an important role in automated image scrutiny ideology. This paper investigates amalgamated feature learning and classifier training approaches for designing an efficient image recognition system. Of late, deep learning is emerging as an upcoming machine learning tool and has fascinated substantial attention in the fast-growing field of spectrophotometric analysis. The main idea of this paper is to inspect the emerging utilization of deep neural networks and examine the current deep learning advancements in various fields such as pattern recognition, segmentation, and classification in visual data analysis. Particularly, we demonstrate the frameworks and the fundamentals of convolutional neural networks, fully connected networks, stacked auto encoders and optimizers, and python deep learning libraries, and interpret their formulations for different operations on various spectrophotometric images. Furthermore, we explore the open challenges and the prospective trends of future research in spectrophotometric image analysis using deep learning.**

***Index Terms*— Convolutional Neural Networks, Deep Learning, Feature extraction, Spectrophotometric data**

I. Introduction

Spectrophotometric analysis using deep learning provides a quantitative pathway for enhancing characterizations of various visual datasets, that serve as an input to the image recognition systems. With the increasing size of visual datasets, it is inefficient or even impossible to manually process the large amount of data. Automated methods significantly improve the efficiency. It attracts considerable attention in the recent works. Particularly, deep learning techniques have been applied in the research of deep learning, natural language processing and image processing. Deep learning is a learning method that processes target classification. It requires less human interventions and provides better accuracy and faster results. The deep learning system automatically learns the features and representations that can be applied to object recognition. Deep learning techniques are widely used in artificial intelligence. They have been successfully applied to natural language processing, computer vision, speech recognition and so on. Using automated systems for discovering hidden features, it has achieved improved performance and efficiency. It has also provided very accurate performance in biomedical applications as well. Off late, deep learning is emerging as an efficient tool that attracts considerable attention in spectrophotometric analysis, including cell segmentation, nuclei detection, image classification, and so on. The most popular deep learning architecture is convolutional neural networks (CNNs). The input images and respective annotations are provided, and a CNN model is designed to learn and generate predictive data representations. These representations are used for target classification of testing data. Unsupervised learning is also sometimes applied to neural networks for data representation learning. Autoencoders and Support Vector Machines (SVM) are unsupervised neural networks, commonly used in spectrophotometric analysis with promising accuracy. The advantage of using unsupervised feature learning is that it does not involve human annotations. There are several books and articles explaining deep learning architectures, historical reviews, and applications in various technical areas. Many authors have presented a historical survey of deep neural networks by summarizing relevant methodologies. The papers reviewed in this survey explains several deep learning algorithms. They also provide speculative ideas for future research. Several deep learning applications in medical image computing are analysed. Deep learning, which learns feature representations and pattern recognition, takes advantage of large-scale high dimensional image data to discover hidden structures for better spectrophotometric analysis. Deep learning can significantly eliminate the liability of feature engineering in predictable deep learning practices. These days, deep learning is the major technique among the best solutions in spectrophotometric analysis. It holds great potential for the field. In this paper, we emphasis on deep learning in spectrophotometric data analysis, which conceals several topics, such as pre-processing, feature extractions followed by training and testing the systems. We also point out several techniques in which deep learning analysis of spectrophotometric data can be carried out. Finally, we discuss the efficiency of the results produced by various deep leaning systems. This survey intents to help other investigators to catch a hint of the state-of-the-art methods in the ground of spectrophotometric analysis.

II. PRE-PROCESSING THE IMAGES

Pre-processing is the initial step performed in any image recognition system. The dataset that is subjected to analysis is first analysed and processed thoroughly to make sure that all the images are formatted in a similar fashion. One of the key steps performed in pre-processing includes labelling of the images and resizing the images. Many more pre-processing can be done to the datasets depending on the application and usability of the given system.

In [1] Kazuki Hirayama et al. and in [3] Rotem Golan et al. proposed a pre-processing method to extract cancerous regions from CT images of lungs using deep learning. In this, he first applied isotropic voxel processing to the target images, followed by perform smoothing and processing using binarization. Then noise is removed using threshold processing. The same process is applied to the extracted region along with binary inversion to remove the background area.

Mesay Belete Bejiga et al. in [2] stated the pre-processing steps handled by them for apply CNN on avalanche search and rescue operations. Since the objects buried in snow will have different image properties, various image segmentation methods are used to differentiate the objects from snow in each frame. Every frame will be analysed with the help of a sliding window and it will be checked for colour differentiations by applying thresholding techniques. The value of the intensity and saturation component is compared to see if the window contains an object or not.

Yoshihiro Shima and Prashengit Dhar in [4], [8] have used morphological pre-processing steps to extract number plate images. Based on binary image processing, edge features and global image features are acquired using connected component analysis. Then projection profile analysis is applied to extract texture and colour-based features.

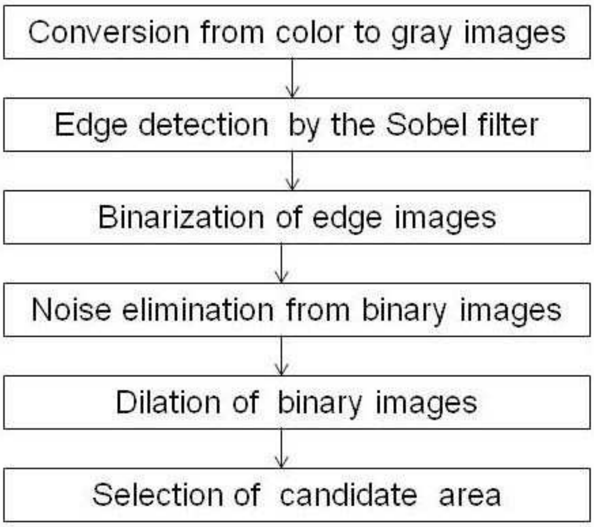

Fig. 1. Morphological Image Processing [4]

III FEATURE EXTRACTION

Once the images have been pre-processed, they are ready to be applied in the system for training. Before this, a main step called feature extraction is carried out, which extracts the required area of interest thereby ignoring the background scene which is not required for analysis. It is the process of mapping image pixels into a relevant feature space. Again, this step can be implemented in various ways depending upon the region of interest and its application. As all the papers discussed use CNN, some use extra methods apart from CNN for feature extraction.

In [1] and [3], the authors have suggested a method to extract the lung nodule region which depicts the presence of cancerous activity. First the false shadows caused by the bronchus and blood vessels are removed using 3D filters and Hessian matrix. Then the required GGO regions are extracted using gradient and concentrated threshold processing, followed by noise reduction. Finally, segmentation is done by using optimum threshold settings for improving accuracy.

The candidate selection method is carried out in [4] for extracting the exact region where the number plate is present. For this, the aspect ratio, the density and area of the required region are used to compute a weighted sum. Scoring is done based on the available weights and the ones with lower scores are deleted.

For the facial recognition system deployed in [7], the unique features of the face such as colour of the eyes, length and width of the nose and ears, spacing between the eyes and the size of each ear are considered. These are then used to perform facial alignments.

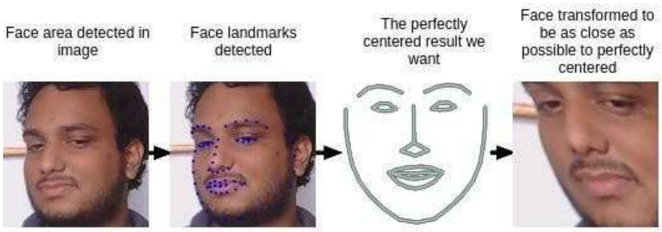

Fig. 2. Face alignment [7]

IV TRAINING THE SYSTEM

The most important step used for the analysis of spectrophotometric data is training the system. After the required regions of interest have been extracted, the system needs to be trained to recognize the features and to classify the datasets based on what it has learnt. CNN is widely used for this. It uses feed- forward neural networks and multi-layer perceptron. The three main layers present in a CNN are Convolutional layer, Pooling layer and fully connected layers. The CNN can be applied to train the system or can be combined with other deep learning techniques to implement training.

For training the system to differentiate between cancerous and non-cancerous lung nodules, two different methods have been adopted in [1] and [3]. In [1], SVM is initially used to further reduce the shadows caused by false positives. Hence a 2-class SVM is built to identify and recognize the initial GGO regions. Then the final region extraction is done with the help of a DCNN, which used the pre-trained AlexNet object recognition model. This same technique of combining the advantages of SVM and CNN to build an effective training model is also carried out in [4], where the system is trained to detect and extract number plates from vehicles.

Back propagation algorithm is used in [3] and [5]. In [3], the extraction of volumetric features from the data is done and is fitted into the convolutional layers, ReLU layers and max pooling layers. Then the CNN is used as a classifier, which is made up of multiple fully connected layers, threshold layers and a softmax layer.

The method in [5] adopts error backpropagation along with gradient-based learning. It minimizes cumulative errors in the database. It utilises the Q-Net architecture, that comprises of two convolutional layers, two sub-sampling layers and two fully- connected layers.

For training the system to recognize facial features, [7] uses a triplet loss function along with CNN to improve performance.

The process of generating triplets keeps executing iteratively on the training dataset until the required distance become minimum.

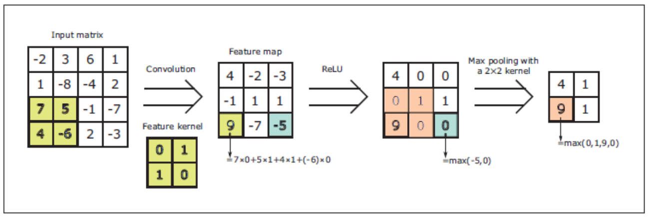

Fig. 3. A sequence of 2D convolution, ReLU, and max pooling operations. The stride value of both the convolution and max pooling operations, along the two axes, is 1. ([3])

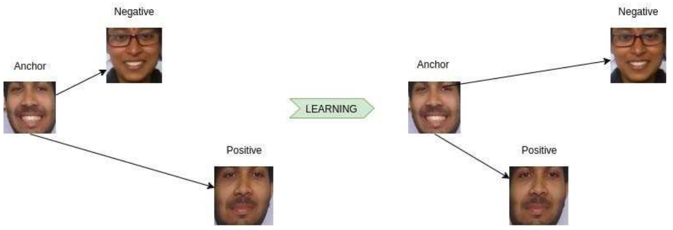

Fig 4: The triplet loss function minimizes the distance between an anchor and a positive and maximizes the distance between the anchor and a negative. Here positive and anchor has the same identity where anchor and negative has the different identity. [7]

The general CNN training is carried out in [2], [6] and [8], where the CNN layers are defined and iteratively run over a number a epochs until the system is trained completely without any overfitting. Dropout functions are used to minimize the effect of overfitting.

V. TESTING THE SYSTEM

After successful training, the effectiveness of the system is measured with the results produced by it during testing. Accuracy is calculated by several means and it a measure of the trustworthiness of a trained system. The performance of the lung nodule detection system in [1] is calculated based on the following equations:

$$\text{True Positive(TP)} = \frac{a}{a+b} \times 100\ [\%]$$

$$\text{False Positive(FP)} = \frac{c}{e}\ [/\text{case}]$$

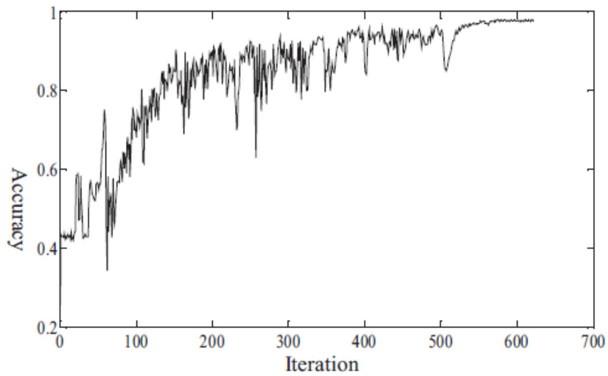

Fig. 5. Testing set results accuracy for the system proposed [5]

Leave-One-Out method in SVM and 3-fold-crossvalidation method in DCNN. The same computations are also performed for the lung system proposed in [3], along with a formula to calculate the sensitivity of the system. sensitivity = TP/(TP +FN). Usually testing is done, and the above computations are used to calculate the overall accuracy.

VI. RESULTS AND DISCUSSIONS

In the survey, we have reviewed different papers that uses CNN to analyse spectrophotometric data. Since the power and efficiency of a system depends on how well it has been processed and trained, each method discussed in this paper gives different results based on the type of techniques adapted by it. To analyse the results of a few methods discussed here, let us consider the test results of the number plate extraction method in [4] and the traffic sign detection methods in [8].

Candidate regions after morphological image processing	Classify as	
	Number plate	Outlier
Success (number plate) 113 (89.7%)	113 (100%)	0 (0%)
Fail (outlier) 13 (10.3%)	1 (7.7%)	12 (92.3%)
Total 126 (100%)	114	12

TABLE 1: CLASSIFICATION ERROR RATE FOR TEST IMAGES [4]

Classifiers	Features	Accuracy
SVM(Cubic)	SURF	82.0%
SVM(Quadratic)	SURF	81.0%
ANN	SURF	93.3%
Decision Trees	SURF	76.0%
KNN	SURF	71.0%
Ensembles (Adaboost)	SURF	68.0%
CNN(Proposed)	CNN Extracted	97.0%

TABLE 2: ACCURACY OF VARIOUS CLASSIFICATION ALGORITHMS [8]

FUTURE ENHANCEMENT

CNN has proved to produced high accuracy and improved efficiency. The efficiency of any system can be improved by adjusting the number of training samples, the number of epochs and iterations used, and the number of hidden layers modelled in the CNN. It can also be combined with other deep learning architectures to create a highly robust and powerful system. Our team is currently working on implementing an efficient CNN based model to detect benign and malignant lung nodules from CT scan images.

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