e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
( Peer-Reviewed, Open Access, Fully Refereed International Journal )
Volume:03/Issue:09/September-2021 Impact Factor- 6.752 www.irjmets.com

# COVID-19 DETECTION USING TRANSFER LEARNING

**Priyanka Gautam Gharde*1, Dattatray Bade*2, Prof. Sachin Bojewar*3**

*1,2,3Vidyalankar Institute of Technology, Mumbai University, India.

## ABSTRACT

Around the globe, healthcare systems are being overwhelmed by the exponential growth of COVID-19 patients. It is difficult to screen every patient with respiratory disease using traditional methods due to the limited number of testing kits available (RT-PCR). The tests also take a long time to complete and have low sensitivity. Patients at high risk of COVID-19 infection may be quarantined while test results are pending if a chest X-ray detects the illness.Most healthcare systems already have X-ray equipment, and because most contemporary X-ray systems are digital, there is no need to transfer the samples. According to our findings, chest X-rays may be used to prioritize patients for additional RT-PCR testing. As an example, it may be helpful in a hospital environment where the current systems are unable to determine whether to retain patients in the ward with other patients or segregate them into COVID-19 sections. A false negative RT-PCR would also assist in identifying individuals with a high probability of COVID who might benefit from repeat testing. To make the suggested testing method more scalable, we also propose the use of current AI algorithms to identify COVID-19 patients using X-ray pictures in an automated way. An artificial intelligence (AI) detector based on CNN is presented. The present study model predicts COVID-19 infection with 90% accuracy using the publicly accessible covid-chestxray-dataset .

**Keywords:** COVID-19, RT-PCR Testing, CNN Etc.

## I. INTRODUCTION

Images have always played a crucial part in human existence, owing to the fact that vision is the most important sense for human beings to possess. Because of this, image processing has a wide range of applications in agricultural, military, security, and medicine [1-4]. The simplicity with which a large number of pictures may be generated is due to advancements in digital technology. With such a large number of pictures, image processing methods must deal with increasingly complicated problems as well as their adaptability to the issue. One example of a difficult issue is the diagnosis of illnesses based on pictures. The complexity of healthcare data is always a major concern for academics and scientists [4]. The extraction of important information for data analysis and decision-making in healthcare data necessitates considerable effort. Machine learning is the only data analysis technique that automates the creation of analytical models by detecting patterns and making choices with little human intervention. When such adaptability is needed, machine learning functions as an essential component of intelligent computer vision systems. Recent advances in the area of 'Machine Learning' have created a new possibility for the development of intelligent computer-controlled devices and software. A vast community of researchers, engineers, and academics are constantly exploring novel ML models in order to use them in the creation of automated systems for applications ranging from object recognition to medical diagnosis. Machine learning, a subtype of 'Artificial Intelligence', learns from data [5]. It examines current data patterns to react to a scenario for which they have not been expressly designed [6-7].

COVID-19 is caused by the coronavirus 2 that causes severe acute respiratory illness. [8]. As a means of preventing the transmission of COVID-19, the WHO has recommended physical separation and contact tracking [6]. COVID-19 patients must be identified quickly and accurately in order to prevent the spread of the COVID-19 disease. They may be diagnosed using a number of different assays. A lack of laboratory equipment makes it difficult to test every individual infected with the virus in poor nations. Tests may take anything from a few hours to a few days, are time-consuming, and are prone to errors in the present situation. The RT-PCR method has poor sensitivity, and it has produced false-positive findings [9]. In order to avoid and regulate COVID-19, it is suggested that a quicker and more reliable detection method be used. For COVID-19 screening, CT scans are frequently utilized in less developed nations, when test kits are scarce. According to certain research [10,11,12], a chest CT scan may assist doctors in evaluating and optimizing preventive and control strategies. As a result, CT scans may be utilized as an alternative to laboratory testing for screening purposes. To solve this issue, we need a technique that is both accurate and quick. Furthermore, CT scans offer numeric information, but owing to the absence of automated tools for processing, only qualitative information is provided. Processing an image is a method for obtaining usable information from a photograph or other picture.

## II. REVIEW OF LITERATURE

Artificial intelligence (AI) is the process of artificially integrating intelligence into computers using machine learning techniques. A mix of neural networks [13–17], fuzzy systems [18–21], and evolutionary algorithms [22] is one of the machine learning methods. The majority of these methods are based on hand-crafted representations of features, wherefeatures are the collection of qualities that may be used to describe an item, a group of objects, or a system. Neural networks find a mapping from the input domain to the output domain by using a constructed representation of the characteristics of a given data set. The hand-crafted representation of features for a particular dataset is strongly affected by an expert's subject knowledge, and therefore, the overall system performance. Deep learning-based methods that replace the requirement for hand-crafted features with an automated feature extraction method may be utilized to build more robust systems.

Rosenblatt [23] developed the first learning algorithm, known as the perception learning algorithm, in 1958 to update the weight parameters of an artificial neuron. Later, it was shown that an artificial neuron can only solve issues with linearly separable convex hulls. Fornon-linearly separable problems such as the XOR function, the model was unable to identifya solution cone (or area). The XOR function issue was successfully addressed by forming a network out of a few artificial neurons. The multi-layered perception network was named after this network. However, understanding such a multi-layered network proved difficult. Rumelhart et al. [24] developed the back-propagation method in 1986 to train a multi-layeredperception by propagating gradients of the total error backward. A multi-layered perception network may have many hidden layers depending on the intricacy of the input. Due to the vanishing gradient issue, training a network with numerous hidden layers becomes challenging [30]. Because of the fully-connected nature of the multi-layered perception network, increasing the number of hidden layers in the network quickly raises the weight parameters. Training huge networks was a challenging job before the development of GPU-based computers. Deep learning-based methods were used to address this issue efficiently, as described in [30] and [31]. To address the aforementioned issue, deep learning offers two distinct methods based on the hierarchical manner of learning featurerepresentation. One technique introduced the idea of layer-by-layer training or pre-training to train a deep stacked auto-encoder model using the unsupervised method described by Hinton in [30]. The pre-training method makes global training of the network using the back-propagation algorithm considerably easier since it assists in determining a suitable set ofstarting weight values for the back-propagation process. Feed-forward neural networks are often trained in the presence of instructional inputs, i.e., the intended values. The weights are updated in the direction of negative gradients of error. A function may be used to determine the error by comparing the anticipated and desired values. Hinton et al. introduced this weightupdate idea in [24], and it is well-known in the literature as the back-propagation method.The Convolutional Neural Network (CNN) is a well-known deep network. It was suggested in [3] by LeCun et al. and is also known as LeNet. [31] demonstrated the efficacy of the convolutional network by tackling the hand-written digit recognition problem (known as the MNIST dataset [25]) with an extremely low error rate. Multiple convolutional and pooling layers may be found in a convolutional network. Convolutional network architecture isinspired by the receptive field of cells in the cat's striate cortex, as suggested by Hubel and Wiesel in [32]. In contrast to the LeNet architecture, which was evaluated on the MNIST dataset [25], the Alex network developed by Alex Krizhevsky et al. [34] demonstrated the efficacy of the convolutional network on a huge dataset consisting of 1.2 million high-dimensional pictures. Krizhevsky et al. utilized the Alex network with 62 million parameters to solve the ImageNet LSVRC-2010 challenge in 2012 [35]. In [26] the Visual Geometry Group (VGG) of Oxford University developed a very large convolutional neural network known as the VGG net, through which they experimentally demonstrated that the performance of a network improves as the depth (or number of layers) of the network rises. The VGG net also regulated network characteristics by replacing the 55 filters with a stack oftwo 33 filters and the 77 filters with a stack of three 33 filters. In a comparison of parameters from 55 filters, a stack of two 33 filters with a stride of 1 lowers weight parameters by 28 percent. Similarly, 62.8 percent of weight parameters may be lowered by replacing 77% ofthe filters with a stack of three 33% filters with a stride of 1. As a result, big scale filters may be replaced with tiny-sized filters without sacrificing performance. The VGG net

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
( Peer-Reviewed, Open Access, Fully Refereed International Journal )
Volume:03/Issue:09/September-2021 Impact Factor- 6.752 www.irjmets.com

may be thought of as a straight extension of LeNet in terms of layer count. The network may be thought of as a sequential concatenation of blocks, with each block having a certain number of convolutional layers and two adjacent blocks linked by a pooling layer. There are many VGG net variations based on the number of layers, including VGG-11, VGG-13, VGG-16, and VGG-19.

There has been a lack of studies done in the context of the COVID-19 pandemic to create automated image-based COVID-19 detection and diagnosis systems. X-ray and CT-scan imaging modalities are used to develop reliable detection systems, which are discussed in the following sections. Techniques may be categorized according to one of two major paradigms: In order to identify and recognize COVID-19, new deep network topologies have been designed. One of the first convolutional networks, COVID-Net [27], was intended to identify instances of COVID-19 automatically from X-ray pictures. The performance of the network was 83.5 percent accurate and 100 percent sensitive in COVID-19 instances. To identify COVID-19 patients from radiography pictures, Hasan et al. [28] developed a CNN-based network called the Coronavirus Recognition Network (CVR-Net), which is based on the concept of convolutional neural networks. Images from X-rays and CT scans were used to train the network and assess its performance. Variable accuracy ratings were obtained depending on the number of classes within an image collection and an average accuracy of 78 percent was obtained for the CT image dataset, according to findings.

## 1. Data set and data acquisition

To investigate and assess the CNN designs, we used X-ray images from three publicly available sources, which we found to be of high quality. There are 200 normal cases and 200 COVID-19 infections that have been confirmed.

## 2. Setup and Results

To examine the performance of the CNN architectures described here and compare it with the proposed CNN-X design, we used a transfer learning (TL) method. Learned weights (TL) is the process of transferring information (learned weights) from one issue to another that is similar. TL mode is used to retrain the CNN models' weights on our X-ray pictures using weights optimised by training the models on the ImageNet dataset in CNN mode. In order to ensure that all pictures from training and testing sets are scaled correctly, each of the architectures' dimensions are determined. This is because none of the techniques in the published work mention pretreatment, so we adopted the same standard. One metrics was collected to evaluate CNN's classification performance: sensitivity . False Negative (FN), True Positive (TP) were recorded in order to compute the aforementioned metrics. Tp refers to disease (COVID-19) X-ray pictures, while FP is considered normal. According to CNN models, sensitivity represents the proportion of sick instances that are recognised properly whereas specificity indicates the percentage of healthy cases that are accurately classified as healthy by CNN models . Considering that COVID-19 chest X-ray pictures are few incontrast to the other three classes, it may be deceptive to depend only on CNN models' sensitivity and specificity.

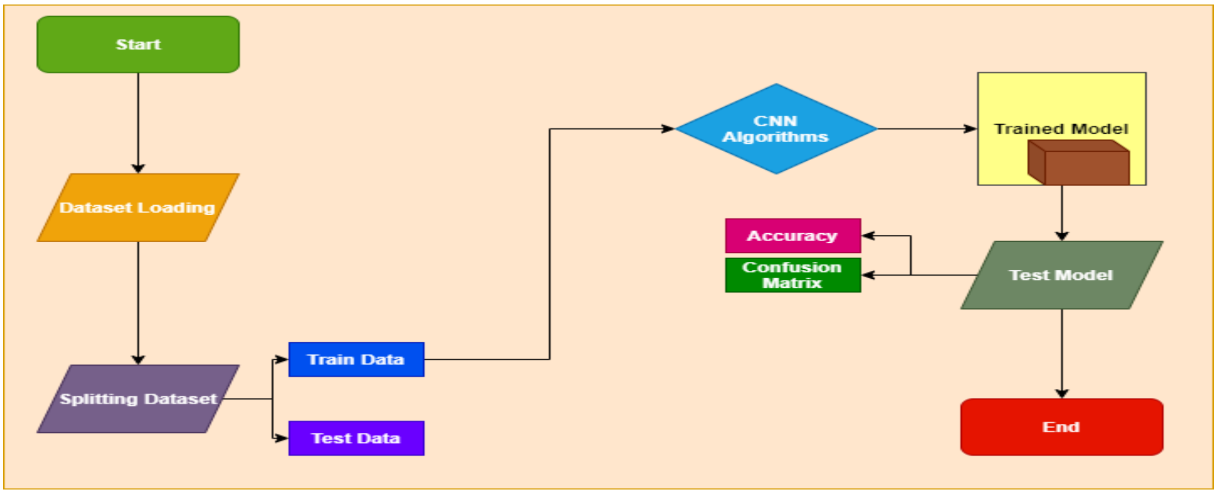



**Figure 1:** Proposed CNN Model

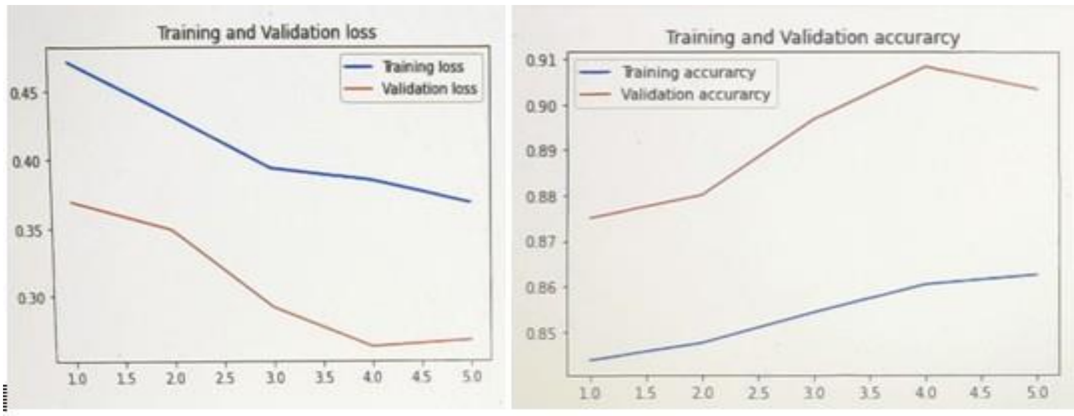
e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
( Peer-Reviewed, Open Access, Fully Refereed International Journal )
Volume:03/Issue:09/September-2021 Impact Factor- 6.752 www.irjmets.com

We performed a variety of tests on a large chest X-ray dataset including 500 normal and COVID-19 samples that were input into well-known pretrained CNN models, includingMobileNet, VGG16, DenseNet121, and ResNet-50, each with a different combination of frozen layers and trainable convolution blocks. 10-fold cross-validation was used to train all of the models. . Our validation dataset tested the model's performance after each epoch. In thecase of evaluation, four parameters were taken into account: loss, accuracy, precision, and recall. Following training, the loss was 0.3684 and 0.2672 for training and validation, respectively (Figure 2). The graph (Fig.3(a) illustrates how training and validation loss fluctuate across epochs, while figure 3(b) displays the fluctuation in accuracy for training and validation. As these figures show, there is a significant difference in accuracy and loss for both training and validation.

```
model.save('/content/drive/My Drive/Covid_Xray/model_vgg16.h5')

Epoch 1/5
75/75 [==============================] - 30s 396ms/step - loss: 0.4704 - acc: 0.8438 - val_loss: 0.3692 - val_acc: 0.8750
Epoch 2/5
75/75 [==============================] - 28s 372ms/step - loss: 0.4328 - acc: 0.8475 - val_loss: 0.3489 - val_acc: 0.8800
Epoch 3/5
75/75 [==============================] - 28s 378ms/step - loss: 0.3936 - acc: 0.8542 - val_loss: 0.2921 - val_acc: 0.8967
Epoch 4/5
75/75 [==============================] - 28s 378ms/step - loss: 0.3847 - acc: 0.8604 - val_loss: 0.2626 - val_acc: 0.9083
Epoch 5/5
75/75 [==============================] - 28s 377ms/step - loss: 0.3684 - acc: 0.8625 - val_loss: 0.2672 - val_acc: 0.9033
```

**Figure 2:** Loss and Accuracy




(a) (b)

**Figure 3:** Graph for Training and Validation (a) Loss (b) Accuracy

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 7, 7, 512)         14714688
_________________________________________________________________
global_average_pooling2d_2 ( (None, 512)               0
_________________________________________________________________
dropout_2 (Dropout)          (None, 512)               0
_________________________________________________________________
batch_normalization_2 (Batch (None, 512)               2048
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 1539
=================================================================
Total params: 14,718,275
Trainable params: 7,081,987
Non-trainable params: 7,636,288
_________________________________________________________________
```

**Figure 4:** Model summary

The model summary is given the figure 4. The vgg16 model takes RGB images with width =7 and height = 7. The global_average_pooling2d_2 tells the output dimension is (None, 512). In these results we found that for total params 48 percents are trainable and rests are non-trainable.

In present study, we selected each model's best performance individually and then tested each model on a test set. ResNet-50 and VGG19 outperformed VGG19 with MobileNet-V2 for all pre-trained CNN models. The performance of VGG16 of the pre-trained CNN models is summarised in Table 1. In this case, we found that VGG19 had a better accuracy rate of 90%.The mean ROC scores of ResNet-50 and VGG16 were 62.78 and 74.64 percent, respectively,while DenseNet121 (80.95 percent) came in second (80.71 percent ).

**Table 1:** Testing result for architectures used

| Experiment | Accuracy |
|---|---|
| VGG 16 | 90 |

## III. CONCLUSION

Using transfer learning, we developed a new method for detecting COVID-19. We conducted both second and third class classifications to ensure that our model can distinguish between COVID-19 radiography pictures from healthy individuals and pneumonia patients. Patient-by-patient cross-validation was used to ensure the robustness and consistency of our model. Furthermore, we conducted an explain ability study in order to better understand and illustrate the workings of the model. Covid-Dense Net seems to be successful in detecting COVID-19 in chest radiography pictures, as shown by our thorough testing.

## IV. REFERENCES

[1] Y. Liu, et al., "Learning deep models for face anti-spoofing: Binary or auxiliary supervision," in Proc. of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 389-398.

[2] S. Sladojevic, et al., "Deep neural networks based recognition of plant diseases by leaf image classification," Computational Intelligence and Neuroscience, vol. 2016, pp. 1-11, 2016.

[3] Y. n. Sun, et al., "Color-based tumor tissue segmentation for the automated estimation of oral cancer parameters," Microscopy Research and Technique, vol. 73, pp. 5-13, 2010.

[4] M. Veta, et al., "Corrections to “Breast cancer histopathology image analysis: A review”[May 14 1400-1411]," IEEE Transactions on Biomedical Engineering, vol. 61, pp. 2819-2819, 2014.

[5] Y. LeCun, et al., "Deep learning," Nature, vol. 521, pp. 436-444, 2015.

[6] T. Mitchell, et al., "Machine learning," Annual Review of Computer Science, vol. 4, pp. 417-433, 1990.

[7] M. Svensén and C. M. Bishop, Pattern recognition and machine learning, New York :Springer, 2007.

[8] F. Shan et al., “Lung Infection Quantification of COVID-19 in CT Images with Deep Learning,” arXiv, Mar. 2020.

[9] MacIntyre CR (2020) Case isolation, contact tracing, and physical distancing are pillars of COVID-19 pandemic control, not optional choices. Lancet Infect Dis 20(10):1105–1106. https://doi.org/10.1016/S1473-3099(20)30512-0 .

[10] Li Y, Xia L (2020) Coronavirus disease 2019 (COVID-19): role of chest CT in diagnosis and management. Am J Roentgenol 214(6):1280–1286. https://doi.org/10.2214/AJR.20.22954.

[11] Zhao W, Zhong Z, Xie X, Yu Q, Liu J (2020) Relation between chest CT findings and clinical conditions of coronavirus disease (COVID-19) pneumonia: a multicenter study. Am J Roentgenol 214(5):1072–1077. https://doi.org/10.2214/AJR.20.22976.

[12] Ai T, Yang Z, Hou H, Zhan C, Chen C, Lv W, Tao Q, Sun Z, Xia L (2020) Correlation of chest CT and RT-PCR testing for coronavirus disease 2019 (COVID-19) in China: a report of 1014 cases. Radiology 296(2):E32–E40. https://doi.org/10.1148/radiol.2020200642.

[13] C. M. Bishop, Neural Networks for Pattern Recognition. Oxford University Press, London, UK, 2000, ISBN: 978-0-19-853864-6.

[14] G. P. Zhang, "Neural networks for classification: A survey", IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 30, no. 4, pp. 451–462,2000. DOI: 10.1109/5326.897072.

[15] R. O. Duda, P. E. Hart, and D. G. Stork, Pattern Classification, 2nd. Wiley, 2001, ISBN:978-0-471-05669-0.

[16] A. Verikas and M. Bacauskiene, "Feature selection with neural networks", Pattern Recognition Letters, vol. 23, no. 11, pp. 1323–1335, 2002. DOI: https://doi.org/10.1016/ S0167-8655(02)000818.

[17] S. Kumar, Neural Networks: A Classroom Approach. Tata McGraw-Hill Education,2004,ISBN: 1259051277.

[18] L. A. Zadeh, "Fuzzy sets", Information and Control, vol. 8, no. 3, pp. 338–353, 1965.DOI: https://doi.org/10.1016/S0019-9958(65)90241-X.

[19] L. A. Zadeh, "Fuzzy logic, neural networks, and soft computing", Commun. ACM, vol.37, no. 3, pp. 77–84, 1994. [Online]. Available: https://doi.org/10.1145/175247.175255.

[20] L. A. Zadeh, "Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic", Fuzzy Sets and Systems, vol. 90, no. 2, pp. 111 – 127,1997. DOI: https://doi.org/10.1016/S0165-0114(97)00077-8.

[21] S. Mitra and Y. Hayashi, "Neuro-Fuzzy Rule Generation: Survey in Soft Computing Framework", IEEE Trans. Neural Netw. Learning Syst., vol. 11, no. 3, pp. 748–768, 2000. DOI: 10.1109/72.846746.

[22] D. E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning, 1st.USA:

[23] Addison-Wesley Longman Publishing Co., Inc., 1989, ISBN: 0201157675.

[24] F. Rosenblatt, "The Perceptron: A Probabilistic Model for Information Storage and Organization in The Brain", Psychological Review, vol. 65, no. 6, pp. 386–408, 1958. DOI:10.1037/h0042519.

[25] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning Representations by Back- Propagating Errors", Nature, vol. 323, no. 6088, pp. 533–536, 1986. DOI: https://doi. org/10.1038/323533a0.

[26] Y. LeCun, C. Cortes, and C. J. C. Burges, The MNIST database for handwritten digits, 1998. [Online]. Available: http://yann.lecun.com/exdb/mnist/.

[27] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition.", in 3rd International Conference on Learning Representations (ICLR), Y. Bengio and Y. LeCun, Eds., San Diego, CA, USA: Conference Track Proceedings, 2015.

[28] Tulin Ozturk, Muhammed Talo, Eylul Azra Yildirim, Ulas Baran Baloglu, Ozal Yildirim, and

[29] U. Rajendra Acharya. Automated detection of COVID-19 cases using deep neural networks with x-ray images. Computers in Biology and Medicine, 121:103792, June 2020.

[30] Joseph Redmon and Ali Farhadi. Yolo9000: Better, faster, stronger. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), July 2017.

[31] Y. LeCun, Y. Bengio, and G. E. Hinton, "Deep learning", Nature, vol. 521, no. 7553, pp. 436–444, 2015. DOI: https://doi.org/10.1038/nature14539.

[32] G. E. Hinton and R. R. Salakhutdinov, "Reducing the Dimensionality of Data with Neural Networks", Science, vol. 313, no. 5786, pp. 504–507, 2006. DOI: 10.1126/science.1127647.

[33] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-Based Learning Applied to Document Recognition", in Intelligent Signal Processing, S. Haykin and B. Kosko, Eds., Proceedings of IEEE, vol. 86, IEEE Press, 2001, pp. 306–351. DOI: 10.1109/5.726791.

[34] D. Hubel and T. Wiesel, "Receptive fields, binocular interaction, and functional architecture in the cat's visual cortex", Journal of Physiology, vol. 160, pp. 106–154, 1962.
DOI:10.1113/jphysiol.1962.sp006837.

[35] G. E. Dahl, T. N. Sainath, and G. E. Hinton, "Improving deep neural networks for LVCSR using rectified linear units and dropout", in IEEE International Conference on Acoustics, Speech and Signal Processing, (ICASSP), Vancouver, British Columbia, Canada, 2013. DOI: 10.1109/ICASSP.2013.6639346.

[36] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet Classification with Deep Convolutional Neural Networks", Communications of the ACM, vol. 60, no. 6, pp. 84– 90, 2017. DOI: 10.1145/3065386. [Online]. Available: https://doi.org/10.1145/3065386.

[37] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy

[38] ,A.Khosla, M. S. Bernstein, A. C. Berg, and F.-F. Li, "ImageNet Large Scale Visual Recognition Challenge", International Journal of Computer Vision (IJCV), vol. 115, no. 3, pp. 211–252, 2015. DOI: 10.1007/s11263-015-0816-y.

[39] Z.-H. Zhou and M. Li, "Semi-supervised learning by disagreement," Knowledge and Information Systems, vol. 24, pp. 415-439, 2010.

[40] A. Krizhevsky, et al., "Imagenet classification with deep convolutional neural networks," in Advances in Neural Information Processing Systems, 2012, pp. 1097- 1105.

[41] Y. LeCun, "LeNet-5, convolutional neural networks," vol. 20, 2015 [Online], Available: http://yann.lecun.com/exdb/lenet/,[Accessed Apr. 4, 2019].