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A Review of Convolution Neural Network Used in Various Applications

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***Abstract*— The technique of deep learning is Convolutional Neural Networks (CNN) is very much effective for detecting features from images automatically. CNN can be used to train large datasets with billions or millions of parameters in form of images as input and convolve it with particular filters to produce the desired outputs. There are various applications of CNN like image recognition, image classification and image detection. This paper presents literature survey of CNN which is applied to various domain that includes medicine, agriculture, document layout. Also, so many CNN models were built to evaluate performance on image detection and recognition. Therefore, in this paper we compare all such models with respect to dataset. And we hope that this paper will help all the beginners who need a guidance about this domain.**

Keywords—CNN, DNN, Deep Learning, Recognition, Segmentation.

I. INTRODUCTION

In recent years an incredible attention in deep learning has been occurred. Between various deep learning models, CNN is the best well- known algorithm and it is a class of artificial neural network used for computer vision tasks. CNN is use for image analysis, classification, recognition and helps as groundwork for the data analysis. For Image segmentation and its classification an algorithm of machine learning has achieved a good result in CNN. It has accomplished expert-level performances in numerous fields. This paper focus in ideas of CNN and its application to several tasks [1].

II. LITERATURE SURVEY

The set of this literature survey is citing that how the CNN is applied to various fields is mention below. Section I – discuss application of medicine used in bacteria in which appropriate identification as well as classification are important to avoid the occurrence of such life-threatening diseases [2]. Second is Brain tumour, convolutional neural network detects by applying segmentation. Section II –CNN introduces an alternate type of deep learning (DL) applied to agriculture [3]. Section III – presents image analysis and last is Section VI – classify the document layout

A. Medicine

1) Bacteria

Lyme disease, Cholera, Strep throat, Botulism, etc. are several infectious diseases for which Microorganisms such as Bacteria are liable for the infection. Hence, appropriate identification as well as classification are important to avoid the occurrence of bacteria is very much essential. Combination of DCNN with SVM, AI system developed, bacteria are classified from microscopic image samples and perform the operation [2]. Composition of region covariance with CNN presented a model of bacteria recognition. With the use of this model, first stage microscopy segmented input image. Then for recognition of visible bacteria strains microscopic image segments are promoted to CNN [4]. For solving the bacterial colony classification problem, deep neural network architecture is presented [5]. At the cellular level in demand to classify foodborne bacterial species, HMI technology with CNNs to rush the process of data analysis U-Net and 1D-CNN were activated. CNN was proposed for rapid detection [6]. The hybrid approaches like CNN-KNN, CNN- SVM and CNN– Naïve Bayes are offered automatically for bacteria identification[7]. Virulence factors (VFs) computational methods focuses on binary classification with sufficient samples. Though, in real-world scenarios thousands of VF classes are present but some of them has a limited number of available samples. The dataset along with its accuracy is discussed in table-1 [8]. The CNN have achieved exceptional accuracies for object recognition and object classification task, still an enormous number of the iterations generate gambles of stuck getting in local optima which is very much costly to train it. Therefore, to train CNN, some hybrid methods have been developed by using genetic algorithm, particle swarm optimization (PSO) and autoencoders [9]. Use of protein primary sequences only classify directly in any protein sequence [10]

2) Brain-tumor-

Dividing the images into various parts and extracts, the area of interest is "image segmentation." This study involves to analysed segmented part of tumor accurately and efficiently from the image of brain tumor; with the help of CNN model higher risk patients get instant help directly communicate through network to surgeons, clinicians; it highly improves patient health in medical system [11]. Sometimes it becomes very difficult and also time-consuming process, hence it has requirement of automatic tumor image segmentation. Most of the scientists used the clustering algorithms such as fuzzy c- means, kmeans, CNN method, Particle Swarm Optimization (PSO) and Support vector machine, techniques like NSC, k- NN, SRC, K-means is for segmentation and compared all these algorithms for better accuracy [12]. But in computer vision, automatic segmentation and early diagnosis of brain tumor is a stimulating problem [13].

B. Agriculture

Deep learning provides a modern technique in various areas; recently it entered in the domain of agriculture. With the help of other existing techniques CNN is compared, also advantages and disadvantaged are listed. The overall findings indicate that precision and classification accuracy, CNN establishes an auspicious technique with high performance [14]. Plant disease image processing use CNN to get more accurate result [15]. A special focus in agricultural system sensing through AI is on the board. The proposed solution perform germination detection and seeds recognition through the image processing [16]. Next, compare performance of HSI data [17]. The performance of different clustering methods is evaluated [18]. To achieve the production rate, Precision Agriculture is supposed to be solution [19]. CNN Prototype model and transfer learning are proposed and examined it.The DCNN originally designed and automatically explore high level spatial information [20].

C. Image Classification

In computer vision deep learning algorithm trained the CNN model which gives outstanding achievements to identify large scale tasks. The basic structure model, CNN methods like feature extraction, pooling operation and research status are reviewed, also it summarized some problems in current research [21]. At mid-2000, CNNs were inactive in development of computing power and huge amount of labelled data, hence there is a need to focus on application of CNN in classification of image task, that covers from predecessors to successor. By analysing its early success, role in deep learning rebuild, selection of some symbolic works and also various improvements done by contribution and challenges over such publication [22]. The deep architecture GPU implementation of CNN variants accomplish the best results intended for object classification and handwritten digit recognition on benchmarks with respect to error-rates mentioned in table. Simple back-propagation method trained deep nets that performs better narrow ones [23]. For the Improvement of current state of DCNN based image classification pipeline several techniques are examine including additional image transformations towards train data and generate more predictions on testing time, also use complementary models apply to advanced resolution images [24].

D. Document Layout

The method called as fast one-dimensional approach proposed to get automatic document layout analysis seeing its tables, text, figures based on CNN [25]. As compared to a classical bidimensional CNN, this method gives fast execution, more data usage and no loss in overall accuracy. DNN is an effective way to analyse layout of document images. It is trained on dataset i.e., PubLayNet which exactly identify the layout of scientific articles and for transfer learning in different areas it is effective base mode. PublayNet dataset matches XML illustrations automatically and above 1 million content PDF articles are available on PubMed Central™ publicly[26]. Existing deep learning methods do not perform exact and time efficient training for document image classify. Computer Vision is highly motivated, two methods are taken, a deep network is train for feature extraction and classification extreme learning machines (ELMs). These methods compared with a previous CNN based approach (DeepDocClassifier) and outperforms with final accuracy of 83.24%. Hence it is more appropriate for the large-scale real-time applications in deep learning-based document classification[27]. DCNNs is inspired for its toughness and generalization. A novel CNN based technique developed towards exactly to documents localization at real-time. First perfect this problem then all four corners of documents are predictably combining by a DCNN. And last using recursive application of a CNN improve this prediction [28]. Recent Deep Learning architectures completely done to classify document . Extract high-quality text from formatted PDFs becomes challenge in scientific literature removal. To report this, Faster R-CNN use for detection of document layout, contextual information that expand the presentation ofregion detection [29]. Also, for limited accessibility of high- quality region-labels in scientific articles, a novel dataset of region labelled interpretations is contributed. Millions of people in the world uses scripts. Handwritten character recognition studies found in literature [30]. The CNN is most popular for its feature extraction and classification. CNN layer has been trained for solving huge class character recognition problem. And as the corresponding classifier discrete Support Vector Machine (SVM) used. CNN is trained on 50 class bangla basic character database samples; all are described properly in table [31].

III. COMPARE AND ANALYSIS

Table 1 shows the classification of bacteria with respect to its categories like microscopic bacteria, bacterial colony, foodborne bacterial species, diagnosis numerous fatal disease which is caused by bacteria, Protein primary sequences, etc. Apply several methods and found that CNN-produced highest accuracy as mentioned. Next in table 2 classify images in agriculture which helps to identify plant disease, seed recognition, Classification of hyperspectral images, Course clustering. Here also CNN model given highest accuracy i.e., 100% for plant disease identification. Table 3 analysis and review of images has been done. In this table, three columns are created one for model that is to be used for analyzing images, second dataset are taken and in third column error rates are shown.

And in last table i.e., table 4 review of document layout has be done and the table is divided into model, categories dataset, accuracy, error rates. Highest accuracy is found by using model SVM and RCNN.

IV. CONCLUSION

In paper, we have been reviewed applications of the CNN used in various fields and know that there is no proof to check why it performs so well. Instead of our best efforts, the total variety may not capture towards it but still we compared its model with respect to its accuracy. Thus, for the researchers who want to work on the convolution neural network this paper is best for review and then to proceed.

TABLE I. BACTERIA CLASSIFICATION ANDREVIEW

Category	Method	Dataset	Accuracy
Microscopic Bacteria Image classification	V3 DCNN architecture	Seven individual kinds of bacteria	96%
Bacteria recognition	A composition of CNN	Rod and Spherical shape bacteria	highly potential
Bacterial colony classification	DNN	Training phase-6600 images and verification phase-5,940 images	98.22%.
Foodborne bacterial species classification	U-Net and 1D-CNN	Spectral Profiles	1-D -90% k-nearest neighbour- 81% and support vectormachine- 81%
Bacteria causes numerous fatal diseases diagnosis	CNN-SVM, CNN-KNN and CNN– Naïve Bayes	Microscopic Image	98.7%
Bacterial -detection, identification, and antibiotic	Deep learning	Bacterial Raman Spectra	1. Average isolate-level - 82% 2. Antibiotictreatment identification - - 97.0±0.3% 3. Staphylococcus aureus (MRSA and MSSA) - 89±0.1% 4. treatment identification -99.7%
Improved Bacteria Classification	Swarm optimization (PSO), Genetic algorithm, Auto encoders	Images of bacteria and genera (E. coli, Listeria, Salmonella, and Staphylococcus)	CNN trained more efficiently
Protein primary sequence in T4SEs	Deep learning	Multiple Bacterial Species	92.2%.

TABLE II. AGRICULTURE REVIEW

Domain	Dataset used	Accuracy	Model
Identify missing vegetation from crop field	Aerial photos : sugar cane plantation in costa rice	79.2% correct prediction (CA)	VGG model
Plant disease image data	Training data, data validation and testing	100% at 30th iteration	CNN model
Seeds recognition, and germination detection	At different stages images of seed germination process	1.test dataset is 83% 2.validation dataset is 97%	Artificial Intelligence on a Low-Power Embedded Sy
Classification of hyperspectral images (HSIs)	HSI : Salinas Valley	99.8%	1D-CNN
	HSI : Indian Pines	98.1%	
Coarse Clustering and Classification of Images	Tea leaves category of images	Classification accuracy is 93.75%	Clustering methods
Plant Image Recognition and Classification	Using remote sensing techniques, a database of images is collected	average accuracy is 99.58%	Deep-CNN
Classification of four smallholder agricultural landscapes	High Spatial Resolution Satellite Images	Area / Random Forest / CNN2-Avg 1 / 77.26 / 82.40 2 / 70.73 / 77.80 3 / 70.08 / 79.22 4 / 81.15 / 84.94	Deep-CNN

TABLE III. IMAGE ANALYSIS AND REVIEW

Model	Dataset and description	Error rates
CNN	Object classification (NORB, CIFAR10) and handwritten digit recognition	2.53%, 19.51%, 0.35%
CNN	NORB (after 1,3,7 epochs)	2.42%, 0.97% and 0.48%
Pre-trained DCNN	Energy-based unsupervised pre-training	0.60%
DCNN-NN	Dual CNN feature extractor f	0.53%
FitNets	Thin, deep networks with intermediate-level to guide training	0.51%
Stochastic pooling	Stochastic rather than deterministic pooling procedure	0.47%
NIN	MLP combined into DCNN architecture	0.47%
Maxout networks	Max-out activation functions	0.45%
Highway Networks	Learning gate mechanism for regulating DCNN information flow	0.45%
Deeply supervised nets	Companion objective function, feature quality feedback	0.39%
MIM	Max-out network in Max-out network	0.35%
RCNN	Recurrent connections in convolutional layer	0.31%
Tree+Max-Avg pooling	Tree pooling followed by gated average max pooling	0.31%
Batch-normalized MIN	BN, Max-out activations, NIN architecture	0.28%
Multicolumn DCNN	Multicolumn DCNNs with data augmentation (elastic distortions)	0.23%
Drop Connect	Ensemble of Drop Connect networks with data augmentation (no elastic distortions)	0.21%
ILSVRC2013 (Clarifai system)	10 neural networks made up of 5 base models and 5 high resolution models	13.6% and 11.7%(after improvement)
Imagenet Large Scale Visual Recognition Challenge 2013	Add more image transformation data	13.55%

TABLE IV. DOCUMENT LAYOUT AND REVIEW

Method	Category	Dataset	Accuracy	Error reduction
Block based classifi cation method	bi-dimensional baseline	Text, Images, Table	97.19%	N/A
	1-D approach		96.75%	
F-RCNN	Document Layout	Context	23.9%	N/A
F-RCNN	Image	170 training pages	97.2%	N/A
M-RCNN			94%	
Schreiber et al. 2017			97.4%	
Tran et al. 2015			95.2%	
Hao et al. 2016	PDF		97.2%	
Silva 2010			92.9%	
Nurminen 2013			92.1%	
Yildiz 2005			64%	
Deep CNN	Images	Tobacco- 3482 images	83.24%	25%
Recursive application of a CNN	4 Corner Images	ICDAR 2015 SmartDoc Competition 1 dataset	86%	N/A
1]DeepDoc classifier 2]GoogLeNet, VGG, ResNet 3]Transfer learning	400, 000 Docume nts Images	Tobacco-3482	91.13%	60%
		large-scale RVL-CDIP dataset	90.97%	11.5%
Support Vector Machine	Standard 50-class BangIa basic character database	Bangla basic character	95.6%	N/A
		Bangla numeral	98.375%	
		Devanagari Numeral	98.54%	
		Oriya numeral	97.2%	
		Telugu numeral	96.5%	
		English numeral	99.10%	

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