International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Artificial Intelligence-Based Pneumonia Detection via Chest X-Ray – A State-of-the-Art Review

Neelkant Newra[1], Lingamgunta Saikumar[2], Saurabh Gupta[3], Sumit Kumar Banchhor*[4]

Submitted: 12/11/2022 **Accepted:** 14/02/2023

Abstract: Artificial intelligence (AI) has emerged as a useful tool for early detection of pneumonia disease in the lungs using chest X-ray (CXR). For pneumonia detection different machine learning, deep learning, and transfer learning algorithms are used but a detailed review comparing the dataset with literature is lacking. This review paper first briefly summarizes different AI-based algorithms on classification, regression, and clustering. Then a detailed comparison of current literature on the ground of different reliable datasets and techniques are presented. Lastly, major challenges faced over the last few years are discussed with their future scopes. Our main objective is to provide a state-of-the-art review of the AI studies detecting pneumonia disease in CXR using data comparison and find the limitations to make suggestions for practitioners.

Keywords: *Artificial intelligence, pneumonia, chest X-ray, machine learning, deep learning, transfer learning, state-of-the-art.*

1. Introduction

Severe pneumonia is a life-threatening bacterial disease caused by the streptococcus pneumonia bacterium that affects one or both lungs in humans [1-3]. According to Walton-Roberts and Rajan's report [4], there is a rise in the global demand for the medical profession currently fulfilled by acute domestic healthcare workers. Due to the shortage of health care profession, it is really hard to tackle the fatalities caused by Pneumonia [5, 6]. According to the World Health Organization, pneumonia is responsible for one out of every three fatalities in India (WHO) [7]. A report confirms the death of 740,180 children under the age of 5 in 2019 [8] and the mortality rate will be even worse if it is not diagnosed early [9]. Many imaging modalities are used by physicians for the early diagnosis of pneumonia.

Although it is quite difficult to make a reliable decision compared to imaging techniques like CT or MRI, due to cost and other factors, chest X-ray (CXR) is generally preferred by doctors for various diagnostic purposes [10]. By studying CXR images, radiologists can also identify pleurisy, pneumonia, nodule, effusion, atelectasis, pericarditis, cardiomegaly, pneumothorax, and many other disorders and diseases [11]. Physicians can diagnose CXR more quickly and precisely with a computer-aided diagnosis (CAD) [12]. Using CAD, chest disorders can be observed as cavitation, infiltrations, blunted phrenic angles, and tiny, wide-spread nodules [13, 14] on CXR pictures. To avoid the limitations of CAD such as feature extraction and feature selection researchers usually favor Artificial Intelligence (AI) based solutions.

As it is now simpler to train a computer using the vast quantity of data created every day by numerous sources and applications [15] [16, 17], AI is a compilation of intelligence that has been created artificially. AI is a broad term and is sometimes related to machine learning (ML) and deep learning (DL). To be precise, AI is the broad term or class which has ML as its subclass and DL as a sub-subclass [18, 19]. To understand the techniques used for pneumonia detection using chest X-rays, an understanding of AI-based algorithms is desirable. A discussion of classification, regression, and clustering algorithms is presented below:

1.1. Classification algorithms

Classification algorithms are mostly part of the supervised algorithm where it divides a broad class into subclasses. Based on that subclass, the new data class is predicted. Some of the classification algorithms widely used are NavieBayes, Decision Tree, Support Vector Machine (SVM), Random Forest, and K Nearest Neighbour (KNN). A brief discussion of these algorithms are presented below:

1.1.1. Navie Bayes

The Naive Bayes technique is a probabilistic-based methodology based on the Bayes theorem [20]. Each class is assigned with a probability which is updated when the data is fed inside the algorithm. The newly updated probability is known as a posterior probability. This

[1,2,3,4]*Department of Biomedical Engineering, National Institute of Technology, Raipur, C.G., India*
** Corresponding Author Email: skbanchhor.bme@nitrr.ac.in*
ORCID ID: 0000-0003-0406-7184

posterior probability is now used to select the class for the data. [21, 22].

1.1.2. Decision Tree

It is like a flowchart structure where nodes represent the test and leaves represent the result or outcomes [23]. It is like an if-else statement where the model learns by taking decisions to move on which branch. They are simple to interpret but sometimes they create an over-completed tree that is not generalized for other data and can be a cause of overfitting. [24, 25].

1.1.3. Random Forest

As the name suggests it is the forest that consists of multiple decision trees. The input is divided and fed to a separate decision tree and the average outcomes from all decision trees are considered [26]. Since it consists of multiple decision trees removing a node doesn't affect much as the tree are randomly selected [27].

1.1.4. SVM

Support Vector Machines are used for both regressions as well as classification. In this technique, a virtual plane is created which tries to keep the distance of the plane and support vector as large as possible [28]. We can use Scalar Vector Classifier (SVC), Nu SVC, and Linear SVC for classification purposes. SVM is also highly effective in high dimension spaces. Overfitting issues arise if the feature size is larger than the sample size. kernel functions and regularisation are generally used to avoid this problem. [29] [30].

1.1.5. KNN

In KNN, the number of classes is known a prior. The data points are clustered based on random cluster centers. Now, the clusters are modified based on new cluster centers which are calculated using the K-nearest neighbor approach. The above steps are repeated till no new cluster centers are formed. [31-33].

1.2. Regression algorithm

In a regression problem, there is an attempt to predict a continuous output, i.e. to translate an input variable to a continuous function [34]. The most commonly used regression algorithms are discussed below:

1.2.1. Linear Regression

It is the simplest regression technique that draws a straight line between the data point and tries to reduce the cost function by optimizing the parameter of the function. The new point is predicted based on the equation of the line [35, 36].

1.2.2. Lasso Regression

Similar to linear regression, Lasso regression involves a shrinking approach where the data points are contracted towards a point with the lowest prediction errors [37, 38].

1.3. Clustering algorithm

Clustering (an unsupervised learning technique) groups the data points based on shared features [39]. The most common clustering algorithms are Fuzzy C-means, K-Means, Hierarchical, etc.

So basically ML is the part of the AI, which makes a machine able to think with the minimum human intervention [40, 41]. While DL is like imitating the human brain. For example, the neural network model is highly influenced by the human neutron, where dendrites are feeding the feature and after processing neuron transfer it to another neuron with the help of an axon. A neuron is linked with multiple other neurons for processing [42, 43]. Transfer learning (TL), on the other hand, is a semi-supervised technique for utilizing an existing model that was created for a different purpose [44]. In the case of CXR, we have very few images, and training a model completely on medical images is not feasible, as it will not learn several simple parameters like boundary detection, void detection, etc. So for edge detection, we already have some pre-developed models like Cellular automata, Hueckel's model, 2-D random field model, and many more [45-47], therefore, one can easily analyze the CXR data on this pre-trained model. TL is advantageous since it saves time because many of the features have already been learned [48].

Recent advances in AI-enhanced systems and graphic processing unit availability have enabled AI developers to work on more image-related data. Due to this reason, the number of studies performed on AI in the last six years has increased dramatically. In this review paper, we had examined the literature from the last six years and presented a detailed comparison on the ground of different reliable datasets and techniques used. The performance is compared and major challenges and future scope are presented.

2. Search Strategy

A thorough literature search was conducted in Web of Science, Google Scholar, Scopus, PubMed, and Embase to retrieve all of the relevant scientific work done before in this domain. We started with the most recently published study and worked our way back till the year 2015. Before 2015, the majority of papers were focused on the retrieval of textual material from CXR and making decisions that are out of the scope of the current study. We have also excluded papers related to COVID-19, published papers other than the English language, and studies with no validation.

3. Comparison of Different Datasets Used in the Literature

The datasets used by prior studies are shown in Table 1.

Figure 1 presents the number of images present in the various dataset and Figure 2 presents the usage of datasets (in %) in the literature. It was observed that prior studies on pneumonia detection usually suffer from the limitation of small datasets. Antani et al. [49] tried to overcome this limitation by assembling a large number of datasets which includes JSRT (247 radiographs) [67], Montgomery (138 CXR) [68], Shenzhen (662 CXR), Indiana, and India datasets, respectively. As all the data were not classified, the major challenge faced by this study was the imbalanced dataset. Later, Wang et al. used the ChestX-ray14 dataset [69] that consisted of 112,120 CXR images (frontal view) synthesized between the years 1992 to 2015. Rajpurkar et al. [50] and Toğaçar et al. [54] utilized the same dataset in their respective models, namely; the Chexnet model and ensemble model, respectively. Antin et al. [51] and Rajaraman et al. [52] used the Mendeley dataset (widely known as the Kaggle dataset). The Kaggle dataset is divided into three folders: one for training, one for testing, and one for validating the model. Although the Kaggle dataset has fewer images than ChestX-ray14, it was more popular among researchers because of its high-quality images that were tagged with Pneumonia/Normal using the Natural Language Processing (NLP) technique. From Figure 2, it can be observed that a majority of the researchers have chosen the Kaggle dataset.

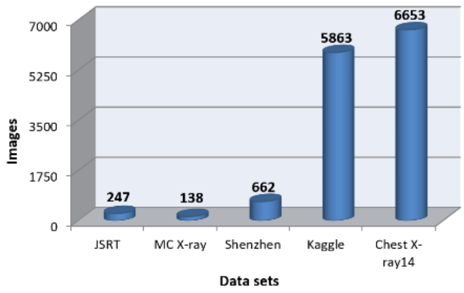

Fig. 1. Collection of images in the various dataset

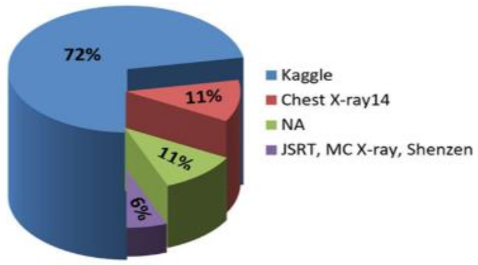

Fig. 2. Usage of the datasets in the literature

Table 1: Comparison of datasets used in the literature

Author	Year	Dataset used	Total images	Test images	Train images	Additional information
Antani, et al. [49]	2015	JSRT, MC X-ray set, and Shenzhen	5440	138	5302	2048 x 2048 pixel images with grayscale depth of 12 bits
Rajpurkar et al. [50]	2017	ChestX-ray14	104988	6351	98637	consist of 14 label diseases
Antin, et al. [51]	2017	Kaggle	5856	624	5232	JPEG images divided into (Pneumonia/Normal)
Rajaraman et al. [52]	2018	Kaggle	5856	624	5232	JPEG images divided into (Pneumonia/Normal)
Abiyev and Ma'aitah [53]	2018	ChestX-ray14	112120	33636	78484	consist of 14 label diseases
Toğaçar et al. [54]	2019	ChestX-ray14	6653	2559	4094	consist of 14 label diseases

Author	Year	Dataset used	Total images	Test images	Train images	Additional information
Altiparmakis [55]	2019	Kaggle	5656	440	5216	JPEG images divided into (Pneumonia/Normal)
Sirazitdinov et al. [56]	2019	Kaggle and Mendeley	26684	1000	25684	JPEG images divided into (Pneumonia/Normal)
Sousa, et al. [57]	2019	Kaggle	5856	624	5232	JPEG images divided into (Pneumonia/Normal)
Bhandary et al. [58]	2019	Kaggle	4000	2000	2000	JPEG images divided into (Pneumonia/Normal)
Acharya et al. [59]	2020	Kaggle	5628	300	5328	JPEG images divided into (Pneumonia/Normal)
Mittal et al. [60]	2020	Kaggle	4978	878	4100	JPEG images divided into (Pneumonia/Normal)
Wu et al. [61]	2020	Kaggle	5839	1928	3911	JPEG images divided into (Pneumonia/Normal)
Islam et al. [62]	2020	Kaggle	5856	624	5232	JPEG images divided into (Pneumonia/Normal)
Rahman et al. [63]	2020	Kaggle	5247	419	4824	JPEG images divided into (Pneumonia/Normal)
Chouhan et al. [64]	2020	Kaggle	5866	634	5232	JPEG images divided into (Pneumonia/Normal)
Sarkar et al. [65]	2020	Kaggle	5856	1168	4688	JPEG images divided into (Pneumonia/Normal)
Liang and Zheng [66]	2020	Kaggle	5856	624	5232	JPEG images divided into (Pneumonia/Normal)

4. Comparison of Different Techniques Used in the Literature

Techniques used in the literature can be divided into three broad categories, namely (a) Pure algorithm-based, (b) CNN-based, and (c) TL-based. Evaluation metrics namely; accuracy [70], precision [71], recall [71], and F1 score [72] are extensively used in these studies. Comparison of techniques and evaluation parameters are shown in Table 2 and comparison of accuracies are presented in Figure 3.

In 2015, before Antani et al. [49], most of the studies on pneumonia detection used NLP (the textual content printed on the CXR) to train their model. But with the advancement in DL, image features start to play a vital role. Antani, et al. [49] used CXR images on a lung segmentation algorithm to detect contours that indicate the disease. Since it was the beginning of the usage of images as detection parameters, the algorithm produced an accuracy of 0.783. Even if the accuracy was low, Antani et al.'s work provides an idea to other researchers to use CXR images features. In 2017, Rajpurkar et al. [50] proposed a CheXNet model based on 121 layer CNN. The CheXNet model takes the CXR pixel as its feature and produce the output for 14 different lung disease including pneumonia. The study obtained an area under the curve (AUC) of 0.768. CheXNet model proposed by Rajpurkar et al. is DenseNet121 trained on ChestXray14 dataset. DenseNet-121 is a 121 layers neural network consisting of five convolutions and pooling layers, one classification layer, three transition layers (6,12,24), and two dense blocks (1x1 and 3x3 Conv) [73]. Following Rajpurkar et al., Antin, et al. tried DenseNet-121 with logistic regression [74] and applied random horizontal flip on the CXR images, and observed an AUC of 0.6037 [51]. It was observed that Antin's model cannot replicate the performance of Rajpurkar, the reason was the lesser number of positive pneumonia samples as compared to non-pneumonia samples, causing bias usually known as the data imbalanced problem [75]. To solve this bias, Rajaraman et al. [52] customized the VGG-16 model [76] [77] with global average pooling (GAP) [78, 79]. This proposed VGG-16 model can effectively learn the complex data, thus reducing the bias and improving the generalization. Accuracy of 0.962 was achieved by the VGG-16 model. In the same year, Abiyev and Ma'aitah [53] worked on a back-propagation neural network (BpNN) and competitive neural network (CpNN) [80] [81]. The CpNN can be trained faster and BpNN can reduce the error gradient. The model achieved an accuracy of 0.924.

In 2019, Toğaçar [54] ensembled the AlexNet [82-84] and the VGG-16 model used by Rajaraman et al. [52] and concatenates it with GG-19 where the mRMR (Minimum Redundancy Maximum Relevance) approach improved classification efficiency by lowering feature set dimension. The model achieved an accuracy of 0.994. Since the dataset used by Toğaçar has very few sample images therefore there were high chances of overfitting. Altiparmakis [55] tried to solve this issue by modifying the ResNet-50 model [85] by taking the top layer as GAP and also adding ridge regression and dropout for regularization and achieved an accuracy of 0.964. While Altiparmakis tried to solve the overfitting issue, Sirazitdinova et al. [56] found that it is very hard to detect pneumonia region as it is very small. To tackle this problem, Sirazitdinova et al. used the Feature Pyramid Network (FPN) principle in the backbone of RetinaNet and Mask-CNN ensemble model [86]. FPN can produce multi-scale feature maps with higher quality data as compared to the typical feature pyramid. In contrast to conventionally stacked convolutional layers, FPN employs residual networks [87] as a basis backbone model since it decreases the influence of deterioration and allowed for developing deeper models. The model attained an accuracy of 0.838.

Sousa et al. [57] completely focused on CNN and had used 50 different CNN architectures to achieve an accuracy of 0.954. Bhandary et al. [58] modified AlexNet [88] and used Principle Component Analysis to enhance the feature vector. The performance of this DL structure was evaluated using the Lung Image Database Consortium-benchmark, Infectious Disease Research Institute lung cancer CT images. The model achieved an accuracy of 0.87.

In 2020, Acharya et al. [59] observed that the deep siamese-based neural network (originally proposed by Wang in 2017) worked very well on symmetric images and hence can be applied to the chest images [89]. In this approach, the model was trained to flip the CXR. Each CXR left-side was flipped to make it right and the network was trained on examining each portion of the chest. Because of flipping, the network can work on small datasets. The model achieved an accuracy of 0.967. For improving the classification, Mittal et al. [60] utilized the CapsNet model [90] [91] [92] and trained it with CXR images. Although the CapsNet model achieved an accuracy of 0.94, convolutions and capsules were formed using the trial-and-error approach in ICCs and ECCs which is inefficient for establishing a good classification or generative model [93]. Wu et al. [61] solve the issue of image classification using the CNN-RF model which has previously given good results for the image classification task, along with good classification it also reduces the computation time [94, 95]. CNN-RF model achieves the accuracy and sensitivity of 0.956 and 0.95, respectively.

A recent approach to tackle the issue of fewer databases is the TL-based approach [96-98]. With a small data size, it is very hard for a model to train on the edge [99, 100]. This problem can be solved by following a two-step solution. In the first step, edge training is performed with the available public dataset and in the next step, this result is fed to the model which can significantly increase the performance. This is the fundamental concept of the TL-based approach. Islam et al. [62], Rahman et al. [63], and Chouhan et al. [64] used the TL-based approach [101]. Islam et al. worked on Squeezenet [102] and Inception V3 [103-105] ensembled architecture and observed accuracy of 0.989 while Rahman and Chouhan worked on Alextnet [62, 105] and ResNet-50 model and achieved accuracies of 0.988 and 0.954, respectively. In the same year, Sarkar et al. [65] improve the detection accuracy of pneumonia clouds (0.983) by working on the Deep separable residual learning method [107, 108]. For edge preservation, bilateral filtering was used and contrast limited adaptive histogram equalization was achieved by using an optimal image enhancement. Very recently, Liang and Zheng [66] proposed a method that utilized residual structure to address the depth model's over-fitting and degradation issues. The method can tackle the overfitting issue and achieve an accuracy of 0.905.

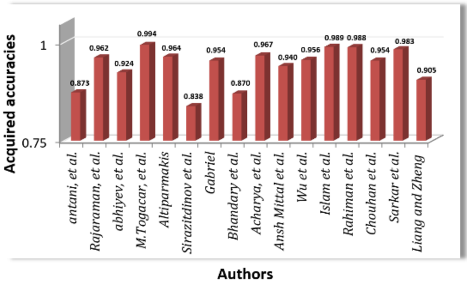

Fig. 3. Accuracy comparison of the studies

5. Ongoing Challenges and Future Scope

Small and unbalanced data size are the two major issues faced by the current studies, which if cared off can improve the accuracy. After 2020, the COVID-19 cases had increased the false detection rate, thus proposed models must be adjusted for both pneumonia and COVID-19. Although the studies had achieved high accuracy but still lack real-time testing and detection of pneumonia cases. This review paper has included only studies related to CXR images which can be further extended with other imaging techniques.

6. Conclusion

This study provides a detailed overview of the pneumonia detection techniques using CXR images. It summarizes the topic, analyzing the usability, accuracy, and sensitivity of each study. All the datasets used by the studies are freely available and accessible with the Kaggle dataset preferred the most. We had observed that the AlexNet model was highly preferred by the researchers and yielded very high accuracies. Lastly, the available dataset needs to be balanced.

Table 2: Comparison of techniques and evaluation parameters used in the literature

Author	Year	Technique Used	Accuracy	Precision	Recall	F1 score
Antani, et al. [49]	2015	Lung segmentation algorithm	0.783	0.741	0.741	0.741
Rajpurkar et al. [50]	2017	CheXNet	0.768 (AUC)	NA	NA	0.435
Antin, et al. [51]	2017	Logistic Regression, and DenseNet121	0.604 (AUC)	NA	NA	NA
Rajaraman et al. [52]	2018	Customized VGG16 model, and GAP	0.962	0.962	0.938	0.95
Abiyev and Ma’aitah [53]	2018	CNN, CpNN, and BpNN	0.924	NA	NA	NA
Toğaçar et al. [54]	2019	AlexNet, VGG-16, and GG-19	0.994	0.996	0.992	0.994
Altiparmakis [55]	2019	ResNet-50	0.964	0.963	0.988	0.975
Sirazitdinov et al. [56]	2019	RetinaNet and Mask R-CNN	0.838	0.759	0.793	0.776
Sousa, et al. [57]	2019	CNN	0.954	0.933	0.997	0.964
Bhandary et al. [58]	2019	MAN-SVM (Modified alexnet)	0.870	0.881	0.858	0.869
Acharya et al. [59]	2020	Deep Siamese based neural network	0.967	0.97	0.98	0.975
Mittal et al. [60]	2020	CapsNet (Convolutions and Dynamic Capsule Routing)	0.940	0.971	0.945	0.958
Wu et al. [61]	2020	CNN-RF	0.956	0.9	0.95	0.924

Author	Year	Technique Used	Accuracy	Precision	Recall	F1 score
Islam et al. [62]	2020	SqueezeNet and Inception-v3	0.989	0.995	0.987	0.991
Rahman et al. [63]	2020	AlexNet, ResNet18, DenseNet201, and SqueezeNet	0.988	0.986	0.991	0.988
Chouhan et al. [64]	2020	AlexNet,DenseNet121,InceptionV3,ResNet18, and GoogLeNet neural network	0.954	0.934	0.998	0.965
Sarkar et al. [65]	2020	Deep separable residual learning	0.983	0.984	0.993	0.988
Liang and Zheng [66]	2020	CNN	0.905	0.891	0.667	0.927

References

[1] D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan, and A. Mittal, 2019, “Pneumonia detection using CNN based feature extraction,” 2019 In 2019 IEEE international conference on electrical, computer and communication technologies (ICECCT), 2019, pp. 1-7.

[2] A. Craig, J. Mai, S. Cai, and Jeyaseelan, S, “Neutrophil recruitment to the lungs during bacterial pneumonia,” *Infect. Immun.*, Vol, 77, no. 2, pp. 568-575, 2009. doi: 10.1128/IAI.00832-08.

[3] J.A. McCullers, “Do specific virus–bacteria pairings drive clinical outcomes of pneumonia?,” *Clinical Microbiology and Infection*, Vol, 19, no. 2, pp.113-118, 2013. doi: 10.1111/1469-0691.12.93.

[4] M. Walton-Roberts, and S.I. Rajan, “Global demand for medical professionals drives Indians abroad despite acute domestic health-care worker shortages,” 2020.

[5] T. Wardlaw, P. Salama, E.W. Johansson, and E. Mason, “Pneumonia: the leading killer of children,” *The Lancet*, Vol, 368, no. 9541, pp. 1048-1050, 2006. doi: 10.1016/S0140-6736(06)69334-3.

[6] R.G. Wunderink, and G.W. Waterer, “Community-acquired pneumonia,” *New England Journal of Medicine*, Vol, 370, no. 6, pp. 543-551, 2014.

[7] Pneumonia. [Online] Available: https://www.who.int/news-room/fact-sheets/detail/pneumonia, 2021. (Accessed on 03/01/2022).

[8] Pneumonia. [Online] Available: https://www.who.int/news-room/fact-sheets/detail/children-reducing-mortality, 2020. (Accessed on 03/01/2022).

[9] M.P. Ledoux, B. Guffroy, Y. Nivoix, C. Simand, and R. Herbrecht, 2020, “Invasive pulmonary aspergillosis,” 2020 In 2020 Seminars in respiratory and critical care medicine vol. 41, no. 01, 2020, pp. 080-098.

[10] GM. Harshvardan, G. Mahendra Kumar, R. Siddharth Swarup, and Pandey Manjusha, “Pneumonia detection using CNN through chest X-ray,” *Journal of Engineering Science and Technology*, Vol, 16, no.1, pp. 861-876, 2021. doi: 10.1109/ICECCT.2019.8869364.

[11] D. Sutton, and J.W.R. Young, “ A short textbook of clinical imaging*”*, Springer Science & Business Media, 2012.

[12] K. Doi, “Computer-aided diagnosis in medical imaging: historical review, current status and future potential”, *Computerized medical imaging and graphics*, Vol, 31, no. 4-5, pp.198-211, 2007.

[13] D. Zhao, D. Zhu, J. Lu, Y. Luo, and G. Zhang, 2018. “Synthetic medical images using F&BGAN for improved lung nodules classification by multi-scale VGG16,” Symmetry, Vol, 10, no. 10, p.519, 2018. doi: 10.3390/sym10000519.

[14] I.W. Harsono, S. Liawatimena, and T.W. Cenggoro, “Lung nodule detection and classification from thorax ct-scan using retinanet with transfer learning,” *Journal of King Saud University-Computer and Information Sciences*, 2020. doi: 10.1016/j.jksuci.2020.03.013.

[15] K. Kallianos, J. Mongan, S. Antani, T. Henry, A. Taylor, J. Abuya, and M. Kohli, “How far have we come? Artificial intelligence for chest radiograph interpretation,” *Clinical Radiology*, Vol, 74, no. 5,

pp.338-345, 2019. doi: 10.1016/j.card.2018.12.015.

[16] A.M. Bur, M. Shew, and J. New, “Artificial intelligence for the otolaryngologist: a state of the art review,” *Otolaryngology–Head and Neck Surgery*, Vol, 160, no. 4, pp.603-611, 2019. doi: 10.1177/0194599819827507.

[17] T. Yigitcanlar, and F. Cugurullo, “The sustainability of artificial intelligence: An urbanistic viewpoint from the lens of smart and sustainable cities,” *Sustainability*, Vol, 12, no. 20, p.8548, 2020. doi: 10.3390/su12208548.

[18] A. Bhardwaj, W. Di, and J. Wei, “Deep Learning Essentials: Your hands-on guide to the fundamentals of deep learning and neural network modeling,” Packt Publishing Ltd, 2018.

[19] R. Allen, “Five lessons for applying machine learning,” *Research-Technology Management*, Vol, 62, no. 3, pp.38-44, 2019. doi: 10.1080/08956308.2019.1587330.

[20] G.I. Webb, E. Keogh, and R. Miikkulainen, “Naïve Bayes,” *Encyclopedia of machine learning*, Vol, 15, pp.713-714, 2010.

[21] K.P. Murphy, ” Naive bayes classifiers, ” *University of British Columbia*, Vol, 18, no. 60, pp.1-8, 2006.

[22] D.D. Lewis, 1998, “Naive (Bayes) at forty: The independence assumption in information retrieval,” 1998 In 1998 European conference on machine learning, 1998, pp. 4-15.

[23] Y.Y. Song, and L.U. Ying, “Decision tree methods: applications for classification and prediction,” *Shanghai archives of psychiatry*, Vol, 27, no. 2, p.130, 2015. doi: 10.11919/j.issn.1002-0829.215044.

[24] Du. Wenliang, and Z. Zhan, ” Building decision tree classifier on private data,” Vol, 14, p.1-8, 2002.

[25] M.A. Friedl, and C.E. Brodley, “Decision tree classification of land cover from remotely sensed data,” *Remote sensing of environment*, Vol, 61, no. 3, pp.399-409, 1997. doi: 10.1016/S0034-4257(97)00049-7.

[26] A.T. Azar, H.I. Elshazly, A.E. Hassanien, and A.M. Elkorany, 2014. “A random forest classifier for lymph diseases,” *Computer methods and programs in biomedicine*, Vol, 113, no. 2, pp.465-473, 2014. doi: 10.1016/j.cmpb.2013.11.004.

[27] B. Xu, Y. Ye, and L. Nie, 2012, “An improved random forest classifier for image classification,” 2012 In 2012 IEEE International Conference on Information and Automation, 2012, pp. 795-800.

[28] Yu. Hwanjo, and Ki. Sungchul, “SVM Tutorial-Classification, Regression and Ranking,” *Handbook of Natural Computing*, Vol, 1, pp.479-506, 2012. doi: 10.1007/978-3-540-92910-9_15.

[29] Yue. Shelong, Li. Ping, and Hao. Peiyi, “SVM classification: Its contents and challenges,” *Applied Mathematics-A Journal of Chinese Universities*, Vol, 18, no. 3, pp.332-342, 2003. doi: 10.1007/s11766-003-0059-5.

[30] Y. Liu, and Y.F. Zheng, 2005, “One-against-all multi-class SVM classification using reliability measures,” 2005 In Proceedings of the 2005 IEEE International Joint Conference on Neural Networks, 2005. vol. 2, pp. 849-854.

[31] M.L. Zhang, and Z.H. Zhou, “ML-KNN: A lazy learning approach to multi-label learning,” *Pattern Recognition*, Vol, 40, no. 7, pp.2038-2048, 2007. doi: 10.1016/j.patcog.2006.12.019.

[32] P. Soucy, and G.W. Mineau, 2001, “A simple KNN algorithm for text categorization,” 2001 In Proceedings 2001 IEEE International Conference on Data Mining, 2001, pp. 647-648.

[33] Shichao Zhang, Xuelong Li, Ming Zong, Xiaofeng Zhu, and Debo Cheng, “Learning K for KNN classification,” *ACM Transactions on Intelligent Systems and Technology (TIST)*, Vol, 8, no. 3, pp.1-19, 2017. doi: 10.1145/2990508.

[34] C. Saunders, A. Gammerman, and V. Vovk, “Ridge regression learning algorithm in dual variables,” P. 515-521, 1998.

[35] G.A. Seber, and A.J. Lee, “Linear regression analysis,” John Wiley & Sons, Vol, 329, 2012.

[36] J. Gross, and J. Groß, 2003. “Linear regression,” Springer Science & Business Media, Vol, 175, 2003.

[37] J. Ranstam, and J.A. Cook, “LASSO regression,” *Journal of British Surgery*, Vol, 105, no. 10, pp.1348-1348, 2018.

[38] R. Tibshirani, “Regression shrinkage and selection via the lasso: a retrospective,” *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, Vol, 73, no. 3, pp.273-282, 2011. doi: 10.1111/j.1467-9868.2011.00771.x.

[39] A. Likas, N. Vlassis, and J.J Verbeek, “The global k-means clustering algorithm,” *Pattern Recognition*, Vol, 36, no. 2, pp.451-461, 2003. doi: 10.1016/S0031-3203(02)00060-2.

[40] I. Goodfellow, Y. Bengio, and A. Courville, “Machine learning basics,” *Deep learning*, Vol, 1, no.7, pp.98-164, 2016.

[41] Xian-Da Zhang, “Machine learning,”. In *A* Matrix Algebra Approach to Artificial Intelligence, Springer, pp. 223-440, 2020.

[42] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, Vol, 521, no. 7553, pp.436-444, 2015.

[43] L. Deng, and D. Yu, 2014. “Deep learning: methods and applications,” *Foundations and trends in signal processing*, Vol, 7, no. 3-4, pp.197-387, 2014. doi: 10.1561/2000000039.

[44] W. Ying, Y. Zhang, J. Huang, and Q. Yang, 2018, “Transfer learning via learning to transfer,” 2018 In 2018 International conference on machine learning, 2018, pp. 5085-5094.

[45] L.S. Davis, “A survey of edge detection techniques,” *Computer graphics and image processing*, Vol, 4, no. 3, pp.248-270, 1975. doi: 10.1016/0146-664X(75)90012-X.

[46] C.L. Chang, Y.J. Zhang, and Y.Y. Gdong, 2004, “Cellular automata for edge detection of images,” 2004, In Proceedings of the 2004 international conference on machine learning and cybernetics Vol. 6, 2004, pp. 3830-3834.

[47] Y.T. Zhou, V. Venkateswar, and R. Chellappa, “Edge detection and linear feature extraction using a 2-D random field model,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol, 11, no. 1, pp.84-95, 1989. doi: 10.1109/34.23115.

[48] C. Khamkar, M. Shah, S. Kalyani, and K. Bhowmick, “Pneumonia Detection Using X-ray Images and Deep Learning,” In Information and Communication Technology for Competitive Strategies (ICTCS 2020), Springer, pp. 141-152, 2021.

[49] S. Antani, and S. Candemir, “Automated detection of lung diseases in chest X-rays,” US National Library of Medicine, 2015.

[50] P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, T. Duan, D. Ding, A. Bagul, C. Langlotz, K. Shpanskaya, and M.P. Lungren, “Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning,” arXiv preprint arXiv:1711.05225, 2017.

[51] B. Antin, J. Kravitz, and E. Martayan, “Detecting pneumonia in chest X-Rays with supervised learning,” Semanticscholar.org, 2017.

[52] S. Rajaraman, S. Candemir, I. Kim, G. Thoma, and S. Antani, “Visualization and interpretation of convolutional neural network predictions in detecting pneumonia in pediatric chest radiographs,” Applied Sciences, Vol, 8, no. 10, p.1715, 2018. doi: 10.3390/app8101715.

[53] R.H. Abiyev, and M.K.S. Ma’aitah, “Deep convolutional neural networks for chest diseases detection,” Journal of healthcare engineering, 2018. doi: 10.1155/2018/4168538.

[54] M. Toğaçar, B. Ergen, and Z. Cömert, “A deep feature learning model for pneumonia detection applying a combination of mRMR feature selection and machine learning models,” IRBM, Vol, 1, pp. 1-11, 2019. doi: 10.1016/j.irbm.2019.10.006.

[55] N. Altiparmakis, “Detecting and Understanding Pneumonia with Deep Learning,” 2019.

[56] I. Sirazitdinov, M. Kholiavchenko, T. Mustafaev, Y. Yixuan, R. Kuleev, and B. Ibragimov, “Deep neural network ensemble for pneumonia localization from a large-scale chest x-ray database,” Computers & electrical engineering, Vol, 78, pp.388-399, 2019. doi: 10.1016/j.compeleceng.2019.08.004.

[57] G.G.B. Sousa, V.R.M. Fernandes, and A.C. de Paiva, 2019, “Optimized deep learning architecture for the diagnosis of pneumonia through chest x-rays,” 2019 In 2019 International Conference on Image Analysis and Recognition, 2019, pp. 353-361.

[58] A. Bhandary, G. Ananth Prabhu, V. Rajinikanth, K.P. Thanaraj, S.C. Satapathy, D.E. Robbins, C. Shasky, Y.D. Zhang, J.M.R. Tavares, and N.S.M. Raja, “Deep-learning framework to detect lung abnormality–A study with chest X-Ray and lung CT scan images,” Pattern Recognition Letters, 129, pp.271-278, 2020. doi: 10.1016/j.patrec.2019.11.013.

[59] A.K. Acharya, and R. Satapathy, “A deep learning based approach towards the automatic diagnosis of pneumonia from chest radiographs,” Biomedical and Pharmacology Journal, Vol, 13, no. 1, pp.449-455, 2020. doi: 10.13005/bpj/1905.

[60] A. Mittal, D. Kumar, M. Mittal, T. Saba, I. Abunadi, A. Rehman, and S. Roy, “Detecting pneumonia using convolutions and dynamic capsule routing for chest X-ray images,” *Sensors*, Vol, 20, no. 4, p.1068, 2020. doi: 10.3390/s20041068.

[61] H. Wu, P. Xie, H. Zhang, D. Li, and M. Cheng, “Predict pneumonia with chest X-ray images based on convolutional deep neural learning networks,” Journal of Intelligent & Fuzzy Systems, Vol, 39, no.3, pp.2893-2907, 2020. doi: 10.3233/JIFS-191438.

[62] K.T. Islam, S.N. Wijewickrema, A. Collins, and S.J. O'Leary, “A Deep Transfer Learning Framework for

Pneumonia Detection from Chest X-ray Images," In VISIGRAPP (5: VISAPP), pp. 286-293, 2020. doi: 10.5220/0008927002860293.

[63] T. Rahman, M.E. Chowdhury, A. Khandakar, K.R. Islam, K.F. Islam, Z.B. Mahbub, M.A. Kadir, and S. Kashem, "Transfer learning with deep convolutional neural network (CNN) for pneumonia detection using chest X-ray," Applied Sciences, Vol, 10, no. 9, p.3233, 2020. doi: 10.3390/app10093233.

[64] V. Chouhan, S.K. Singh, A. Khamparia, D. Gupta, P. Tiwari, C. Moreira, R. Damaševičius, and V.H.C. De Albuquerque, 2020. "A novel transfer learning based approach for pneumonia detection in chest X-ray images," Applied Sciences, Vol, 10, no. 2, p.559, 2020. doi: 10.3390/app10020559.

[65] R. Sarkar, A. Hazra, K. Sadhu, and P. Ghosh, "A novel method for pneumonia diagnosis from chest X-ray images using deep residual learning with separable convolutional networks," In Computer Vision and Machine Intelligence in Medical Image Analysis, Springer, pp. 1-12 Springer, 2020. doi: 10.1007/978-981-13-8798-2_1.

[66] G. Liang, and L. Zheng, 2020. "A transfer learning method with deep residual network for pediatric pneumonia diagnosis," Computer methods and programs in biomedicine, 187, p.104964. doi: 10.1016/j.cmpb.2019.06.023.

[67] JSRT Database. [Online] Available: http://db.jsrt.or.jp/eng.php, (Accessed on 03/01/2022).

[68] "Montgomery County X-ray Set". [Online] Available: In: (). url: https://ceb.nlm.nih.gov/repositories/ tuberculosis-chest-x-rayimage-data-sets/.

[69] X. Wang, Y. Peng, L. Lu, Z.Lu, M. Bagheri, and R.M. Summers, 2017a. "Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases," 2017 In Proceedings of the 2017 IEEE conference on computer vision and pattern recognition 2017 pp. 2097-2106.

[70] J.A. Swets, "Measuring the accuracy of diagnostic systems," Science, vol, 240, no., 4857, pp. 1285-1293, 1988, doi: 10.1126/science.3287615.

[71] A. Tharwat, "Classification assessment methods," *Applied Computing and Informatics*, Vol, 17, no. 1, pp. 168-192, 2020. doi: 10.1016/j.aci.2018.08.003.

[72] C. Goutte, and E. Gaussier, 2005, "A probabilistic interpretation of precision, recall and F-score, with implication for evaluation," 2005 In 2005 European conference on information retrieval, 2005, pp. 345-359.

[73] G. Huang, Z. Liu, L. Van Der Maaten, and K.Q.Weinberger, 2017, "Densely connected convolutional networks," 2017 In Proceedings of the 2017 IEEE conference on computer vision and pattern recognition, 2017, pp. 4700-4708.

[74] D.G. Kleinbaum, K. Dietz, M. Gail, M. Klein, and M. Klein, "Logistic regression," New York, NY, USA: Springer-Verlag, 2002, pp. 536.

[75] Y.D. Zhang, V.V. Govindaraj, C. Tang, W. Zhu, and J. Sun, "High performance multiple sclerosis classification by data augmentation and AlexNet transfer learning model," *Journal of Medical Imaging and Health Informatics*, vol, 9, no., 9, pp.2012-2021, 2019, doi: 10.1166/jmihi.2019.2692.

[76] X. Xie, X. Han, Q. Liao, and G. Shi, 2017, "Visualization and pruning of SSD with the base network VGG16," 2017 In Proceedings of the 2017 International Conference on Deep Learning Technologies, 2017, pp. 90-94.

[77] C. Alippi, S. Disabato, and M. Roveri, 2018, "Moving convolutional neural networks to embedded systems: the alexnet and VGG-16 case," 2018 In 2018 17th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN), 2018, pp. 212-223.

[78] R.L. Kumar, J. Kakarla, B.V. Isunuri, and M. Singh, "Multi-class brain tumor classification using residual network and global average pooling," *Multimedia Tools and Applications*, vol, 80, no., 9, pp.13429-13438, 2021, doi: 10.1007/s11042-020-10335-4.

[79] Y. Li, and K.Wang, "Modified convolutional neural network with global average pooling for intelligent fault diagnosis of industrial gearbox," *Eksploatacja i Niezawodność*, vol, 22, no., 1, 2020, doi: 10.17531/ein.2020.1.8.

[80] R. Hecht-Nielsen, "Theory of the backpropagation neural network," *In Neural networks for perception*, pp. 65-93, 1992, doi: 10.1016/B978-0-12-741252-8.50010-8.

[81] A. Rathinam, S. Padmini, and V. Ravikumar, "Application of supervised learning artificial neural networks [CPNN, BPNN] for solving power flow problem," *(ICTES 2007)*, pp. 156-160, 2007, doi: 10.1049/ic:20070603.

[82] H. Alaskar, N. Alzhrani, A. Hussain, and F. Almarshed, 2019, "The implementation of pretrained AlexNet on PCG classification," 2019 In

2019 International Conference on Intelligent Computing, 2019, pp. 784-794.

[83] Z.W. Yuan, and J. Zhang, 2016, “Feature extraction and image retrieval based on AlexNet,” 2016 In 2016 *Eighth International Conference on Digital Image Processing (ICDIP 2016)* Vol. 10033, 2016, p. 100330E.

[84] W. Nawaz, S. Ahmed, A. Tahir, and H.A. Khan, 2018, “Classification of breast cancer histology images using alexnet,” 2018 In 2018 International conference image analysis and recognition, 2018, pp. 869-876.

[85] L.Wen, X. Li, and L. Gao, “A transfer convolutional neural network for fault diagnosis based on ResNet-50,” *Neural Computing & Applications*, vol,32, no., 10, pp. 6111-6124 2020, doi: 10.1007/s00521-019-04097-w.

[86] M. Zlocha, Q. Dou, and B. Glocker, 2019, “Improving RetinaNet for CT lesion detection with dense masks from weak RECIST labels,” 2019 In 2019 International Conference on Medical Image Computing and Computer-Assisted Intervention, 2019, pp. 402-410.

[87] H. Qassim, A. Verma, and D. Feinzimer, 2018, “Compressed residual-VGG16 CNN model for big data places image recognition” 2018 In 2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC), 2018, pp. 169-175.

[88] T. Shanthi, and R.S. Sabeenian, “Modified Alexnet architecture for classification of diabetic retinopathy images,” *Computers & Electrical Engineering*, *76*, pp.56-64, 2019.

[89] C. Shen, Z. Jin, Y. Zhao, Z. Fu, R. Jiang, Y. Chen, and X.S. Hua, 2017, “Deep siamese network with multi-level similarity perception for person re-identification,” 2017 In Proceedings of the 2017 25th ACM international conference on Multimedia, 2017, pp. 1942-1950.

[90] S. Toraman, T.B. Alakus, and I. Turkoglu, “Convolutional capsnet: A novel artificial neural network approach to detect COVID-19 disease from X-ray images using capsule networks,” *Chaos, Solitons & Fractals*, vol, 140, pp. 110122, 2020, doi: 10.1016/j.chaos.2020.110122.

[91] H. Xiang, Y.S. Huang, C.H. Lee, T.Y.C. Chien, C.K. Lee, L. Liu, A. Li, X. Lin, and R.F. Chang, “3-D Res-CapsNet convolutional neural network on automated breast ultrasound tumor diagnosis,” *European Journal of Radiology*, 138, p.109608, 2021, doi: 10.1016/j.ejrad.2021.109608.

[92] R. Mukhometzianov, and J. Carrillo, “CapsNet comparative performance evaluation for image classification,” *arXiv preprint*, 2018, arXiv:1805.11195.

[93] B. Jia, and Q. Huang, “DE-CapsNet: A diverse enhanced capsule network with disperse dynamic routing,” *Applied Sciences*, vol, 10, no. , 3, pp.884, 2020, doi: 10.3390/app10030884.

[94] F. Sultana, A. Sufian, and P. Dutta, 2018, “Advancements in image classification using convolutional neural network,” 2018 In 2018 Fourth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN), 2018, pp. 122-129.

[95] G. Liang, H. Hong, W. Xie, and L. Zheng, “Combining convolutional neural network with recursive neural network for blood cell image classification,” *IEEE Access*, vol, 6, pp. 36188-36197, 2018, doi: 10.1109/ACCESS.2018.2846685.

[96] M. Hussain, J.J. Bird, and D.R. Faria, 2018, September. “A study on CNN transfer learning for image classification,” In 2018 *UK Workshop on Computational Intelligence*, vol, 840, pp. 191-202, doi: 10.1007/978-3-319-97982-3_16.

[97] L. Torrey, J. Shavlik, E.S. Olivas, J.M. Guerrero, M.M. Sober, J.M. Benedito, and A.S. Lopez, 2010. Handbook of research on machine learning applications and trends. *Information Science Reference, Hershey PA*, pp.242-264.

[98] K. Weiss, T.M. Khoshgoftaar, and D. Wang, “A survey of transfer learning,” *Journal of Big data*, vol, 3, no. , 1, pp.1-40, May. 2016, Art no. 9.

[99] E. Li, Z. Zhou, and X. Chen, 2018, “Edge intelligence: On-demand deep learning model co-inference with device-edge synergy,” In Proceedings of the 2018 *Workshop on Mobile Edge Communications* pp. 31-36, doi: 10.1145/3229556.3229562.

[100] Q. Xia, W. Ye, Z. Tao, J. Wu, and Q. Li, “A Survey of Federated Learning for Edge Computing: Research Problems and Solutions,” *High-Confidence Computing*, pp.100008, 2021, doi: 10.1016/j.hcc.2021.100008.

[101] P. Ballester and R.M. Araujo, 2016, “On the performance of GoogLeNet and AlexNet applied to sketches,” 2016 In 2016 Thirtieth AAAI Conference on Artificial Intelligence, 2016, pp.1124-128.

[102] F.N. Iandola, S. Han, M.W. Moskewicz, K. Ashraf, W.J. Dally, and K. Keutzer, “SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5

MB model size," *arXiv preprint,* 2016, arXiv:1602.07360.

[103] X. Xia, C. Xu, and B. Nan, 2017, "Inception-v3 for flower classification," 2017 In 2017 2nd International Conference on Image, Vision and Computing (ICIVC), 2017, pp. 783-787.

[104] C. Wang, D. Chen, L. Hao, X. Liu, Y. Zeng, J. Chen, and G. Zhang, "Pulmonary image classification based on inception-v3 transfer learning model," *IEEE Access,* vol, 7, pp. 146533-146541, 2019a. doi: 10.1109/ACCESS.2019.2946000.

[105] M. Saini, and S. Susan, 2019, "Data augmentation of minority class with transfer learning for classification of imbalanced breast cancer dataset using inception-V3," 2019 In 2019 Iberian Conference on Pattern Recognition and Image Analysis, 2019, pp. 409-420.

[106] W. Yu, K. Yang, Y. Bai, T. Xiao, H. Yao, and Y. Rui, 2016, "Visualizing and comparing AlexNet and VGG using deconvolutional layers," 2016 In Proceedings of the 2016, 33 rd International Conference on Machine Learning, 2016.

[107] J. Wang, Z. Fang, N. Lang, H. Yuan, M.Y. Su, and P. Baldi, "A multi-resolution approach for spinal metastasis detection using deep Siamese neural networks," *Computers in biology and medicine,* vol, 84, pp. 137-146, 2017b. doi: 10.1016/j.compbiomed.2017.03.024.

[108] B. Wang, Y. Lei, N. Li, and T. Yan, "Deep separable convolutional network for remaining useful life prediction of machinery," *Mechanical Systems and Signal Processing,* vol, 134, pp. 106330, 2019b. doi: 10.1016/j.ymssp.2019.106330.