Original Article

Application Of Neural Network For The Detection Of Covid-19 Or Viral Pneumonia

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DOI: 10.47750/pnr.2023.14.03.405

Abstract

A bacterial infection in the lungs can cause viral pneumonia, a disease. Later the middle of December 2019, there have been multiple episodes of pneumonia in Wuhan City, China, with no known cause; it has since been discovered that this pneumonia is actually a new respiratory condition brought on by coronavirus infection. Humans who have lung abnormalities are more likely to develop high-risk conditions; this risk can be decreased with much quicker and more effective therapy. The symptoms of Covid-19 pneumonia are similar to those of viral pneumonia; they are not distinctive. X-ray or Computed Tomography (CT) scan images are used to identify lung abnormalities. Even for a skilled radiologist, it might be challenging to identify Covid-19/Viral pneumonia by looking at the X-ray images. For prompt and effective treatment, accurate diagnosis is essential. In this epidemic condition, delayed diagnosis can cause the number of cases to double, hence a suitable tool is required is necessary for the early identification of Covid-19. This paper highlights various AI techniques as a part of our contribution to swift identification and curie Covid-19 to front-line corona. The safety of Covid-19 people who have viral pneumonia is a concern. Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), two AI technologies from Deep Learning (DL), were utilized to identify Covid-19/Viral pneumonia. The Algorithm is taught utilizing non-public local hospitals or Covid-19 wards, as well as X-ray images of healthy lungs, fake lungs from viral pneumonia, and ostentatious lungs from Covid-19 that are all publicly available. The model is also validated over a lengthy period of time using the transfer learning technique. The results correspond with clinically tested positive Covid-19 patients who underwent Swap testing conducted by medical professionals, giving us an accuracy of 78 to 82 percent. We discovered that each DL model has a unique expertise after testing the various models.

Keywords: Covid-19, Viral pneumonia, Deep Learning (DL), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN).

I. Introduction:

Recently, numerous causes of pneumonia were discovered in Wuhan, China, with causes that are unknown. It was believed to be a minor respiratory condition brought on by a coronavirus up until February 12, 2020, when the International Committee on Taxonomy of Viruses formally designated a new coronavirus, severe acute respiratory syndrome coronavirus 2. (SARS-CoV-2) [1,2,3]. The serious increase in mortality rates around the globe has been deemed a global pandemic by the WHO. This has led to the worldwide healthcare systems collapsing, necessitating an immediate response to recognize and reduce the escalating number of COVID cases [4]. The symptoms of COVID-19 found in patients are extremely diverse, including pneumonia, ARDS (acute respiratory distress syndrome), fever, dry cough, sore throats, and other conditions that are comparable to viral pneumonia symptoms. [5]. Since a significant risk to humanity has been established by the discovery of a novel COVID-19 mutation in the UK [6]. Reverse transcription-polymerase chain reaction (RT-PCR) and SWAB are the two diagnostic tests for

COVID-19, and both have low sensitivity and prolonged test times. Additionally, the procedure takes longer because specific labs are required for the test's execution and samples must be transported there. To make matters worse, there is a shortage of an expensive test kit [7]. Chest To quickly identify and isolate a single person, radiographs like X-rays and CT scans might provide all individuals with pneumonia positive symptoms. An Artificial Intelligence (AI) assist that automatically detects the patient's infection could be a significant change for filtering COVID-19 patients from typical pneumonia patients and separate isolation of patients because there aren't many experts available to distinguish patients as having a lot in common with COVID-19 and pneumonia patients. The priority order of the patient testing sample submissions can also be determined using this.

The topic of deep learning is now seeing a lot of research activity. Convolutional neural networks (CNN) in particular have made significant progress in the identification or classification of images [8]. The CNN's fundamental idea is to create an artificial neural network that resembles the human brain. The primary advantage of CNNs is that they have the capacity to exclude more significant features from the entire image than hand-crafted features [8, 9]. Researchers created a number of CNN-based deep networks, and these networks achieved cutting-edge outcomes in target identification, localization, disjuncture detection, and recognition in computer vision [10–11]. In addition to resolving issues with natural machine vision, CNNs have produced excellent results in the resolution of medical issues, such as the detection of breast cancer [12], the segmentation of brain tumours [13], the diagnosis of Alzheimer's disease, the recognition of skin lesions [14, 15], etc. Here are presented in-depth articles [16, 17] on deep learning in medical image processing. As far as we are concerned, we are aware of a few studies that classify pneumonia using deep learning. Using the transition leaning technique, Antin et alanalysis .'s of a DenseNet-121 sheet in 2017 yielded an AUC of 0.60 percent [18]. CheXNet[19], a 121-layer convolution neural network that made use of DenseNet[20], was introduced by Rajpurkar, et al. in 2017. 10,000 chest X-ray frontal views of people with 14 different diseases were uploaded to their network. Four expert radiologists and the f1 score metric, which is the cumulative average of the exactness and recall metrics, were used to assess the performance of their network. The f1 score of CheXNet was 0.435 (95 percent CI 0.387, 0.481), which was greater than the f1 score of the typical anesthesiologist, which was 0.387. (95 percent CI 0.330, 0.442).

On other side, approaches based on RNN architecture have also been proposed. The most well-liked RNN is LSTM [19], which has the ability to learn about long-term dependencies. Typically, a model with SDP knowledge introduced utilising long short-term memory networks (LSTM) was recommended by Xu et al. [21] to help investigate key text structures for relationship classification. On the SemEval-2010 task 8 dataset, Cai et al's [22] model outperformed earlier networks by integrating LSTM with SDP encoding into neural networks without taking SDP information into consideration as a standard feature. On the KBP37 dataset, Zhang [23] used a simplistic RNN-based model and outperformed CNN methods. Although these methods take advantage of the automated extraction of RNN features, their effectiveness is somewhat constrained because some of the data collected by RNN does not contain local characteristics.

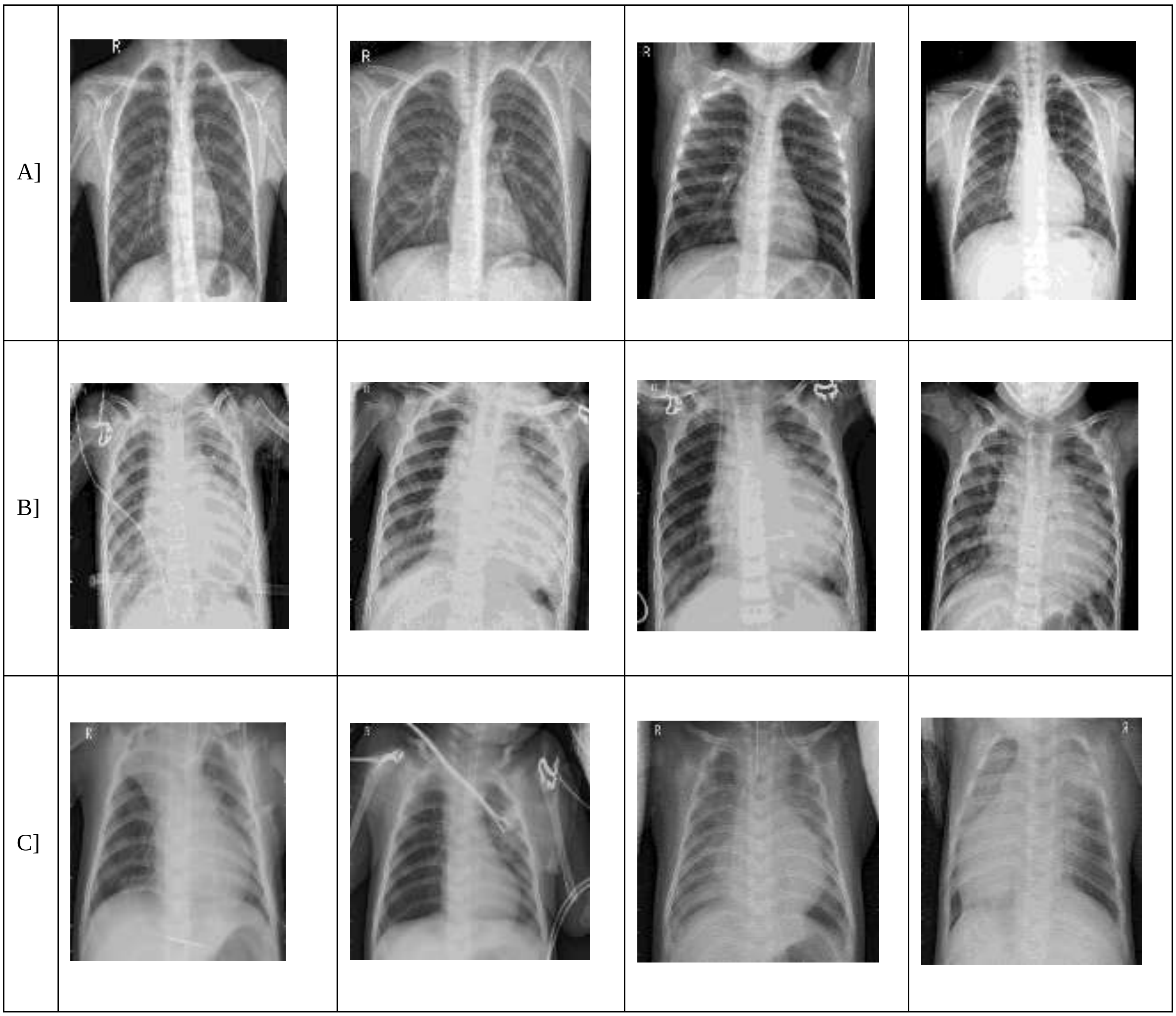
In addition to the methods outlined above, there are some studies that use a combination of CNN and RNN to perform the task of relationship categorization. Additionally, certain sentence classification work may have been advantageous [24]. A well-representative method of categorising connections was presented by Rotsztejn et al. [25] using ensemble CNNs and RNNs. There is other extensively employed works that rely on attention [26]. The SemEval-2018 problem 7 has three out of four subtasks, and this technique performs the best on all four. However, ensemble learning-focused approaches can be more sophisticated and require more time and computational effort than single frameworks. Since dataset sizes are constrained, ensemble models may take a long time to adjust their parameters and may also be more susceptible to overfitting. To effectively and efficiently identify between different relationship types, we want to build a straightforward, single deep learning model without overtraining the model.

II. Description of Dataset:

The dataset used in this study is made up of 5932 frontal chest X-ray pictures from Kaggle and unnamed local hospitals or Covid-19 Wards. The photos in the collection have 96 dpi resolutions and range in size from 728x368 to 2746x2382. The collection contains 1340 photographs of normal cases, 3878 images of pneumonia cases, 1462 images of pneumonia with Covid-19, and 164 images of pneumonia with Covid-19 novel variants. Table 1 displays the dispensation training data, validation data, and testing data phases of the model presented in this paper along with X-ray samples from the dataset.

Table 1. Distribution of dataset

	Train	Validation	Test
Normal	1340	365	365
Pneumonia	3878	490	490
Covid-19	1462	112	112
Covid-19 new Variant	164	53	53



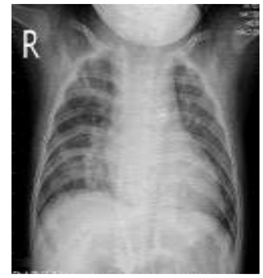
D]				

Fig. 1. Data samples from the dataset, (a) shows normal cases and (b) shows pneumonia cases
(c) shows Covid-19 cases (d) shows Covid-19 New Variant

III. Methodology and Experimental Setup:

An Intel(R) Core (TM) i5-8300H CPU 2.30 GHz cpu with a 64-bit operating system, single NVIDIA GeForce GTX 1050 with 4 GB VRAM and 32 GB RAM and x64-based processor was the hardware used to monitor networks. Using TensorFlow 1.1.0 backend on the GPU, the computer runs Keras 2.0.4 on Windows 10.

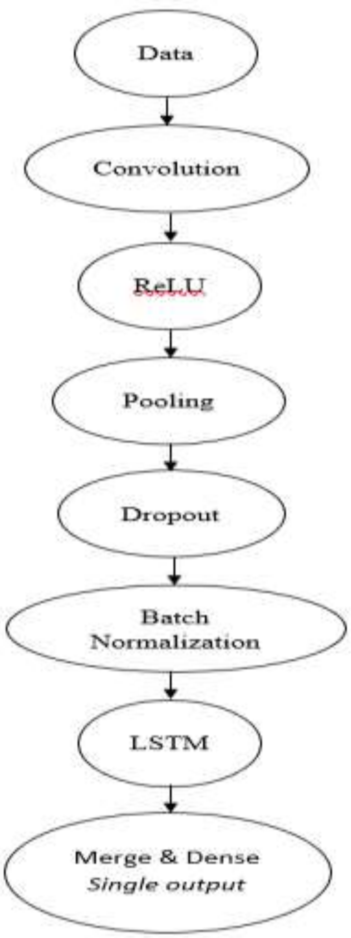


Figure 2. Flowchart of CNN+LSTM (Vgg16 + RNN)

Initially, we will use the Convolutional Neural Network, where the input images are passed through a sequence of layers, i.e. convolutionary, pooling, flattening and completely connected layers, and then the CNN output that classifies images is produced. After constructing CNN models from scratch, RNN structure using LSTM was linked to the output on CNN. Consequently, one of the pre-trained VGG-16 models will be used to identify image and verify accuracy for training data and validation data.

A. Convolution, ReLU: -

The biggest adjustments dictated the amount of divisions to be used; this was specifically related to the kernel sizes employed. Four divisions were set up since the ideal 1-dimensional kernel volumes were three, five, seven, and nine. Viewing words showed to recover the most crucial features and produce improved fidelity in these kernel sizes. The ideal number of filters was found to be 128. In order to further prevent overfitting, a hill regression (l2) kernel regularizer was applied after the convolutional layer. L2's parameter was set to 0.01.

The activation layer of the ReLU proved to be critical to achieving greater fidelity. This layer doesn't have parameters.

B. Pooling, Dropout and Batch Neutralization: -

The main overfitting issue was solved by pooling, but it was found that it hampers the accuracy. The ideal kernel size for the testing was 2, with the input height being halved.

It was known that the dropout layer was the best choice to minimize overfitting. Forcing other weights to better hypothesize the network, 0.5 has been set as the dropout. This approach, while ensuring concurrence, led to greater fidelity and a deeper interpretation of the results. To assist with the overfitting of the LSTM network, batch standardization or normalization was applied to the network. This layer does not have any parameters.

C. LSTM, Concatenation, Dense Layer: -

The LSTM layer of each branch has 128 units. Less or more units may cause overfitting or fidelity to be compromised. There are no tuning requirements for the dense layer or the merging layer. Although there was no profound impact on the optimizer, the RMSprop showed the strongest effects. The rate of learning was improved to 0.01 and the decay in the rate of learning was set at 0.1. The loftiest average fidelity was obtained by these criteria.

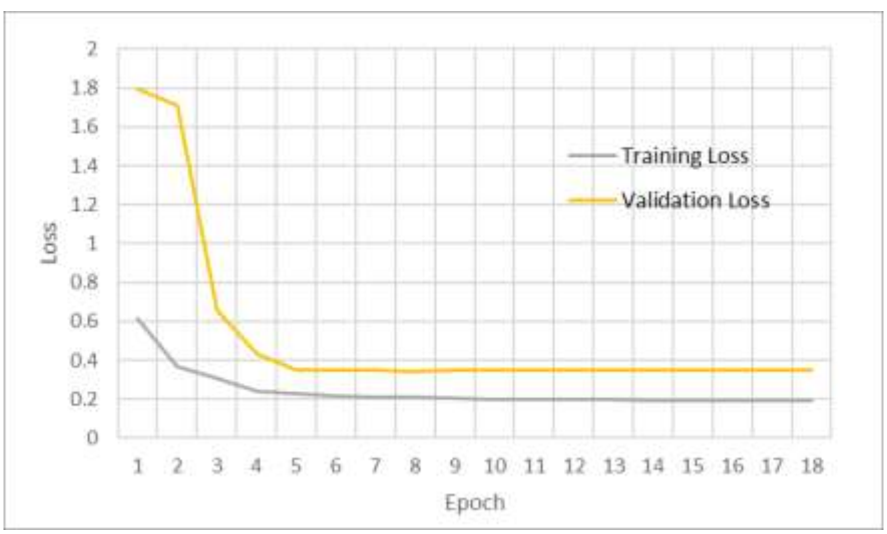


Figure 3. The loss of values in prediction by the model

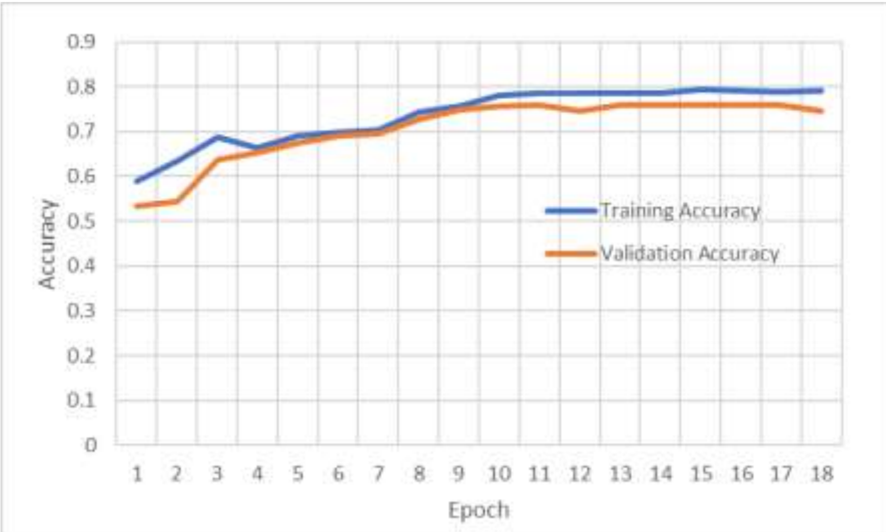


Figure 4. The accuracy in prediction by the model

Table 2. The structure and parameters of the networks proposed

Proposed Model	Convolution			Activation	Pooling	Branch Dropout	Batch Normalization	LSTM	Merge Dropout	Optimizer			Accuracy
	Kernel Size	Filters	Kernel Regularizer	Type	Pool Size	Rate	Present	Unit	Rate	Type	Learning Rate1	Learning Rate Decay	
Vgg16 + RNN	3/5/7/9	128	L2(0.01)	ReLU	1	0.75	Yes	0	0	RMSprop	0.001	0.01	0.7931

IV. Result and Analysis: -

After running the framework and testing for multiple times, 79.3 percent fidelity was obtained by the highest performing proposed model. In spite of the principal difficulty of overfitting, this fidelity was accomplished. To try to minimize overfitting and generalize the experience, multiple trials and combinations were reviewed. Figure 3 indicates the loss of the model being proposed. The accuracy of the proposed model shown in Figure 4.

Layers were able to aid remember overfitting; Max Pooling, Dropout, and Normalization were included. Pooling tended to generalize the learning process by minimizing dimensionality; pooling worked better in all networks at a scale of 1. At various positions in the network, dropout layers were evaluated. They have been highly useful after pooling, before batch normalization, or in some circumstances, after concatenation of all the layers. Dropout was often shown to be advantageous at a rate greater than or equal to 0.75. In both increasing fidelity and minimizing overfitting, batch normalization has often been found to be beneficial.

Boundaries of regularization, learning rate, and decay were important factors in minimizing overfitting. Without any additional benefit, every operation regularizer increased fidelity, while the kernel's hill regression regularizer reduced overfitting. The optimal kernel regularizer was L2 (0.001). Moving the learning rate from its baseline was normally not beneficial until followed by a decay in the learning rate. A higher learning rate (0.001) and decay of 0.01 have been initiated by the highest performing model. This mixture allowed the accuracy percentage to leap to the high 70's as seen in Figure, and then remain there with no alterations. Without the degradation, because of overfitting, the training accuracy will slip down to below 75 percent. The loss, despite hitting its lowest, still did not fluctuate too much.

In order to prevent the network from fetid, depth is kept low.

An overfit is more likely the deeper the network is. Deeper networks were no longer able to gather useful information because the data no longer contained as many Covid-19 New Variant images. Attempts were fruitless to incorporate additional thick or convolutional layers.

Table 2 shows the structure and parameters of the networks proposed. The accuracy is low, i.e. 79.3 percent, due to less data available in early stages, but the accuracy increases as train data and the number of iterations will increase and decrease respectively.

V. Conclusion:

This research uses the chest X-ray dataset from multi-branch convolution with the LSTM network to demonstrate the usefulness of the present integrated kernel. It is evident that different convolutional divisions can extract crucial characteristics from textural data in a basic network. In addition, LSTM layers may use the data to dive further into analyzing the feedback. The precision of our best performing proposed model greatly increases the CNN+LSTM (Vgg16 + RNN) model baseline. The accuracy of the model has decreased because of less available train data to increase it Transfer learning method has been attempted but does not have any impact on the accuracy, so data set must be increased and trained again. Overfitting was a concern for several iterations of the model, but the right layers and boundaries were able to stop the degradation and reach new fidelity peaks on the dataset.

Compliance with Ethical Standards

Ethical Approval: There is no ethical approval needed in the present study.

Consent to Participate: There is no consent to participate needed in the present study.

Consent to Publish: There is no consent to publish needed in the present study.

Funding details: There is no funding details to be mentioned in the manuscript.

Competing Interests: There is no competing interests to be mentioned in the present study.

Availability of data and materials: There is no need to mention the availability of data and materials in the present study.

VI. References: -

[1] C. Sohrabi, Z. Alsafi, N. O'Neill, M. Khan, A. Kerwan, A. Al-Jabir, C. Iosifidis, R. Agha, World health organization declares global emergency: a review of the 2019 novel coronavirus (COVID-19), Int. J. Surg. (2020)

[2] C. -C. Lai, T.-P. Shih, W.-C. Ko, H.-J. Tang, P.-R. Hsueh, Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and corona virus disease-2019 (COVID-19): the epidemic and the challenges, Int. J. Antimicro. Ag. (2020) 105924.

[3] Gorbalenya AE, Baker SC, Baric RS, et al. Servere acute respiratory syndromerelated coronavirus: the species and its viruses – a statement of coronavirus studay group. BioRxiv. 2020.

[4] H.A. Rothan, S.N. Byrareddy, The epidemiology and pathogenesis of coronavirus diseases (COVID-19) outbreak, J. Autoimmun. (2020) 102433.

[5] Harrison X. Bai, Ben Hsieh, Zeng Xiong, Kasey Halsey, Ji Whae Choi, Thi My Linh Tran, Ian Pan, Lin-Bo Shi, Dong-Cui Wang, Ji Mei, Xiao-Long Jiang, Qiu-Hua Zeng, Thomas K. Egglin, Ping-Feng Hu, Saurabh Agarwal, Fang-Fang Xie, Sha Li, Terrance Healey, Michael K. Atalay, Wei-Hua Liao, " Perfomance of Radiologists in Differentiating COVID-19 from Non-COVID-19 Viral Pneumonia at chest CT." Radiology , Volume 296, No. 2, March 2020.

[6] A. A. Dawood, "Mutated COVID-19 may foretell a great risk for mankind in the future", New Microbes and New Infections, Volume 35, May 2020.

[7] "Rapid increase of a SARS-CoV-2 variant with multiple spike protein mutations observed in the United Kingdom", European Center for Disease prevention and Control, December 2020.

[8] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in Advances in neural information processing systems, 2012, pp. 1097-1105.
[9] X. Xie, Z. Zhao, C. Zheng, F. Wang, J. Liu, Chest CT for typical 2019-nCoV pneumonia: relationship to negative RT-PCR testing, Radiology 2020 200343.
[10] A. Krizhevsky, I. Sutskever, and G.E.Hinton, “Imagenet classification with deep convolutional neural networks,” in Advances in neural information processing systems, 2012, pp. 1097-1105.
[11] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in International Conference on Medical image computing and computer-assisted intervention, 2015, pp. 234-241: Springer.
[12] D. A. Ragab, M. Sharkas, S. Marshall, and J. Ren, "Breast cancer detection using deep convolutional neural networks and support vector machines," PeerJ, vol. 7, p. e6201, 2019.
[13] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images," IEEE transactions on medical imaging, vol. 35, no. 5, pp. 1240-1251, 2016.
[14] A. Esteva et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, p. 115, 2017.
[15] E. Ayan and H. M. Ünver, "Data augmentation importance for classification of skin lesions via deep learning," in 2018 Electric Electronics, Computer Science, Biomedical Engineerings' Meeting (EBBT), 2018, pp. 1-4: IEEE.
[16] J. Ker, L. Wang, J. Rao, and T. Lim, "Deep learning applications in medical image analysis," IEEE Access, vol. 6, pp. 9375-9389, 2018.
[17] G. Litjens et al., "A survey on deep learning in medical image analysis," Medical image analysis, vol. 42, pp. 60-88, 2017.
[18] B. Antin, J. Kravitz, and E. Martayan, "Detecting Pneumonia in Chest X-Rays with Supervised Learning."
[19] P. Rajpurkar et al., "Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning," arXiv preprint arXiv:1711.05225, 2017.
[20] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 4700-4708.
[21] Joey Tianyi Zhou, Kai Di, Jiawei Du, Xi Peng, Hao Yang, Sinno Jialin Pan, Ivor W. Tsang, Yong Liu Zheng Qin, Rick Siow Mong Goh, “SC2Net: Sparse LSTMs for Sparse Coding”, The Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18), pp. 4588 – 4595 April 2018.
[22] Y. Xu, L. Mou, G. Li, Y. Chen, H. Peng, and Z. Jin, “Classifying relations via long short term memory networks along shortest dependency paths,” Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, 2015, pp. 1785-1794.
[23] R. Zhang, F. Meng, Y. Zhou, and B. Liu, “Relation classification via recurrent neural network with attention and tensor layers, Big Data Mining and Analytics, Volume: 1, Issue: 3, pp. 234-244, September 2018
[24] A. Hassan and A. Mahmood, “Convolutional recurrent deep learning model for sentence classification”, IEEE Access, Volume: 6, pp. 13949 – 13957, March 2018.
[25] J. Rotsztejn, N. Hollenstein, and C. Zhang, “ETH-DS3Lab at SemEval-2018 task 7: Effectively combining recurrent and convolutional neural networks for relation classification and extraction”, Proceedings of The 12th International Workshop on Semantic Evaluation, pp. 689–696, June 2018.
[26] N. Li, H. Zhang, and Y. Chen, “Convolutional neural network with SDPbased attention for relation classification”, 2018 IEEE International Conference on Big Data and Smart Computing (BigComp), pp. 615-618. Jan 2018.