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One Shot Cluster based Approach for the Detection of COVID -19 from Chest X–Ray Images

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Abstract

Corona virus disease (COVID-19) has infected over more than 10 million people around the globe and killed at least 500K worldwide by the end of June 2020. As this disease continues to evolve and scientists and researchers around the world now trying to find out the way to combat this disease in most effective way. Chest X-rays are widely available modality for immediate care in diagnosing COVID-19. Precise detection and diagnosis of COVID-19 from these chest X-rays would be practical for the current situation. This paper proposes one shot cluster based approach for the accurate detection of COVID-19 chest x-rays. The main objective of one shot learning (OSL) is to mimic the way humans learn in order to make classification or prediction on a wide range of similar but novel problems. The core constraint of this type of task is that the algorithm should decide on the class of a test instance after seeing just one test example. For this purpose we have experimented with widely known Generalized Regression and Probabilistic Neural Networks. Experiments conducted with publicly available chest x-ray images demonstrate that the method can detect COVID-19 accurately with high precision. The obtained results have outperformed many of the convolutional neural network based existing methods proposed in the literature.

1 Introduction

The world has witnessed over 10 million cases and 500K deaths due to Corona Virus disease (COVID-19) outbreak as of 30 June 2020 [1]. With this pandemic, to combat the spreading of COVID-19 effective testing methodologies and immediate medical treatment is much required one to know. Clinical symptoms analysis and radiography images (CT/Chest X-ray) are other diagnosis tools of COVID-19. In radiography images, the early stages have features including bilateral, multi-focal, posterior distribution and pulmonary consolidation in the late stage. One of the major challenges with typical x-ray images is categorizing with various viral pneumonia and COVID-19 since they have similar features. It is quite difficult for radiologists to distinguish COVID-19 from other viral pneumonias which can sometimes lead to wrong diagnosis. This may lead to a non-COVID viral pneumonia being falsely labeled as highly suspicious of having COVID-19. Recently, researchers are now focusing on developing some AI models to overcome the issues and some significant discoveries are also revealed in imaging studies of COVID-19. Study on classifying and detecting the presence of pneumonia based on a ConvNet model [2,3]. For early diagnosis of pneumonia chest X-ray images based on Xception and VGG16 is proposed in [4]. Experimented suggested that VGG-16 network performed better than X-ception network. ConvNet models followed by different classifiers for the detection of normal and abnormal pneumonia X-rays images is addressed in [5]. COVIDX-Net model comprising of seven CNN models to diagnose COVID-19 is proposed in [6]. COVID-Net [7] a deep model in classifying normal, non-COVID pneumonia, and COVID-19 is reported. A Detection Model based on GAN and Deep Transfer Learning is proposed in [8]. Three deep transfer models, such as Alexnet, Googlenet, and Restnet18 were selected for investigation. Machine Learning (ML) algorithms are utilized to understand the patterns from the data. In these days, researchers are employing ML in a variety of tasks including biological data mining [9,10], image analysis [11], financial forecasting [12], anomaly detection [13–15], disease detection [16,17], natural language processing [18,19], assay detection [20]. More recent studies on COVID-19 detection that employed various ML algorithms, in particular, deep learning (DL) models can be seen in the literature [21]. These algorithms for detection / classification requires huge amount of data and more we have better the results. It is sometimes difficult to get more data due to limitations exists in particular fields, thus it will be more convenient to learn from few examples / data. The objective of one shot learning is to mimic the way humans learn in order to make classification or prediction on a wide range of similar but novel problems. The core constraint of this type of task is that the algorithm should decide on the class of a test instance after seeing just one test example. The main contributions of this work are:

- Humans have demonstrated the ability of learning object categories at a rapid pace from few examples. Hence, the idea of one shot cluster based approach is introduced for this purpose.
- Since, requirement of huge training examples and learning time is much difficult in the early appearance of medical field, the advantage of one shot learning will help us to solve the problem using ensemble of efficient classifiers.
- Experimenting and analyzing COVID-19 chest x-ray images is of lot importance in the current pandemic.

2 Proposed Pipeline

2.1 One Shot Learning and Feature Representation

The need for one-shot learning is obliviated by following key considerations: (a). *Human Learning element – Learning to Learn*: Learning in humans happens with few examples. Humans can relate new concepts to already learned concepts thereby enriching their domain knowledge. (b). *Scalability constraints with deep learning*: Deep Learning has definitely set new benchmarks in performance for specific learning tasks like object recognition, language understanding & machine translation. However, these algorithms need millions of training examples to build their intelligent behaviour. (c).

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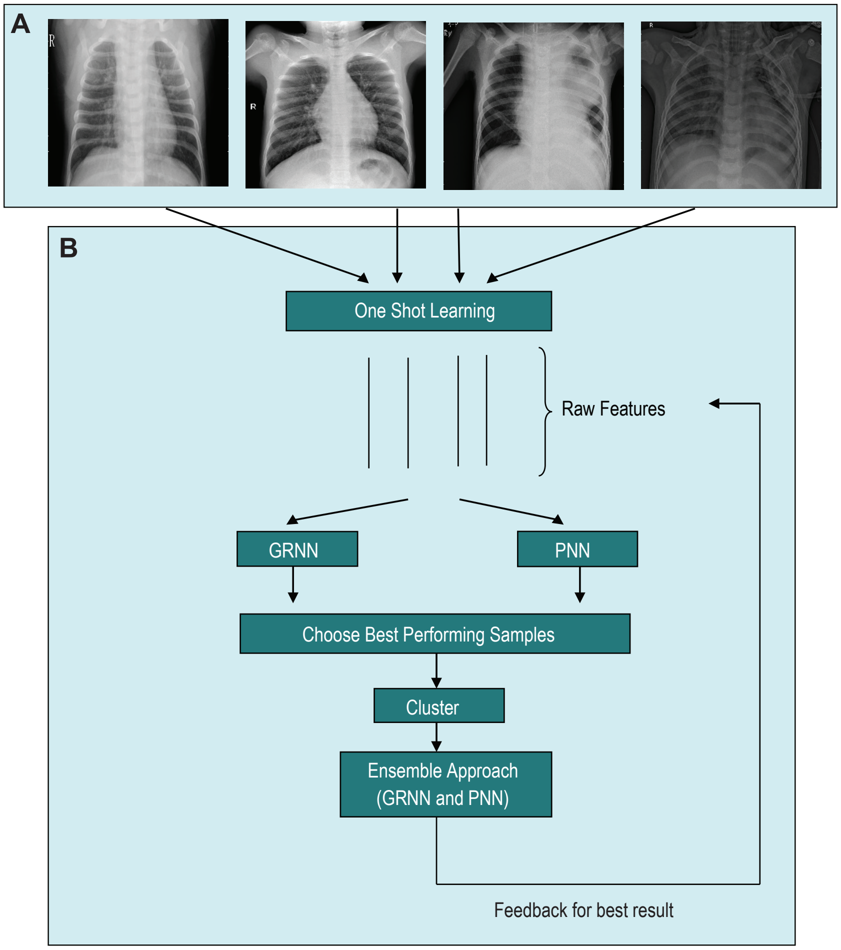

Figure 1. Block diagram of the proposed one shot based COVID-19 detection pipeline.

Domains with sparse data: In certain domains, availability of millions of data points for training the model is a challenge. In such applications, getting large number of training examples has practical constraints and recognition needs to be performed with only a few available data points. For N-way K-shot learning, suppose we are given with a set of labeled images, $S_{Label} = \{(Xi, Yi)\}_{(i=1)}^{(N\times K)}$, where X_i is the image, $Y_i \in$ class set, N is the number of classes in S_{Label} and K is the number of images per class in S_{Label}. For one-shot learning, $K = 1$. Features are raw data (gray values) of the images, which is standardized to 100×100. Figure 1 shows the block diagram of the proposed model.

2.2 Neural Network based Classifiers

Artificial Neural Networks (ANNs) are considered to be one of the important parts of Artificial Intelligence (AI) and with wide range of applications including, regression, forecasting and prediction, classification, and many more. ANNs are useful since they can learn from the data and they have global approximation abilities. In recent past, Generalized Regression Neural Networks (GRNN) and Probabilistic Neural Network (PNN) have shown in wide range of applications to solve real world problems. As the weights of these networks can be calculated analytically, GRNN are variants of the Radial Basis Functions (RBF) network. GRNN uses a Gaussian activation function in the hidden layer and its a single pass network, which consists of input, hidden, summation and output layers. The number of input units depends on the total number of observation parameters i.e. an input vector I (feature matrix F_i). The input layer connected to the pattern layer consists of neurons provides training patterns and its output to the summation layer to perform normalization of the resultant output set. Each of the pattern layers is connected to the summation neurons and calculates the weight vector using the following equation 1.

$$F(I) = \frac{\sum_{i=1}^{n} T_i W_i}{\sum_{i=1}^{n} W_i}, \quad \text{with} \\ W_i = e^{\left[\frac{||I-I_t||^2}{2h^2}\right]}. \tag{1}$$

On the other hand, PNN is also a four-layer neural system, which is influenced by the Bayesian network. This approach has been studied well from the decades (1960s). As it models the Bayesian classifier and misclassification rate is minimized. Bayes' classifier is usually criticized due to lack of information about the class probability distributions and makes use of nonparametric techniques, whereas the inherent advantage of PNN is the better generalization and convergence properties when compared to that of Bayesian classifier in classification problems [22]. PNN is similar to that of supervised learning architecture, but PNN does not carry weights in its hidden layer. Each node of hidden layer acts as weights of an example vector. The hidden node activation is defined as the product of example vector E and input feature vector F given as $h_i = E_i \times F$. The class output activations are carried out using the following equation 2:

$$S_j = \frac{\sum_{i=1}^{n} e^{\frac{h_i - 1}{\phi^2}}}{N} \tag{2}$$

where N is example vectors belonging to class S, h_i is hidden node activation and ϕ is smoothing factor. PNN have some advantages compared to other neural architectures. PNN networks usually faster to train, often more accurate and relatively insensitive to outliers. As PNN approaches Bayes classification thus predicates accurate target probability scores. In order to take the advantage of ensemble process, in this work we have combined the results obtained from GRNN and PNN models to solve classification problem. The classifiers can then be combined using one of several different combination rules such as abstract level, rank level and measurement level. In this work, we have used simple majority voting based method for which always lead to a performance improvement.

2.3 Dataset

Experiments are performed on a publicly available dataset, created by Joseph Cohen, containing COVID-19 x-ray images [23]. The dataset is composed of training and testing. Further it has divided into four categories namely COVID-19, normal, pneumonia bacterial and pneumonia virus. In each class the number of samples considered are total of 306, with a break-down of 69, 79, 79, and 79, respectively.

3 Experimentation and Comparative Analysis

The proposed model was implemented in Matlab with Intel Core i7 − 6700 @3.4 GHz and 8GB RAM. We have conducted three types of experiment. First we have considered 2 classes (COVID-19 and Normal), second type of experiment is conducted using 3 classes (COVID-19, normal and pneumonia bacteria), lastly using 4 classes (COVID-19, normal, pneumonia bacteria and pneumonia virus). Total of 306 x-ray images were

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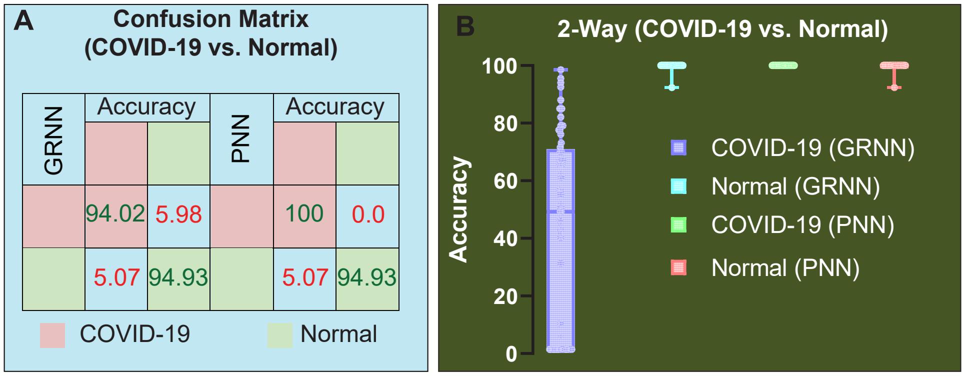

Figure 2. A. Confusion Matrix for 2 Clasess using GRNN and PNN approaches. B. Detection accuracy of GRNN and PNN under COVID-19 and Normal cases. The box plots are filled with accuracy of individual samples and the whiskers denote the maximum and minimum values.

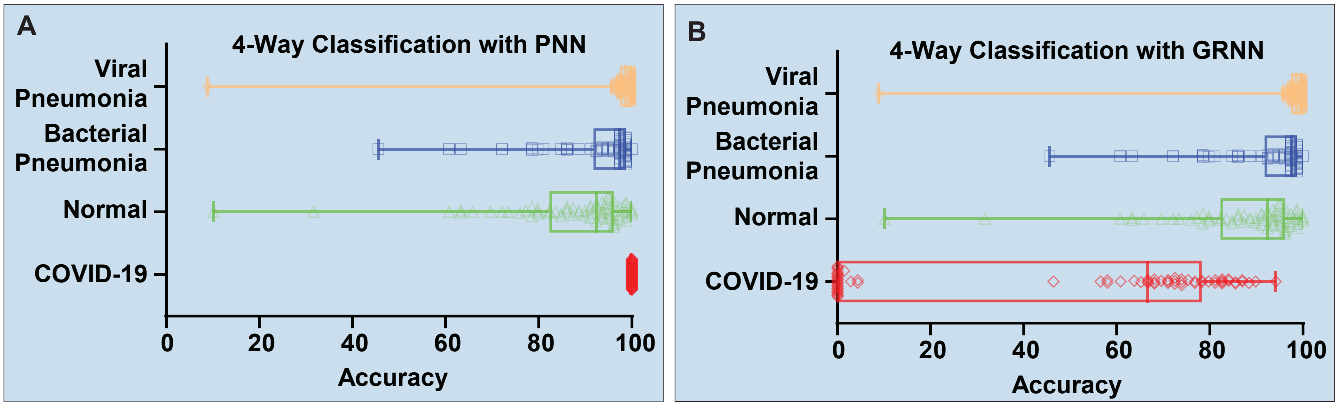

Figure 3. Box plots showing detection accuracy under all the classes. The whiskers show the minimum and maximum ranges with the small shapes embedded within each box denotes the individual values. The vertial line within the box denotes the mean detection accuracy. The left subfigure (A) is for PNN and the right one (B) is for GRNN.

considered for the experiment purpose. We have randomly selected one image in each category for training purpose and rest of the images are used for testing purpose. Figure 2 shows the detection accuracy for 2 class considered using GRNN and PNN approach. It is quite evident that the proposed approach performs very well when only one shot (one image) is considered for training.

It is very much necessity to test how each image contributes for the success. In this regard, we used leave out one method, where every time one image will be considered for training and remaining images in the database will be used for testing purpose. Figure 2(b) shows the accuracy of the proposed GRNN and PNN approaches for both the cases, i.e., COVID-19 and Normal. These figures gives insight on how each sample contributes for the success of result. It is noted from the figure that when sample numbers 2, 13, 25 and 50 are used for training under GRNN for COVID-19 case, we achieve maximum accuracy (i.e., more than 90%). This will enrich the knowledge and helps us in designing our model better. Whereas in normal case, apart from first sample, all the samples achieves 100% when train. Whereas PNN outperforms well compared to GRNN approach and archives 100% result.

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As the class size increases analyzing the performances of the models are crucial. The second type of experiment is working with all the classes and we are much interested to see the performance behavior when considered. We have conducted the experiment in the similar manner as two class. Figure 3 shows the detection accuracy for GRNN and PNN approaches under all the cases. It is very interesting to see how each image in the database contributes for the detection accuracy. Even the class size been increased to 4, the proposed approach is able to perform well. It is observed that some of the images are not perform well when used for training. For other three cases it is interesting on how the images contributes for the success. Whereas in case of PNN approach, the results are better compared to GRNN. By noting figures 3(a) and 3(b), we can cluster images that have performed well in the experiment.

Table 1. Performance accuracy of the proposed and existing deep models for 2, 3 and 4 classes

Methods	Class	COVID-19	Normal	Pneu. Bac.	Pneu. Vir	Average	Train	Test
Alexnet [31, 32]	2	**100**	**100**	–	–	**100**	130	18
	3	**100**	77.7	77.8	–	85.1	200	27
	4	**100**	64.3	44.4	50	64.67	270	36
Googlenet [31, 34]	2	**100**	**100**	–	–	100	130	18
	3	81.8	75	87.5	–	81.4	200	27
	4	**100**	**100**	70	66.7	84.0	270	36
Resnet18 [31, 33]	2	**100**	**100**	–	–	100	130	18
	3	100	100	64.3	–	81.4	200	27
	4	100	100	50	40	72.5	270	36
Proposed Method	2	**100**	**100**	–	–	**100**	**02**	**148**
			Cluster 1 (3 Samples)					
	3	100	63.29	72.15	–	78.45	3	227
			Cluster 2 (5 Samples)					
	3	100	78.48	75.94	–	84.8	5	227
			Cluster 3 (6 Samples)					
	3	**100**	**100**	**70.8**	–	**90.2**	**6**	**227**
			Cluster 1 (4 Samples)					
	4	100	60.7	58.2	22.7	60.42	4	306
			Cluster 2 (7 Samples)					
	4	100	70.8	73.4	39.2	70.85	7	306
			Cluster 3 (9 Samples)					
	4	100	98.7	51.89	46.01	74.12	9	306
			Cluster 4 (12 Samples)					
	4	100	77.2	64.5	78.7	80.05	12	306
			Cluster 5 (16 Samples)					
	4	**100**	**100**	**82.27**	**54.4**	**84.17**	**16**	**306**

3.1 Cluster Approach

This section highlights very important aspect of this work, where we cluster samples that performed well in our training phase. From the Fig. 3, it is quite evident that the results obtained from the GRNN and PNN have bit of variations. Most of the samples have given good performance for COVID-19, Pneumonia Bacteria and Pneumonia Virus under PNN approach. Considering these variations we have selected the best performing samples for our next level of detection process. We started with clustering one sample for each class and selection of samples are done based on the performance obtained. Table 1 shows the detection accuracy for the samples considered under all the classes using ensemble approach. From the Table 1 it is evident that the proposed idea with only 2 samples (one from each class) we were able to achieve 100% detection rate and the same has been compared with well-known deep learning models such as AlexNet [24], GoogLeNet [25] and ResNet [26]. The compared models use 130 samples for training and 18 for testing.

Table 1 also shows the performance for 3 classes. Initially we tried with training one sample from each class and tested our ensemble approach and an average of 78.45% accuracy was achieved. Our experiment was continued with adding one more samples for class 2 and 3 and an average of 84.8% detection accuracy was reported. Our interest is to improve the accuracy of class 2 i.e., Normal case. In this connection we added one more sample from class 2 and total of 6 samples were considered in cluster 3. The proposed method outperformed well known existing approaches and achieved an average of 90.2% with 100% under COVID-19 and Normal cases.

Finally, we tested our approach on 4 classes and Table 1 shows the performance accuracy. We started with one sample from each class and total of 4 samples were considered for training. An average detection rate of 60.42% was achieved and the detection rate for pneumonia virus is very less compared to others. We continued our clustering approach by adding few more samples to the existing considered. We added one more samples for the class 2, 3 and 4 and total of seven samples were considered for our next experiment. From the Table 1, it is quite evident that detection accuracy is improved with 10%. However, detection rates of Pneumonia virus and Normal can still be improved. We added one sample from class 2 and 4 and total of 9 samples were considered for experiment. From the results it is evident that the results of normal class is significantly improved whereas accuracy of pneumonia virus has come down. Samples of class 3 and 4 are very similar and that is the case for both virus and bacteria class results are not upto the mark. Cluster 4 with 12 samples achieved overall average of 80.02 with significant improve in class 4. Finally, cluster 5 with 16 samples we were able to achieve an average of 84.17%. Certainly the proposed idea of one shot with cluster approach has considerable impact when compared to existing deep learning models.

4 Conclusion

This paper address one shot cluster based approach for efficient classification of COVID-19 chest x-ray images. The main objective was to study the ability of learning image categories at a fast pace and with less sample size. For this purpose we tested our model with COVID-19 chest x-ray images. For the various advantages the application of GRNN and PNN was introduced in this study and experimented with publicly available dataset. The introduction of one shot cluster approach is the first of its kind in the literature and outperformed well known deep models with very less training samples. This is an initial effort in understanding the behavior of the existing neural network models. There is still long run exists to understand and analyze the models in different applications of computer vision and pattern recognition.

Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Authors and Contributors: This work was carried out in close collaboration between all co-authors. VNMA first defined the research theme and contributed an early design of the system. VNMA and MM further implemented and refined the system development. VNMA and MM wrote the paper. All authors have contributed to, seen and approved the final manuscript.

Ethical Approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent: Informed consent was obtained from all individual participants included in the study.

References

1. Worldometers. Worldometers, editor. Coronavirus Update (Live): 10,409,239 Cases and 508,084 Deaths from COVID-19 Virus Pandemic - Worldometer. Worldometers; 2020. Accessed: 30 June 2020. Available from: https://www.worldometers.info/coronavirus/.
2. Kermany DS, Goldbaum M, Cai W, Valentim CC, Liang H, Baxter SL, et al. Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell. 2018;172(5):1122–1131.
3. Stephen O, Sain M, Maduh UJ, Jeong DU. An efficient deep learning approach to pneumonia classification in healthcare. Journal of healthcare engineering. 2019;2019:4180949.
4. Bhandary A, Prabhu GA, Rajinikanth V, Thanaraj KP, Satapathy SC, Robbins DE, et al. Deep-learning framework to detect lung abnormality–A study with chest X-Ray and lung CT scan images. Pattern Recognition Letters. 2020;129:271–278.
5. Jaiswal AK, Tiwari P, Kumar S, Gupta D, Khanna A, Rodrigues JJ. Identifying pneumonia in chest X-rays: A deep learning approach. Measurement. 2019;145:511–518.
6. Hemdan EED, Shouman MA, Karar ME. Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images. arXiv preprint arXiv:200311055. 2020;.
7. Wang L, Wong A. COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-Ray Images. arXiv preprint arXiv:200309871. 2020;.
8. Loey M, Smarandache F, M Khalifa NE. Within the Lack of Chest COVID-19 X-ray Dataset: A Novel Detection Model Based on GAN and Deep Transfer Learning. Symmetry. 2020;12(4):651.

9. Mahmud M, Kaiser MS, Hussain A, Vassanelli S. Applications of Deep Learning and Reinforcement Learning to Biological Data. IEEE Trans Neural Netw Learn Syst. 2018 Jun;29(6):2063–2079.

10. Mahmud M, Kaiser MS, Hussain A. Deep Learning in Mining Biological Data. arXiv:200300108 [cs, q-bio, stat]. 2020 Feb;p. 1–36. ArXiv: 2003.00108. Available from: http://arxiv.org/abs/2003.00108.

11. Ali HM, Kaiser MS, Mahmud M. Application of Convolutional Neural Network in Segmenting Brain Regions from MRI Data. In: Liang P, Goel V, Shan C, editors. Brain Informatics. Cham: Springer; 2019. p. 136–146.

12. Orojo O, Tepper J, McGinnity TM, Mahmud M. A Multi-recurrent Network for Crude Oil Price Prediction. In: Proc. SSCI; 2019. p. 2940–2945.

13. Yahaya SW, Lotfi A, Mahmud M, Machado P, Kubota N. Gesture Recognition Intermediary Robot for Abnormality Detection in Human Activities. In: Proc. SSCI; 2019. p. 1415–1421.

14. Yahaya SW, Lotfi A, Mahmud M. A consensus novelty detection ensemble approach for anomaly detection in activities of daily living. Applied Soft Computing. 2019;83:105613.

15. Fabietti M, Mahmud M, Lotfi A, Averna A, Guggenmo D, Nudo R, et al. Neural Network-based Artifact Detection in Local Field Potentials Recorded from Chronically Implanted Neural Probes. In: Proc. IJCNN; 2020. p. 1–8.

16. Noor MBT, Zenia NZ, Kaiser MS, Mahmud M, Al Mamun S. Detecting Neurodegenerative Disease from MRI: A Brief Review on a Deep Learning Perspective. In: Liang P, Goel V, Shan C, editors. Brain Informatics. Cham: Springer; 2019. p. 115–125.

17. Miah Y, Prima CNE, Seema SJ, Mahmud M, Kaiser MS. Performance Comparison of Machine Learning Techniques in Identifying Dementia from Open Access Clinical Datasets. In: Proc. ICACIn. Springer, Singapore; 2020. p. 69–78.

18. Rabby G, Azad S, Mahmud M, Zamli KZ, Rahman MM. TeKET: a Tree-Based Unsupervised Keyphrase Extraction Technique. Cogn Comput. 2020;12:811–833.

19. Watkins J, Fabietti M, Mahmud M. SENSE: a Student Performance Quantifier using Sentiment Analysis. In: Proc. IJCNN; 2020. p. 1–6.

20. Tania MH, et al. Assay Type Detection Using Advanced Machine Learning Algorithms. In: Proc. SKIMA; 2019. p. 1–8.

21. Dey N, Rajinikanth V, Fong SJ, Kaiser MS, Mahmud M. Social-Group-Optimization Assisted Kapur's Entropy and Morphological Segmentation for Automated Detection of COVID-19 Infection from Computed Tomography Images. Cogn Comput. 2020;p. 1–12. Available from: https://doi.org/10.1007/s12559-020-09751-3.

22. Specht DF. Probabilistic neural networks. Neural networks. 1990;3(1):109–118.

23. Cohen JP, Morrison P, Dao L, Roth K, Duong TQ, Ghassemi M. COVID-19 Image Data Collection: Prospective Predictions Are the Future. arXiv preprint arXiv:200611988. 2020;.

24. Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. In: Advances in neural information processing systems; 2012. p. 1097–1105.

25. Aswathy P, Mishra D, et al. Deep GoogLeNet Features for Visual Object Tracking. In: Proc. ICIIS. IEEE; 2018. p. 60–66.

26. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 770–778.