

## **EXAMINE THE USE OF ANOMALY DETECTION TO DETECT COVID-19 FROM CHEST X-RAY IMAGE DATASET**

### **Literature Review**

#### **a. Covid-19 detection from xray images using neural networks**

With COVID-19 spreading rapidly many research studies were performed to detect the virus and to help the overwhelmed healthcare system. Jacob et al.,[2] in his review discusses the pattern of lung abnormalities and manifestations in chest X-rays for COVID -19 and suggested that chest X-rays can be a reliable means to identify COVID-19 cases. Some of the research studies used several deep learning techniques on covid x-ray images for detection.[3]-[5]. Few researchers approached the study as a classification problem, where they considered a set of x-ray images with different chest infections including pneumonia and covid-19 as input.[3]-[5]. They used DNN models to classify covid from other diseases. From their experiments, ResNet50 produced an accuracy of 88.92% [3] and VGG-19 model produced an overall accuracy of 93.3% [5] in detecting Covid-19 while DenseNet showed a prediction accuracy of 93.26 % in detecting pneumonia[4]. In[6], the authors examined the influence of augmentation with respect to detection accuracy, dataset diversity, augmentation methodology, and network size. They have compared the performance of 17 deep learning algorithms with and without different geometric augmentations on three sets of data. Performance comparison based on accuracy and MCC [Matthews Correlation Coefficient] were done on 17 pre-trained neural networks including AlexNet, SqueezeNet, GoogleNet, ResNet-50 and so forth. However, the authors concluded that the accuracy and MCC for models which use augmentation was lower than that of the model which did not use augmentation. To fine tune the existing deep learning networks for medical imaging process from overfitting and low transfer efficiency Shuaijing Xu et.al. in [7], designed a hierarchical convolutional neural network (CNN) structure for ChestXray14 and proposed a new network called CXNet-m1. By using a sinloss function in CXNet-m1, the author claims to achieve better accuracy rate, recall rate, F1-score, and AUC value as compared to the best performing deep network model, ResNet-50-DCNN.

#### **b. Imbalance approach on image classification**

In order to balance class distribution in imbalanced data sets, Sun et al.,[8] discusses two techniques - undersampling and oversampling. Under-sampling randomly removes the majority class records whereas over-sampling increases the records in the minority class to get a balanced class distribution. A combination of oversampling and undersampling is proposed by Chawla et.al.,[9] which is claimed to achieve better performance in terms of ROC curve. They use synthetic minority oversampling technique (SMOTE) rather than replacement for oversampling. SMOTE has garnered praise in several real world applications[9] and biomedical research[11]. Since Baseline SMOTE[9] gained much attention, and several extensions of SMOTE like ADASYN, MWMOTE, WSMOTE, k-means SMOTE are also popular now.[10].

### c. Anomaly Detection in chest x-rays

Anomaly detection is studied extensively in several domains[12]. However, anomaly detection in image data poses several challenges. Among anomaly detection methods, deep autoencoders play an important role and are used widely.[13] Autoencoders learn the common factors in normal data and since abnormal data do not contain these factors, the data cannot be reconstructed by the autoencoder for abnormal data. It is seen that autoencoders work well with simple abnormal samples and image anomaly detection is challenging for autoencoders. Principal component analysis and autoencoder[15] based anomaly detection depicts that models trained only on normal data cannot reconstruct accuracies accurately. AnoGAN[16] is a Generative adversarial network(GAN) based method to detect abnormalities. The generator is trained on normal data and cannot generate abnormal images. Thus, any reconstruction error indicates the presence of anomalies. Several other combinations of autoencoders and losses in GAN can be seen in recent works (OCGAN [16], DAOL [19], PIAD [18]). However, these methods pose a difficulty of choosing the right dissimilarity metric and searching the right degree of compression or size of bottleneck. In [20], the author proposes a new method to support anomaly detection in medical imaging by comparing with the state of the art works. They use autoencoders to understand the representation of normal data and optimization is done by considering the perceptual loss. They used a set of anomalous examples with limited variation to choose the model's hyper parameters, which helped them to overcome the problem of setting up the model for new data. This method produced 0.926 ROC AUC in detection of abnormal chest x rays. Xhang et al., proposed a confidence aware anomaly detection model to differentiate viral pneumonia cases from non viral or healthy cases. They assign an anomaly score to each X Ray image and use a contrastive loss function to ensure that the scores generated for anomalies are significantly larger than non viral and normal cases. Their approach produced 87.57% AUC for viral pneumonia screening and 83.61% for unseen COVID-19 data.

## References:

- [3] Albahli S, Yar G Fast and Accurate Detection of COVID-19 Along With 14 Other Chest Pathologies Using a Multi-Level Classification: Algorithm Development and Validation Study J Med Internet Res 2021;23(2):e23693 URL: <https://www.jmir.org/2021/2/e23693> DOI: 10.2196/23693 Rank-Q1
- [4] Saleh Albahli, Nasir Ayub, Muhammad Shiraz, Coronavirus disease (COVID-19) detection using X-ray images and enhanced DenseNet, Applied Soft Computing, Volume 110, 2021, 107645, ISSN 1568-4946, <https://doi.org/10.1016/j.asoc.2021.107645>.Rank-Q1
- [5] Wang, L., Lin, Z.Q. Wong, A. COVID-Net: a tailored deep convolutional neural network design for detection of COVID- 19 cases from chest X-ray images. Sci Rep 10, 19549 (2020). <https://doi.org/10.1038/s41598-020-76550-z>Rank-Q1
- [6] Elgendi M, Nasir MU, Tang Q, Smith D, Grenier J-P, Batte C, Spieler B, Leslie WD, Menon C, Fletcher RR, Howard N, Ward R, Parker W and Nicolaou S (2021) The Effectiveness of Image Augmentation in Deep Learning Networks for Detecting COVID-19: A Geometric Transformation Perspective. Front. Med. 8:629134. doi: 10.3389/fmed.2021.629134.Rank-Q1
- [7] S. Xu, H. Wu and R. Bie, "CXNet-m1: Anomaly Detection on Chest X-Rays With Image-Based Deep Learning," in IEEE Access, vol. 7, pp. 4466-4477, 2019, doi: 10.1109/ACCESS.2018.2885997.Rank-Q1
- [8]Sun, Z., Song, Q., Zhu, X., Sun, H., Xu, B. and Zhou, Y., 2015. A novel ensemble method for classifying imbalanced data. Pattern Recognition, 48(5), pp.1623-1637.Rank-Q1
- [9] Chawla, N.V., Bowyer, K.W., Hall, L.O. and Kegelmeyer, W.P., 2002. SMOTE: synthetic minority over-sampling technique. Journal of artificial intelligence research, 16, pp.321-357.Rank-Q2
- [10]Zhu, Q., Wu, Q. and Fan, Z., 2021. A novel oversampling technique for class-imbalanced learning based on SMOTE and natural neighbors. Information Sciences, 565, pp.438-455.Rank-Q1
- [11]M. Nakamura, Y. Kajiwara, A. Otsuka, H. Kimura Lvq-smote-learning vector quantization based synthetic minority over-sampling technique for biomedical dataRank-Q1
- [12] Chalapathy, R., Chawla, S.: Deep learning for anomaly detection: a survey. arXiv preprint arXiv:1901.03407 (2019)
- [13]Zhou, C., Paffenroth, R.C.: Anomaly detection with robust deep autoencoders. In: Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 665–674. ACM (2017)
- [14] . Pidhorskyi, S., Almohsen, R., Doretto, G.: Generative probabilistic novelty detection with adversarial autoencoders. In: Advances in Neural Information Processing Systems, pp. 6822–6833 (2018)
- [15]G. Williams, R. Baxter, H. He, S. Hawkins, and L. Gu, ``A comparative

study of RNN for outlier detection in data mining," in Proc. IEEE Int. Conf. Data Mining, Dec. 2002, pp. 709712.

[16] T. Schlegl, P. Seeböck, S. M. Waldstein, U. Schmidt-Erfurth, and G. Langs, "Unsupervised anomaly detection with generative adversarial networks to guide marker discovery," in Proc. Int. Conf. Inf. Process. Med. Imag. Cham, Switzerland: Springer, 2017, pp. 146157.

[17] P. Perera, R. Nallapati, and B. Xiang, "OCGAN: One-class novelty detection using GANs with constrained latent representations," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2019, pp. 28982906.

[18] N. Tuluptceva, B. Bakker, I. Fedulova, and A. Konushin, "Perceptual image anomaly detection," in Pattern Recognition, S. Palaiahnakote, G. S. di Baja, L. Wang, and W. Q. Yan, Eds. Cham, Switzerland: Springer, 2020, pp. 164178.

[19] Y. Tang, Y. Tang, J. Xiao, R. M. Summers, and M. Han, "Deep adversarial one-class learning for normal and abnormal chest radiograph classification," in Proc. Med. Imag., Comput.-Aided Diagnosis, vol. 10950, Mar. 2019, Art. no. 1095018.

[20] Shvetsova, N., Bakker, B., Fedulova, I., Schulz, H. and Dylov, D.V., 2021. Anomaly detection in medical imaging with deep perceptual autoencoders. IEEE Access, 9, pp.118571-118583.

[21] Zhang, J., Xie, Y., Pang, G., Liao, Z., Verjans, J., Li, W., Sun, Z., He, J., Li, Y., Shen, C. and Xia, Y., 2020. Viral pneumonia screening on chest X-rays using confidence-aware anomaly detection. IEEE transactions on medical imaging, 40(3), pp.879-890.