JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

TRANSFER LEARNING MODEL BASED BACTERIA IMAGE CLASSIFICATION

Mehak, Er. Komal Ahuja
Research Scholar, Asst. Professor
Department of Computer Science & Engg.
Global Research Inst. of Management & Technology, Radaur

Abstract- This work presents the concept of bacteria image classification using ResNet and proposed AlexNet based deep learning method. The CNN system has a problem with accuracy, then proposed method is used for improving the system. The fundamental test of picture de-obscuring is to devise effective and dependable calculations for recuperating however much data as could reasonably be expected from the given information. The use of ResNet network in existing system works only for large datasets in system but sometimes it can cause problems in gradient value hence reducing accuracy. But the AlexNet method uses 5 convolutional layers and 3 overlapping layers. Due to this, it helps to improve accuracy of system as compared to other existing methods. Also it uses BM-DNN system to handle RMSE value of network. The use of DNN provides better execution rate as compared to other conventional error minimization methods.

Keywords: *Image Processing, Machine Learning, Deep Learning, Alex Net etc.*

I. INTRODUCTION

The discipline of machine learning (ML) has undergone significant progress during the past few decades. Deep Learning (DL) and Artificial Neural Networks (ANN) in particular have grown in popularity. Some ideas that can be credited to DL have been there since the turn of the century, but for a variety of reasons, the ML community did not give them any credit. With the use of Convolutional Neural Networks (CNNs) to solve image processing issues, it has altered. A learning system called CNN uses convolution to combine data from many computing levels. The input of the system is transformed into the most informative representation in the context of the problem being solved through successive applications of convolution.

Some issues that were thought to be computationally hard to address with ANNs have now become feasible thanks to the development of CNNs and their effective Graphics Processing Unit (GPU) implementations. In parallel, teams using CNNs won a number of image recognition competitions in the 2011–2012 academic years. This generated a great deal of interest in the field of DL. The CNN system, which outperformed other approaches by a wide margin and won the large-scale object identification Image Net competition, is one of the most well-known results from this time period.

Deep learning is currently gaining significant interest across many industries, but particularly in the interpretation of medical images. It is predicted that by 2021, deep learning will account for $300 million of the global market for medical imaging. As a result, by 2021, it will receive on its own more funding for medical imaging than the entire analysis sector did in 2016. The most successful supervised machine learning method is this one. This method uses deep neural network models, a type of neural network that approximates the human brain more closely than simple neural networks by applying advanced mechanisms. The usage of a deep neural network model is implied by the phrase "deep learning." The neuron, a basic computational unit in a neural network that receives multiple input signals as inputs, combines them linearly using weights, and then passes the combined signals via nonlinear operations to produce output signals, is a notion that was inspired by research on the human brain.

The mapping of a set of virtual neurons and the attribution of numerical values or "weights" to the connections between them form the basis of an AI software for feature extraction and categorization. In the iterative learning process used by neural networks, each time a new data vector is provided, the weights attached to the input values are changed. In order to be able to anticipate the right class label of input samples, the network learns throughout the learning phase by modifying the weights. The back propagation technique, which was proposed in the 1980s, is the most widely used Neural Network (NN) training procedure.

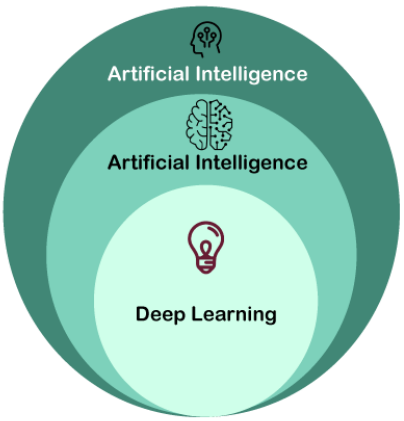


Fig 1: Deep Learning Structure [1]

According to the survey, it is crucial to identify the type of bacteria if a patient has an undiagnosed bacterial infection. However, because it is challenging to identify the type of bacteria using conventional methods, it is crucial to develop a method that quantifies bacteria similarity in order to identify

bacteria species and provide patients with potential medical therapies. In K-Means, the distinction between pixels was ignored, and the measure of comparability was the distance between k-neighbourhoods. The pixels may be nonlocal in this way. Additional investigations will be carried out to uncover additional relevant aspects. It is crucial to identify critical features for bacteria differentiation. To achieve this, it suggests employing trained deep neural networks to classify and analyses a dataset of bacterial images. Other driving methods can be executed with extra ordinary focus using this method.

II. CHALLENGES FOR DEEP LEARNING

The greatest revolutionary advancement in radiology since the introduction of digital imaging may be deep learning technology used for medical imaging. The majority of researchers think that within the next 15 years, deep learning-based apps will replace humans and that intelligent robots will not only do the majority of diagnosis but also aid in disease prediction, prescription of medications, and treatment guidance. Although the idea of using deep learning-based algorithms to analyse medical imaging data is an exciting and developing area of research, there are a number of obstacles standing in the way of its advancement. These difficulties are:

1. Dataset

Deep learning needs a sizable training dataset since the quality and quantity of the dataset have a significant impact on the classification accuracy of the classifier. However, the lack of dataset availability is one of the main obstacles to deep learning's success in medical imaging. On the other hand, developing significant amounts of medical imaging data can be difficult because annotation involves a lot of time from medical professionals and, in order to avoid human mistake, numerous expert opinions are needed.

2. Privacy and Legal Issue

Compared to sharing photographs from the real world, sharing medical data is significantly more sophisticated and challenging. Data privacy is essentially a sociological and technical issue that needs to be approached collaboratively from both vantage points. When privacy is spoken up in the healthcare industry, HIPAA comes to mind. Patients now have legal protections for their personally identifiable information, and healthcare practitioners are now required to safeguard it and limit its use and distribution.

One crucial challenge to deal with is how to communicate sensitive data while restricting disclosure and its distribution by making sure the data has enough utility, i.e. While 0.04% of US citizens have a unique 3-digit Zip code, gender, and birth year, 87% of US citizens have a unique 5-digit Zip code, gender, and birth date. Unfortunately, the limited data access restrictions also lower information content that might be very important.

3. Data Interoperability and Data Standards

One of the main obstacles is the lack of data standards and interoperability. Currently, data types vary from hardware to hardware, leading to significant visual fluctuation caused by sensors and other factors. Additionally, the variety of applications in the medical sector necessitate the combination of multiple distinct datasets for improved algorithm learning and accuracy. Interoperability is the cornerstone of crucial advancements in the health industry, but it still needs to happen. Health data needs to be standardized and shared between providers, much like the ATM network concept. HIPAA, HL7, HITECH, and other health standardization agencies have established some standards and guidelines to attain interoperability level.

4. Black Box and Deep Learning

When it originally started more than a century ago, medical imaging challenged established paradigms. Deep learning algorithms have given fresh life to medical imaging applications and opened up new opportunities. Although it resolves issues that were previously believed to be intractable by machine learning algorithms, deep learning is not without issues. One of the biggest problems is the "black-box problem," which refers to the fact that although the math used to build a neural network is straightforward, how the output was arrived at is incredibly complex. For example, machine learning algorithms take a lot of data as input, search for patterns, and build predictive models, but understanding how the models worked is problematic.

III. RESEARCH METHODOLOGY

Supervised convolutional models have recently irrevocably altered the field of computer vision and machine learning. Convolutional Neural Networks have replaced the conventional matching of manually created low level vision characteristics with complementary classifiers thanks to the recent development of massive supervised datasets and quicker training models employing Graphic Processing Units. Deep feed forward networks, or CNNs, are built around a hierarchy of abstract layers and simultaneously learn the classifier and low level information. Even under challenging situations including posture, scale, and occlusions, it has been demonstrated that these networks perform on par with neurons in the primate inferior temporal cortex. The DNN overcame the gradient problem by substituting a memory cell with long- and short-term nonlinear capabilities for the conventional artificial neuron.

More and more data is being analysed using machine learning, and the complexity of the data being used also rises. The development of deep learning over the past ten years has aided in the development of more effective learning models. The majority of machine learning projects focus on categorization issues.

Learning a feature extractor using machine learning is another method for extracting features from the data. A learning system is constructed to extract features from the input rather than creating a system to categorize some input photographs. This implies that, in the case of images, the network is directly learning higher-level features from the input pixels. For a number of reasons, we think that this strategy is preferable than using custom features. The trained model can be adjusted to many different types of inputs by being trained on each data set, as opposed to handmade features that may need to be hand-tuned for each data set.

In this study, AlexNet is used to analyse a database of bacterial images, and the DNN network system is used to reduce errors. When compared to other conventional networks, using DNN improves network error-reduction capabilities. Because AlexNet is a pretrained model that can handle big picture datasets at once and also produces superior classification results, using it in a system helps to increase accuracy.

AlexNet is a convolutional neural network that is 8 layers deep. It consists of 5 convolutional layers and 3 fully connected layer networks. It can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. The network takes an image as input and outputs a label for the object in the image together with the

probabilities for each of the object categories. The image Data store automatically labels the images based on folder names and stores the data as an Image Data store object. An image data store enables you to store large image data, including data that does not fit in memory, and efficiently read batches of images during training of a convolutional neural network. Divide the data into training and validation data sets. Use 70% of the images for training and 30% for validation. The network requires input images of size 227-by-227-by-3, but the images in the image data stores have different sizes. Use an augmented image data store to automatically resize the training images. Multiple Convolutional Kernels (filters) extract interesting features in an image.

In a single convolutional layer, there are usually many kernels of the same size. The first two Convolutional layers are followed by the Overlapping Max Pooling layers that we describe next. The third, fourth and fifth convolutional layers are connected directly. The fifth convolutional layer is followed by an Overlapping Max Pooling layer, the output of which goes into a series of two fully connected layers. The second fully connected layer feeds into a Softmax classifier with 1000 class labels. ReLu nonlinearity is applied after all the convolution and fully connected layers. The ReLu nonlinearity of the first and second convolution layers are followed by a local normalization step before doing pooling. But researchers later didn't find normalization very useful.

A collection of bacterial images is used in the suggested system model to analyse the effectiveness of deep neural networks. Initial training and test datasets are used, and the same datasets are then subjected to pre-processing.

In order to increase system accuracy, feature extraction is conducted to images and then trained using previously learned deep neural networks. However, it results in some RMSE values that the DNN system reduces. At the destination, the final output is displayed. The data pre-processing block improves the amount and quality of the data as well as corrects difficulties with overfitting and dataset imbalances.

First, to conform to the expected input of the model, the input images to be recognized were scaled from their original dimensions to 224*224, and the number of channels was set at three. Then, to artificially boost the quantity of photos for the training process, data augmentation was used. Finally, three sets: training, validation, and testing were created from the newly acquired datasets.

IV. RESULTS & DISCUSSION

This work provides the concept of bacteria image classification and analysis using advanced deep neural networks. The use of deep learning provides the better accuracy as compared to existing machine learning techniques. This work is studied on Bacteria dataset in which three types of datasets with 20 images are used for implementation as shown. Also it provides results with flower databased for comparison and performance measurement. The input images from each dataset is shown in Fig 2. It is used for further processing.

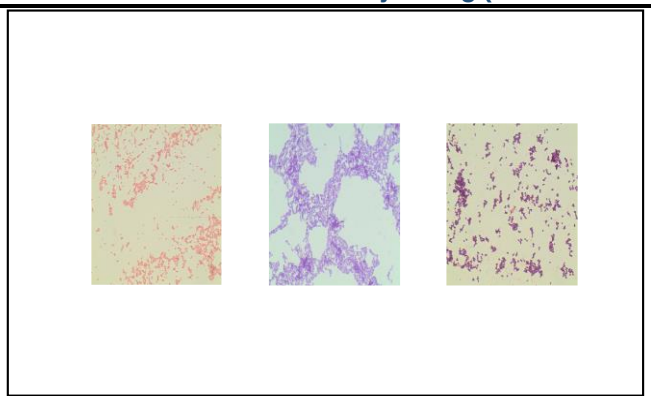


Fig 2: Input Images from Database

This work provides the results using bacteria database with pretrained models in DNN. While CNN has only 2 convolutional layers and AlexNet has 5 convolutional layers in system, Resnet has hundreds of convolutional layers in network. This deep neural architecture is going further and becomes more and more complex especially for image databases. The increase in depth can cause a problem for training more databases together due to increase in stacking layers. For this, its performance gets slightly decreased as compared to other networks. This Resnet network has more complexity as compared to other networks. The results are shown. The classified output using network is shown in Fig 4.4. It provides single predicted output with accuracy of 96%.

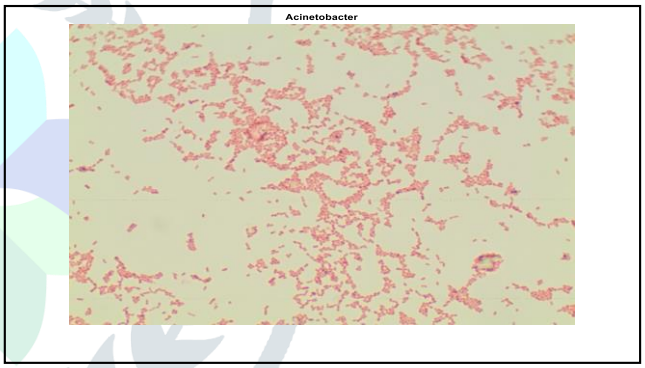


Fig 3: Classified Bacteria Image Output using ResNet

The CNN framework objects to precision, at that point proposed technique is utilized for improving the framework. This work portrays the execution of two more profound variations, in particular with 2 and 5 convolutional layers. The 2-layer design has two sequential layers, after this a shrouded layer and delicate max activity is performed. The 3-layer design has an extra convolutional + pooling layer before the covered up and delicate max ones.

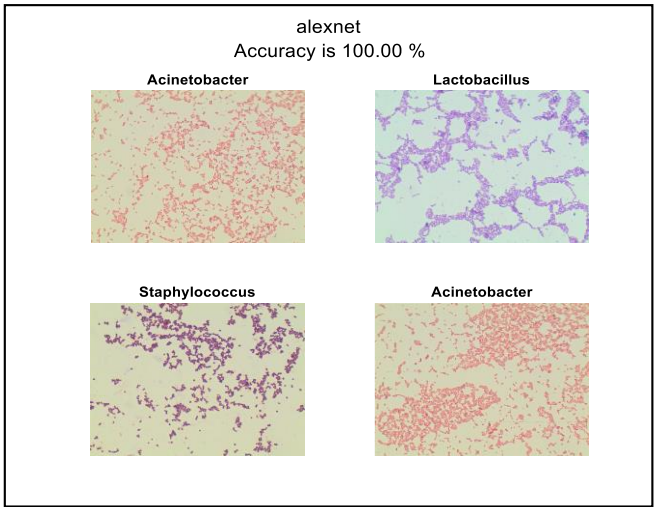


Fig 4: Classified Bacteria Output using Proposed Method

Table 1 shows the performance comparison of system. It shows that performance of AlexNet is better than ResNet in terms of accuracy parameters.

Table 1: Performance Comparison of System

Parameters	RESNET	Proposed (AlexNet DNN)
Accuracy	96%	99%
RMSE	0.07	0.01

V. CONCLUSION

This work presents the concept of bacteria image dataset analysis using advanced deep learning method. The conventional CNN system has a problem with accuracy, then proposed method is used for improving the system. The fundamental test of picture identification is to devise effective and dependable calculations for recuperating however much data as could reasonably be expected from the given information. It overlooked the separation among pixels and likeness was given as the separation between k-neighbourhoods. The use of PCA method provides only identification of features in images but it does not help to improve accuracy of system. The use of ResNet network in existing system works only for large datasets in system but sometimes it can cause problems in gradient value hence reducing accuracy. It is because of large number of convolutional layer networks that increase complexity of system. Due to this, it requires better deep learning method for improving accuracy of system. The CNN method uses only 2 convolutional layers for feature mapping. But the proposed method uses 5 convolutional layers and 3 overlapping layers. Due to this, it helps to improve accuracy of system as compared to other existing methods. Also it uses BM-DNN system to handle RMSE value of network. The use of DNN provides better execution rate as compared to other conventional error minimization methods.
In future, it can work for more databases for medical purposes for image classification.

REFFERENCES

[1] D. Linden and T. B. Reddy. Handbook of Batteries. *McGraw-Hill Professional: New York*, 2002.

[2] R. Hartley and A. Zisserman. Multiple View Geometry in Computer Vision. *Cambridge University Press*, second edition, 2003.

[3] Sivaramakrishnan Rajaraman, Jen Siegelman, "Iteratively Pruned Deep Learning Ensembles for COVID-19 Detection in Chest X-rays", *IEEE Access Journal*, 2020, pp.01-11.

[4] Muhammad Sharif, Javaria Amin, Ayesha Siddiqa, "Recognition of Different Types of Leukocytes using YOLOv2 and Optimized Bag-of-Features", ", *IEEE Access Journal*, 2020, pp.01-17.

[5] TreesukonTreebupachatsakul, SuvitPoomrittigul, "Bacteria Classification using Image Processing and Deep learning", *IEEE Access Journal*, 2019, pp.01-03.

[6] Wamiq M. Ahmed, Bulent Bayraktar, Arun K. Bhunia, "Classification of Bacterial Contamination Using Image Processing and Distributed Computing", *IEEE Journal Of Biomedical And Health Informatics*, Vol. 17, No. 1, January 2013.

[7] Siddharth Singh Chouhan, Ajay Kaul, "Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards Plant Pathology ", *IEEE Access Journal*, 2018, pp.01-12.

[8] Changming Du, Jun Tang, Jianmin Mo, "Decontamination of Bacteria by Gas–Liquid Gliding Arc Discharge: Application to Escherichia coli", *IEEE Transactions on Plasma Science*, Vol. 42, No. 9, September 2014, pp. 2221-2228.

[9] Ahmed Karam Eldaly, Yoann Altmann, "De-convolution and Restoration of Optical Endomicroscopy Images", *IEEE Transactions on Computational Imaging*, 2018, pp. 01-12.

[10] Baosu Guo , Jichao Zhuang, "Color Difference Detection of Polysilicon Wafers

[11] Using Optimized Support Vector Machine by Magnetic Bacteria Optimization Algorithm With Elitist Strategy", *IEEE Transactions on Semiconductor Manufacturing*, Vol. 33, No. 2, May 2020, pp. 267-282.

[12] Stefan Jaeger, Alexandros Karargyris, "Automatic Tuberculosis Screening Using Chest Radiographs", *Automatic Tuberculosis Screening Using Chest Radiographs*, 2014, pp.01-13.

[13] Soo-Yeon Ji, Dong Hyun Jeong, "Signature Infrared Bacteria Spectra Analyzed by an Advanced Integrative Computational Approach Developed for Identifying Bacteria Similarity", *IEEE Journal of Selected Topics In Quantum Electronics*, Vol. 25, No. 1, 2019.

[14] Muhammad Burhan Khan, Humaira Nisar, "Image Processing and Analysis of Phase-Contrast Microscopic Images of Activated Sludge to Monitor the Wastewater Treatment Plants", *IEEE Access Journal*, 2017, pp.01-14.

[15] A. J. Moreno,E.Gonzalez, "Spatial Resolution in Micrometric Periodic Assemblies of Magnetotactic Bacteria and Magnetic Nanoparticles", *IEEE Transactions on Magnetics*, Vol. 49, No. 8, August 2013, pp. 4572-4575.

[16] Toshio Moriya, Kazuhiro Mio, "Novel convergence-oriented approach for evaluation and optimization of workflow in single-particle two-dimensional averaging of electron microscope images", *Oxford University Press*, 2013, pp.491-514.