Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.777611

AN AMALGAMATED DEEP LEARNING APPROACH FOR LUNG SEGMENTATION USING X-RAY IMAGES

Annu Mishra[1,*], Pankaj Gupta[2] and Peeyush Tewari[3]
[1]Computer Science and Engineering, BIT Mesra, Noida India
[2]Computer Science and Engineering, BIT Mesra, Ranchi, India
[3]Department of Mathematics, BIT Mesra, Jaipur India

Abstract- The X-ray images are considered to be an affordable means to diagnose the diseases especially the cardio vascular diseases. Chest X-rays are even examined by modern doctors in order to identify the disease and cure them accordingly. Due to opacified nature of the X-Ray images and different morphology of human body, the lung segmentation of human chest becomes very tedious. In this paper, we have introduced an approach to overcome this limitation and achieve the art-of-state lung segmentation despite of different anatomy and opacity. The approach involves division formula based on U-Net. The used the previously trained models MobileNetV2 and InceptionResNetV2. The result acquired shows the increase in the efficiency of segmentation by 2.5% with respect to Dice score and 2.37% with respect to IoU when compared it with the tradition U-Net.
Keywords-U-Net, lung segmentation, chest X-Rays, biomedical images

1. Introduction

Chest X-rays are considered to be most widely used and cost-effective means to detect lung diseases. This makes lung segmentation very crucial where the area of lung is separated from the tissues in order to diagnose the respiratory disorders [1]. There are several methods used for this purpose and CNN is considered to be most suitable network. In this context, the U-Net has already gained much attention for segmentation and categorization of the Region of Interests. As the name indicates, this network depicts the U-shaped paradigm consisting of encoder and decoder [2]. The X-Ray images when fed into the framework of U-Net gives certain results beneficial for image segmentation. The CNN architecture used huge amount of dataset for training and testing purpose. Due to this the pre-trained network is used for further enhancement to optimize the CPU power and processing time. There are several techniques used for image segmentation which includes the evaluation of image boundary image texture region of interest and hey image gradient [3][4]. Various researchers have worked upon the U-Net model to achieve the art of state of image segmentation. The combination of U-Net along with other biomedical segmentation network improves the overall performance of the combined model by making use of the advantages of the models observed under consideration [5][6]. Chest radiographs are broadly utilized in the clinical space and as of now, chest X-radiation especially assumes a significant part in the finding of ailments like pneumonia and Coronavirus sickness [7]. The new improvements of profound learning methods prompted a promising execution in clinical picture order and forecast errands. With the accessibility of chest X-beam datasets and arising patterns in information designing methods, there is a development in ongoing related distributions. As of late, there have been a couple of review papers that tended to chest X-Ray characterization utilizing profound learning procedures. Nonetheless, they come up short on examination of the patterns of late investigations. This efficient survey paper investigates and gives a thorough examination of the connected investigations that have utilized profound learning procedures to dissect chest X-Ray pictures. We present the cutting edge profound learning based pneumonia and Coronavirus location arrangements, patterns in ongoing examinations, openly accessible datasets, direction to follow a profound educational experience, difficulties and potential future exploration bearings in this space. The disclosures and the finishes of the explored work have been coordinated such that analysts and designers working in a similar space can utilize this work to help them in taking choices on their exploration. Overall clinical practices, the radiologists search for the white spots called penetrates in the lungs to recognize a disease to analyse pneumonia utilizing chest radiographs [8]. Also, this investigation will assist the radiologists with deciding if the patient has any entanglements connected with pneumonia like the pleural emanations which are known as the overabundance liquid encompassing the lungs. In the conclusion, attributes like the airspace opacities of the chest radiographs are dissected by the radiologists to distinguish the contamination of the infections.

2. Related Work

The authors of [9] propounded an effective CNN model based on the previously trained neural network the modern was designed for segmenting the images from chest X ray using unit they used three data sets and the performance scores were 97.28, 96.50 and 97.41 Another author of [10] proposed the similar model using three DL architectures as an encoder module for text and non-text image separation. After various waves of Covid 19, several disorders related to respiratory system aroused the researchers worked rigorously on these disorders [11] in order to find a definite solution for the problem. In one of the work by [12], the researchers developed a classification method based on unequally distributed classes to identify COVID-19 disorders using an encoder VAE(Variational Encoders) [13][14]. They endeavoured to resolve the issue by using solo Variational Auto Encoders (VAEs). Right off the bat, chest X-Ray pictures are changed over completely to an inert space by learning the main elements utilizing VAEs. Besides, a great many deep rooted information resampling strategies are utilized to adjust the prior imbalanced classes in the dormant vector type of the dataset. At long last, the adjusted dataset in the new component space is utilized to prepare notable characterization models to arrange chest X-Ray pictures into three distinct classes called., " Coronavirus", "Pneumonia", and "Ordinary". Specialists recommend that the essential methods of infection transmission are respiratory emissions of a Coronavirus tainted person. The Reverse Transcription-Polymerase Chain Reaction (RT-PCR) test for recognizing the sickness is performed on respiratory examples and calls for a lot of investment and finance. Also, this test is there by involuted inferable from the restricted accessibility of test kits [15][16]. In another contribution by [17], where the authors proposed structure of the lung segmentation model in two phases; during stage one, the fluffy connectedness (FC) picture division calculation was adjusted to perform starting lung parenchyma extraction. Along with it, the lung volume utilizing rib-confine data without unequivocally portraying lungs was evaluated. This simple, however proficient lung volume assessment framework permits examination of volume contrasts between rib confine and FC based lung volume estimations. Critical volume contrast demonstrates the presence of pathology, which summons the second phase of the proposed structure for the refinement of portioned lung. In stage two[18][19], surface based highlights are used to distinguish unusual imaging designs that could have been missed during the principal phase of the calculation. This refinement stage is additionally finished by an original adjoining life structure directed division way to deal with incorporate irregularities with powerless surfaces, and pleura districts. They assessed the exactness and proficiency of the proposed technique on nearly 500 CT Scans examines with the presence of a wide range of irregularities. It has been observed the standard U-Net model yields the Dice Score of 0.97 [20][21] on the diverse routine dataset where N equals to 36 [22]. However, the lung tissue resource consortium and anatomy3 data sets results in the Dice Score of .94 and 0 .92 respectively. The hybrid methos proves to illustrate better results as compared to the tradition methods. The article [23] introduces another composite lung segmentation strategy introduced that consequently identifies collapse of an ordinary calculation and, when required, resorts to a more composite and tricky calculation, as would be considered normal to create improved results even if exposed to strange cases. In a huge quantitative assessment on a data set of 160 outputs from various sources, the mixture strategy is displayed to perform considerably better compared to a regular methodology at a somewhat low expansion in computational expense.

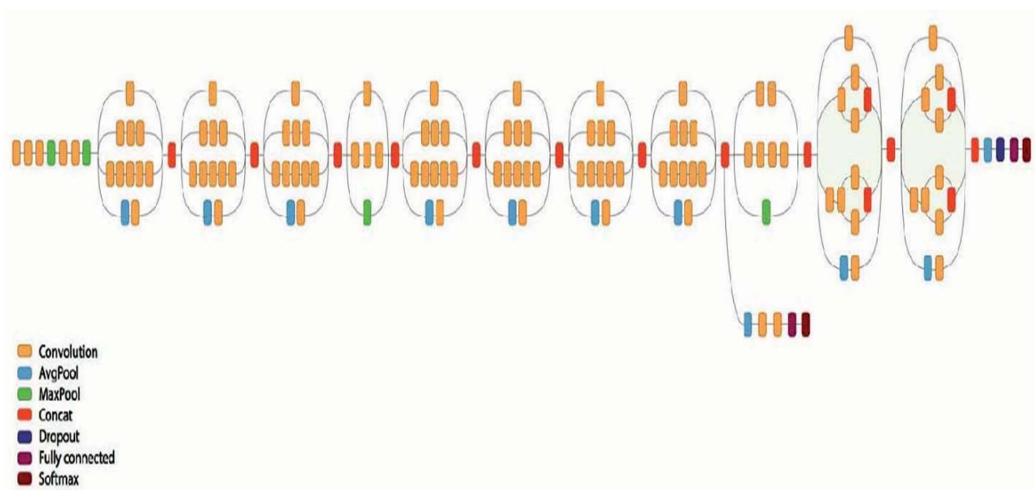

Fig 1: Architecture of InceptionResNetV2[13]

3. Proposed Work

Our propounded architecture consists of the combination of two extremely renowned models that is MobileNetV2 and InceptionResNetV2. MobileNetV2 is a strategy in light of CNN that is propounded by Google with further developed execution and improvement to be more productive. The overall architecture of MobileNetV2 depends on a reversed residual block where the type in and type out of the residual blocks are narrow bottleneck layers inverse to conventional block models which utilizes extended portrayals in the input a MobileNetV2 utilizes lightweight depth wise convolutions [24] to channel highlights in the middle of the extension layer. Furthermore, it is vital to eliminate non-linearities in the layers to keep up with illustrative nature. InceptionResNetV2 has proven to derive better results in terms of biomedical images especially in the areas of image models like X Rays. In article [25], the authors have clearly mentioned the advantages of using InceptionResNetV2 in the area of biomedical images especially the lung segmentation domain. In this review, an order utilizing a dataset containing pneumonia and typical lungs X-beam pictures is pointed. Figure 1 depicts the overall architecture of InceptionResNetV2. In a proposed architecture we used to extremely pronounce models MobileNetV2 and InceptionResNetV2 along with the encoder of unit the models were pre trained [26] and those required less CPU time as well as resources. The meta learner consists of three layers which are very dense with size of 32, 64 and 128. The dropout value was thus maintained as 0.4. We also incorporated batch normalization before the full convolutional layer. Batch Normalization in like manner makes preparing more grounded to the boundary scale[20]. Consistently, immense learning rates may augment the size of layer boundaries, which might expand the angle in course of backpropagation and cause model shortcoming. In any case, with the utilization of Batch Normalization [21], backpropagation through a layer is undisturbed by the measurments of its boundaries. This normalisation helps us to gain the reasonable number of features [27] along with the maximum for mapping of input parameters to the output parameters.

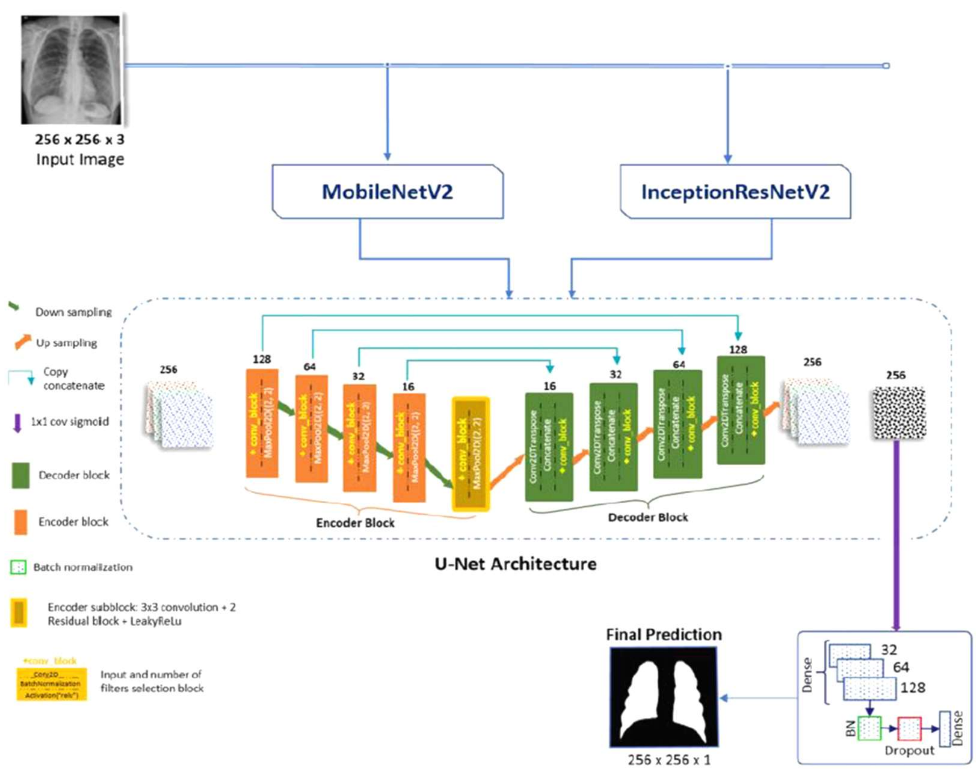

Fig 2: Architecture of the proposed network

In our model U-Net, InceptionResNetV2 and MobileNetV2 are all stacked together the encoder is loaded with the other two pre trained networks to give the better results. Zero padding was required in the encoder block. Figure 2 depicts the architecture of proposed network.

4. Experiment

The network was tuned by several hyper parameters. These parameters increase the complexity of the model but gives efficient result in the overall empirical observations. However, when compared with thar parameters of traditional U-Net along with MobileNetV2 [16] and U-Net along with InceptionResNetV2 [17], the number of parameters in U-Net along with InceptionResNetV2 and MobileNetV2 both, were 8.16% and 0.20% respectively. Some of the major parameters are number of iterations taken under consideration, the rate of learning by the network and the size of the input. To gain the results that would justify the overall observation we considered 60 iterations, optimized the learning rate to 0.001 and input size as 16. Figure 3 depicts the learning rate of the proposed network.

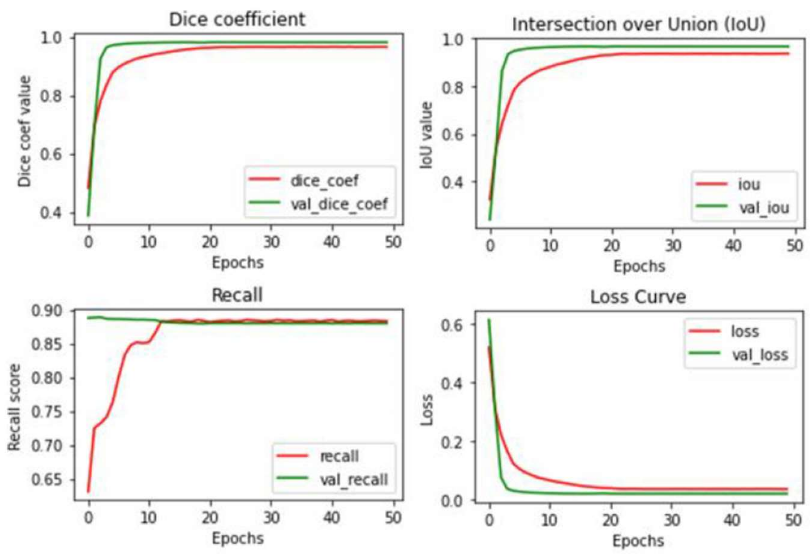

Fig 3: Training curve of U-Net along with InceptionResNetV2 and MobileNetV2

5. Results

We considered 5 metrices to compare out result with other networks which has achieved art-of-state level. The networks we compared with are traditional U-Net, U-Net with MobileNetV2, U-Net with InceptionResNetV2 and our proposed model that is U-Net with MobileNetV2 and InceptionResNetV2. The metrices covered are Dice Coefficient, Loss, IoU, Recall and Precision. Table 1 depicts the metrices and its corresponding values for each network.

Table 1: Comparison of various models with respect to significant metrices

	Dice Coefficient	**Loss**	**IoU**	**Recall**	**Precision**
U-Net	0.957	0.033	0.937	0.875	0.976
U-Net with MobileNetV2	0.966	0.029	0.948	0.892	0.981

U-Net with InceptionResNetV2	0.972	0.024	0.957	0.901	0.996
Proposed network	0.984	0.017	0.966	0.912	0.998

The increase in the Dice coefficient and decrease in the loss of the proposed model signifies the art of state. Figure 4 represents the accuracy and loss graph for 20 epochs. The graph depicts the increase in accuracy and decrease in loss. Apart from it, Figure 5 represents the segmented result of the sample along with the binary mask. The segmentation results as well as the tabular comparison clearly represents the efficiency of the proposed model especially for the lung segmentation in case of X-Ray inputs.

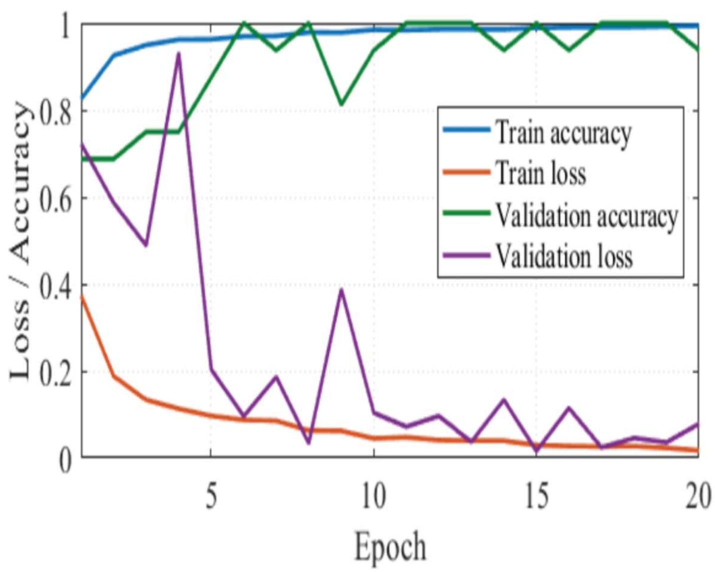

Fig 4: Accuracy and loss graph of the proposed model

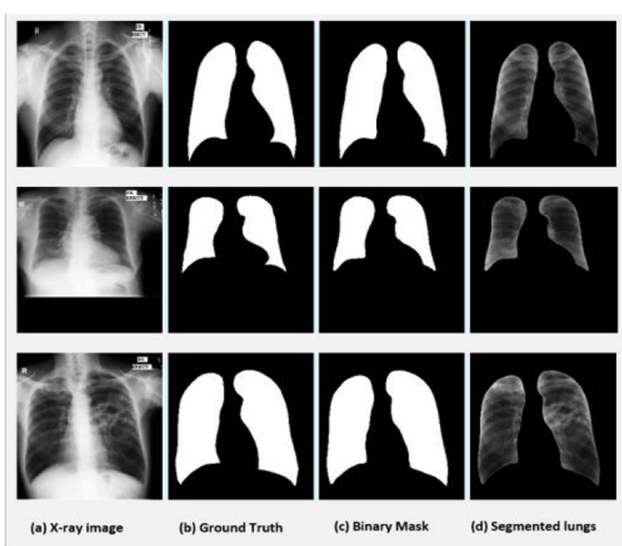

Fig 5: Lung segmentation on X-Ray

6. Conclusion

The proposed network of U-Net with MobileNetV2 and InceptionResNetV2 in the encoder side helps to gain the result in limited time and computational complexity. It makes the encoder of U-net loaded with many features and thus results in better segmentation output. We would further like to work on the same model for other modalities and even we would try to implement better results with model for multi modal image segmentation.

References

[1] Mukherjee, H., Sreerama, P., Dhar, A., Obaidullah, S. M., Roy, K., Mahmud, M., & Santosh, K. C. (2021). Automatic lung health screening using respiratory sounds. *Journal of Medical Systems*, *45*, 1-9.

[2] O. Ronneberger, P. Fischer, T. Brox. U-net: convolutional networks for biomedical image segmentation, in International Conference on Medical Image Computing and Computer-Assisted Intervention (Springer, 2015), pp. 234–241

[3] Mishra, A., Gupta, P., & Tewari, P. (2023, May). Biomedical Image Segmentation Using Integrated FCM Clustering Modified with Regularized Level Set Method. In 2023 International Conference on Disruptive Technologies (ICDT) (pp. 344-348). IEEE.

[4] Huang, H., Lin, L., Tong, R., Hu, H., Zhang, Q., Iwamoto, Y., ... & Wu, J. (2020, May). Unet 3+: A full-scale connected unet for medical image segmentation. In *ICASSP 2020-2020 IEEE international conference on acoustics, speech and signal processing (ICASSP)* (pp. 1055-1059). IEEE.

[5] Cleverley, J., Piper, J., & Jones, M. M. (2020). The role of chest radiography in confirming covid-19 pneumonia. *bmj*, *370*.

[6] Lasker, A., Ghosh, M., Obaidullah, S. M., Chakraborty, C., & Roy, K. (2023). LWSNet-a novel deep-learning architecture to segregate Covid-19 and pneumonia from x-ray imagery. Multimedia Tools and Applications, 82(14), 21801-21823.

[7] Ghosh, M., Roy, S. S., Mukherjee, H., Obaidullah, S. M., Santosh, K. C., & Roy, K. (2022). Understanding movie poster: transfer-deep learning approach for graphic-rich text recognition. The Visual Computer, 1-20.

[8] Chatterjee, S., Maity, S., Bhattacharjee, M., Banerjee, S., Das, A. K., & Ding, W. (2023). Variational autoencoder based imbalanced COVID-19 detection using chest X-ray images. *New Generation Computing*, *41*(1), 25-60.

[9] Raveendran, A. V., Jayadevan, R., & Sashidharan, S. (2021). Long COVID: an overview. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, *15*(3), 869-875.

[10] Mansoor, A., Bagci, U., Xu, Z., Foster, B., Olivier, K. N., Elinoff, J. M., ... & Mollura, D. J. (2014). A generic approach to pathological lung segmentation. *IEEE transactions on medical imaging*, *33*(12), 2293-2310.

[11] Hofmanninger, J., Prayer, F., Pan, J., Röhrich, S., Prosch, H., & Langs, G. (2020). Automatic lung segmentation in routine imaging is primarily a data diversity problem, not a methodology problem. *European Radiology Experimental*, *4*(1), 1-13.

[12] van Rikxoort, E. M., de Hoop, B., Viergever, M. A., Prokop, M., & van Ginneken, B. (2009). Automatic lung segmentation from thoracic computed tomography scans using a hybrid approach with error detection. Medical physics, 36(7), 2934-2947.

[13] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. (2018). Mobilenetv2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4510-4520).

[14] DEMİR, A., & YILMAZ, F. (2020, November). Inception-ResNet-v2 with LeakyReLU and averagepooling for more reliable and accurate classification of chest X-ray images. In 2020 Medical Technologies Congress (TIPTEKNO) (pp. 1-4). IEEE.

[15] Mishra, A., Gupta, P., & Tewari, P. (2022). Global U-net with amalgamation of inception model and improved kernel variation for MRI brain image segmentation. Multimedia Tools and Applications, 81(16), 23339-23354.

[16] Kanadath, A., Jothi, J. A. A., & Urolagin, S. (2021, June). Histopathology image segmentation using MobileNetV2 based U-net model. In 2021 International Conference on Intelligent Technologies (CONIT) (pp. 1-8). IEEE.

[17] Siciarz, P., & McCurdy, B. (2022). U-net architecture with embedded Inception-ResNet-v2 image encoding modules for automatic segmentation of organs-at-risk in head and neck cancer radiation therapy based on computed tomography scans. Physics in Medicine & Biology, 67(11), 115007.

[18] Chaturvedi, Ravi Prakash, And Udayan Ghose. "A Novel Model Of Texture Pattern Based Object Identification Using Convoluted Multi-Angular (Cma) Pattern Extraction Method." (2022).

[19] Chaturvedi, Ravi Prakash, and Udayan Ghose. "Evaluation of Small Object Detection in Scarcity of Data in the Dataset Using Yolov7." 2023 International Conference on Disruptive Technologies (ICDT). IEEE, 2023.

[20] Mishra, A., Gupta, P., & Tewari, P. (2022). Global U-net with amalgamation of inception model and improved kernel variation for MRI brain image segmentation. Multimedia Tools and Applications, 81(16), 23339-23354.

[21] Mishra, A., Gupta, P., & Tewari, P. (2023, May). Biomedical Image Segmentation Using Integrated FCM Clustering Modified with Regularized Level Set Method. In 2023 International Conference on Disruptive Technologies (ICDT) (pp. 344-348). IEEE.

[22] Chaturvedi, Ravi Prakash, and Udayan Ghose. "A review of small object and movement detection based loss function and optimized technique." Journal of Intelligent Systems 32.1 (2023): 20220324.

[23] Chaturvedi, Ravi Prakash, and Udayan Ghose. "Comparison of Various Classification Techniques on Brain Tumor Detection." Advances in Smart Communication and Imaging Systems: Select Proceedings of MedCom 2020. Springer Singapore, 2021.

[24] Chaturvedi, Ravi Prakash, and Udayan Ghose. "Small object detection using retinanet with hybrid anchor box hyper tuning using interface of Bayesian mathematics." Journal of Information and Optimization Sciences 43.8 (2022): 2099-2110.

[25] Chaturvedi, Ravi Prakash & Ghose, Udayan(2023) An effective framework for detecting the object from the video sequences by utilizing deep learning with hybrid technology, Journal of Information and Optimization Sciences, 44:1, 113-126

[26] Sharma, H., Aggarwal, G., & Kumar, S. (2022). Literature Survey for Design and Analysis of a Multi-Level Algorithmic Technique for Encryption and Decryption. Grenze International Journal of Engineering & Technology (GIJET), 8(2).

[27] Kumar, S., Sharma, M. H., Tiwari, M. V. K., & Namita, M. (2023). DETECTION AND PREVENTION OF CANCER IN EARLY STAGES USING LINEAR REGRESSION ALGORITHM. Journal of Data Acquisition and Processing, 38(2), 4238.