International Journal of Recent Development in Computer Technology & Software Applications
Vol. 5, Issue 1 – 2021
ISSN: 2581-6276

Lung Cancer Diagnosis using Deep Learning Methods in Health Care Systems

P. Manju Bala[1], S. Usharani[1], G. Leema Roselin[1], A. Balachandar[1], M. Pavithra[1]

[1]*Department of Computer Science and Engineering, IFET College of Engineering, Villupuram, Tamilnadu, India.*

Abstract

The deep learning method for detecting lung disease in thoracic X-rays of the general population will be verified. Retrospective assessment of a deep learning system with patients' chest x-rays. The field under Receiver Operating characteristic feature Curves (ROC) including clinical metrics comprising sensitiveness and false-positive (FPR) have been generated to evaluate the effectiveness of the algorithm for the identification of visible lung cancers. Tests utilizing relatively good and negative results are compared. That deep learning system was used between 2008 and 2012, as its performance was calculated for a screening sample receiving thoracic radiography. Researchers are now striving to boost the effectiveness of CAD in computational tomography screening for cancer through different deep learning approaches. For the detection of lung cancer most advanced depth education algorithms and architectures are used. These systems are split into two (1) detection systems that identify candidate nodules from the initial CT scan, and (2) false alarm control systems that categories them into malignant or benign tumors from a collection of candidate nodules. They are classified into two categories. The major features and performance of several methods are described. A deep learning model has found similarly effective lung nodules in radiologists that are beneficial for radiologists who treat low-incidence patients with lung conditions.

Introduction

Lung cancer seems to be the world's largest cause of mortality due to cancer, responsible for approximately 1/4 of cancer fatalities [1]. Because the majority of the time, the earliest stage of screening for lung disease is discovered at an advanced stage, a method for reducing lung cancer mortality has been developed [2].The NLSS has convincingly proven the ability of low-dosage CT to decrease lung cancer deaths [3] with an average dose rate of 1.5 mSv. In contrast, either early identification of lung cancer or a reduction in mortality from lung cancer may be proved by the use of chest radiography as just a diagnostic tool [4]. Therefore, it's disputed if chest radiography should be used to test for lung cancer. However, chest x-rays are extensively utilised as a first-screening technique for numerous major thoracic disorders, especially lung disease, due to their inexpensive cost, simple accessibility, low radiation levels, and adequate capacity for diagnosis [5]. However, ongoing limitations of tube radiographs as a diagnostic tool [6] remain as a consequence of the lack of sensitivity to the detection of lung, significant interreader variability and vulnerable to observer error. Deep learning methods have recently placed themselves in chest x-rays [7], and have been shown to be good in enriched situations for diagnosis [8]. The author [9] stated that even a deep neural model had anaccuracy of 0.92 to 0.99 in its validating sets of data with a prevalence of around 60 to 68 percent of lung cancer of 71 to 91 percent, a specificity of 93 to 100 percent, and the AUC curve. The author[10] showed a similar diagnostic performance for another deeper learning algorithm for specialists in the research population of lung disease, consisting of 75% of lung disease, including x-rays. They also demonstrated that their algorithm's support enhanced sensitivity (from 65% to 73%) and lowered FPR (from 20% to 18%). In addition to real-world clinical practice data sets, previous research has used randomly selected sets to test its deep learning algorithms.The purpose of this research was to examine, using a deep learning system to identify nodules in the chest, X-rays compared to radiography, the efficiency of this healthy screening population with an estimated risk for cancer.

Materials and Methods

For Lunit's analysis of chest x-rays with a deeply learned algorithm, Lunit (Seoul, Korea) has given technological support [11]. However, the Lunit has no involvement in the learning'splan, collection of data, analysis, and interpretation, study conduct, or decision to publish the paper.All data within the study was completely accessible and monitored by the first researcher (J.H.L.). The research has been authorised by the Seoul National University Hospital Institute Review Board and has been excused from the need for informed written consent. The study population was not reported.

Collection and Population Study

Tha chest images were obtained by participants taking part in the Seoul University College Healthcare System Gangnam Center medical examination and screening programme from January 2008 to December 2012 [12]. The facility conducts a full medical examination and screening programme for non-communicable conditions including malignancy [13] as well as chest x-ray is a major test within this screening programme for detecting any pulmonary illnesses that require further diagnosis or treatment. The research respondents paid their own expenses for screening costs and were not evaluated on the basis of predetermined risk factors for lung cancer. In this regard, the target group was an average overall risk population rather than a lung-screening group carefully selected for older people who were already smoking cigarettes [14]. Everyone who has had chest x-rays, rather than diagnostic criteria or signs, undergoes a complete medical inspection [15]. This study covers modern, deep neural model for lung cancer diagnosis. Almost all of the work offered is focused on deep learning models (CNN). CNN is a neural class that can learn variables from a range of inputs during training.They usually consist of many layers, like convolutionary layers, deconvolution layers, bundled layers etc. In recent days, many designs have been developed to increase the performance of the CNN standard and overcome certain restrictions [16]. This includes residual networks, startups, Xception and density networks. In classification, segmentation, detection and immediate tasks, CNN has demonstrated its fascinating achievements. The most commonly utilised picture data was other sets of information, including the text in NLP applications [17]. They were effectively employed.

Datasets

Datasets are a crucial element of any method of machine training or profound learning. The accuracy of the evidence available contributes to the development, training and improvement of algorithms. The supplied data must always be verified and labelled by specialists in medical image analysis in ways that are relevant to advancement. One such section presents data sets for the identification of lung cancer that have been utilised in recent research.

Database of Lung images

The LIDC-IDRI dataset [18] includes 1020 instances from many academic institutes and some firms in the field of healthcare imaging. An Xml document with CT scan annotations is included in each case. Certified and experienced thoracic radiologists execute these annotations in a two-stage process[19]. Each radiologist classifies the results into three groups separately during the first step. And each radiologist evaluates their classifications and the other radiologists' classifications anonymously, as in the second stage. Thus, all 4 radiologists individually evaluate each annotation. The database comprises of 1018 CT scanners, with such a total of 244,527 pictures, from 1010 people [20]. The analysis may be established at 2 levels with this dataset. Victim diagnosis (diagnostics linked to the client) and nodular diagnosis. The resolution of DICON CT scans varies between 65 and 764 slices, with a sharpness of 512 512 width. For this dataset, the average slice width is 240. The nodules are divided into four tiers. (1) A malignant that is an original lung disease (4) a metastasis lesion linked to primary extrathoraxial malignancy (1) unknown (not available data), (2) Benign ornamental malignant illness. In addition, for each disease, information on how the diagnosis is made is available.Including choices such as (1) Unknown (not apparent how such a diagnosis has been confirmed), (2) a two-year stable nodule evaluation of radiological imaging, (3) biopsy and, (4) treatment option as well as (5) advance or response .

LUNA16

A post of LIDC-IDRI data sets, the LUNA16 data [21], filters several criteria into heterogeneous scans. As lung nodules can be extremely tiny, it is important to choose a small layer. Thus, scans bigger than 2.5 mm were deleted with a lower image quality. In addition, images were also eliminated due to the consistent spacing of the slices or lack of slices. This resulted in 887 CT imagesand the total of 36,200 radiologist observations. Only 3 mm nodules are considered

International Journal of Recent Development in Computer Technology & Software Applications
Vol. 5, Issue 1 – 2021
ISSN: 2581-6276

relevant in this data, as the other notes are not thought to be useful for lung screening methods. Nodules that were close to the total of their respective radii reported by various writers were combined[22]. The position and diameter of the annotations were average in this situation. In that scenario, it leads to a collection of nodules of 2299, 1500, 1192 and 780, respectively, recorded by radiologists 1, 2, 3 or 4. A chest CT scan in figure 1 is presented in several slices with thyroid tumors as an example. For other datasets, a similar type of image is acquired.

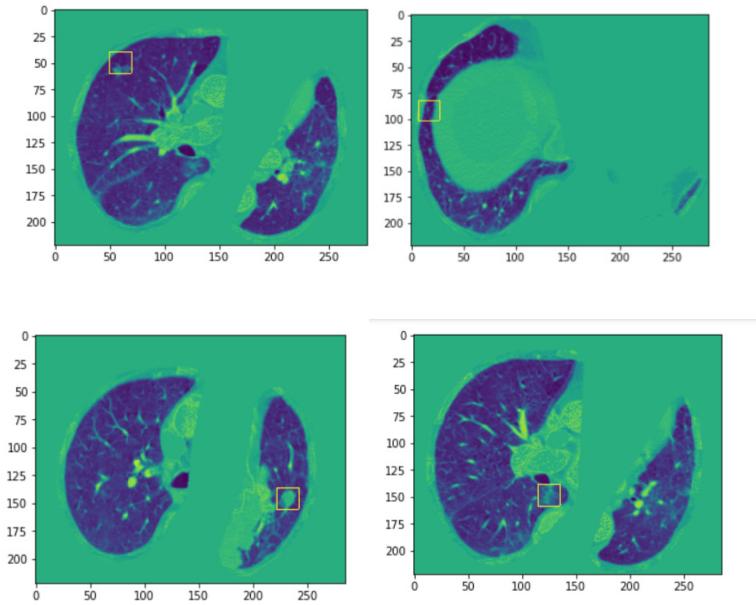


Figure 1.CT images of lung nodule

System for detecting deep nodule

The standard structure is separated into two major objectives due to the difficulties of finding lung nodules and the significance of attempting to discover all of them. The first is concerned with identifying nodule possibilities [23]. This attempts to find all the genuine nodules in the Computed tomography region, which frequently contains a lot of false positives. The second step then focuses on categorizing the previous stored possibilities as malignant or benign nodules. The goal of the second stage is to minimize the enormous number of errors created in the first [24]. Some studies do not employ this method, instead detecting and classifying nodules immediately from Computed tomography. Research in this area that provides a complete workflow through CT scans to final prediction of identified nodules was discussed. A few of them, as previously said, split the dataset into candidate's creation and false positive minimization, whilst other doesn't. Design, image pre-processing, and learning approach, among other things, may vary amongst studies [25] [26]. The use of a two-dimensional or three-dimensional method is a significant difference among methods. Three-dimensional convolutional layers are required for 3D structures, which raises the number of variables, computation complexity, and classification accuracy significantly [27][28]. As a result, some methods employ

2D convolution layer, which have less variables and so enable for the training of larger and more complicated structures on less capable technology [29].

Two Dimensional (2D) Deep Learning Model

2D kernels are twisted with 2D images in a two-dimensional method, or the artificial learning network's input is two-dimensional. This will not imply that these buildings are devoid of all 3d data [30]. The Computer aided system generates a set of candidates including a score that indicates how likely the area is to be a nodules. As input, the Over Feat system takes a 222_222 RGB picture patch. It is made up of Convolutional Levels with 95 to 1032 cores ranging in size from 4_4 to 8_8 [31][32]. It employs half wave correction and 4_4 and 6_6 maximum pooling kernels. The first Completely Coupled (CC) keyframe 4097 features are fed into a quadratic K Nearest classifier with Python optimal cross-validation. The researchers devised three distinct systems, one for each diagonal sector (a, b, and c) [33]. The highest performing approach for fusing these findings was a late efficacy studies employing CAD data. This has been accomplished by combining the outputs of the three components a, b, and c, as well as the CAD platform's rating [34]. The likelihood that the candidate is a nodule is then estimated using a second stage classifier. The CAD system created 37,262 possible locations on its own. True nodules made up 78 percent of the respondents. The CPM for the entire model is 0.72. A CAD system that classifies lung lesions using deep features collected from a feature vector. They combine patient CT images with clinical criteria from the Kaggle repository [35][36]. There are 234 cases with clinical data obtained from biopsies, surgical excision, advancement, or radiographic data assessment showing 2 years of nodular status at two different levels. They chose clinical information because it is the sole technique to determine the likelihood of cancer. First, using the labels given in the datasets, lesions are retrieved from 3D CT scans. They are then put into a 5 layer de-noising classifier developed using L-BFGS one by one. The fourth level is then used to retrieve acquired characteristics. For each example, the characteristics from the fourth layer have been used to build a feature map with 250 pixels. The categorization for lesions is then obtained by feeding these vectors into a discrete feature selection. The radiologist's [37] comments are utilized to extract features for each lesion Approximately 4 mm in diameter. Based on the size of the nodules, they constructed an adjustable square display [38]. The classifier is then given a set size input by resizing each horizontal line to a specified number. Lesions having a grading of 0, 3, or 4 are considered cancerous. With a sensitive of 0.8335 and a scanning speed of 0.38 FP/scan, they were able to attain an accuracy rate of 85.01 percent. The researchers use various classes based on DNN [39] and CNN. The Kaggle repository [40] was used, with the trained data downsized to 64_64 ROIs. They employed the technique for DNN, which comprises of a pessimistic coating artificial neural network for DNN. Figure 2 depicts the classification method, which uses back propagation algorithm to train DBMs (Deep Boltzmann Machines). The Convolution layers layers' dimension is set to 2 for the CNN to connect to the central spatial distribution. The artificial neuron is a gaussian, and the complexity is reduced using max-pooling. For the very first layer, they utilize four feature vectors, then six processing

International Journal of Recent Development in Computer Technology & Software Applications
Vol. 5, Issue 1 – 2021
ISSN: 2581-6276

elements, and ultimately an FC layer to categorize the nodule. To obtain an initial model, the DNN is first developed unsupervised algorithm. The categorization assignment is then good through a classification model. From the bottom - up approach, the DNN trains one layer at a time. To estimate the greatest file, the learning is depending upon the gradient lineage technique and the lipschitz convergence technique. The DNN has a precision of 0.825 and a accuracy of 0.725. The CNN has a precision of 0.735 and an accuracy of 0.789, respectively.

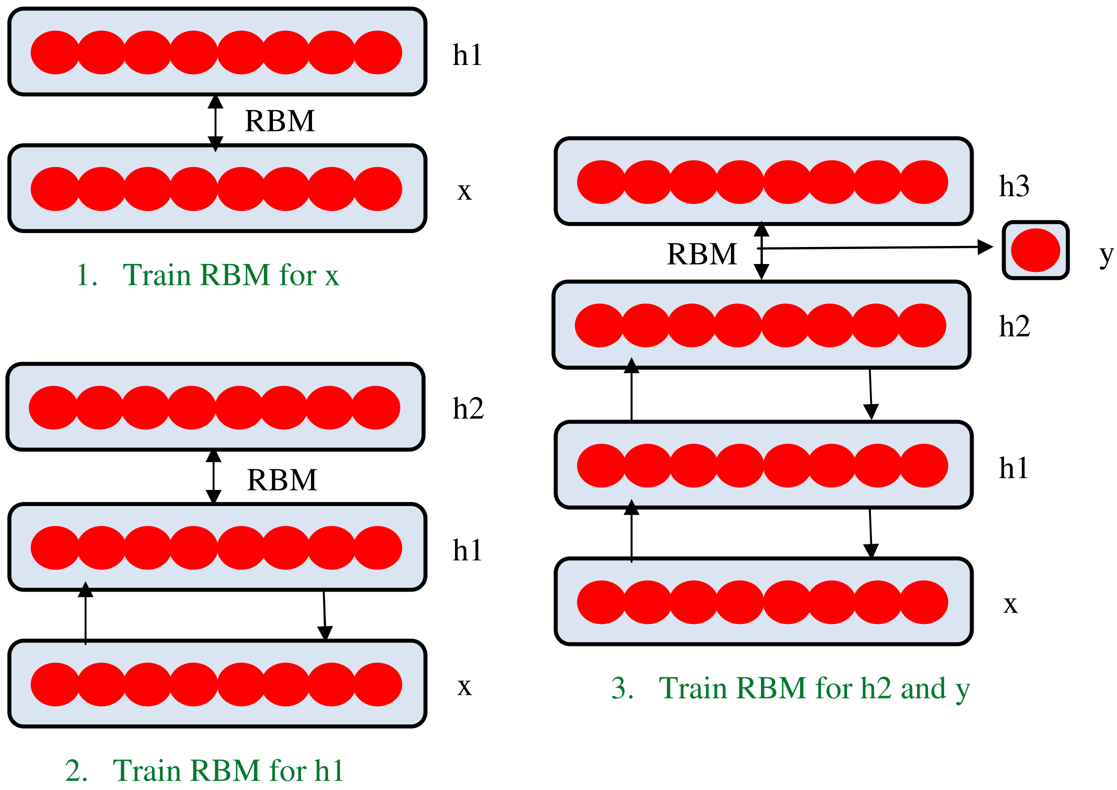


Figure 2.Framework for Deep Neural Network

Performance analysis

Table 1 shows the technical specifications of the deep learning model for lung cancer diagnosis over the full testing group.

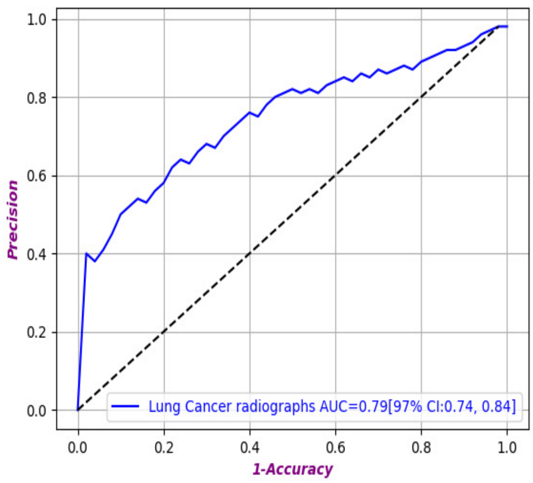
Table 1.Specifications of the deep learning model for lung cancer diagnosis

Methodology	Precision in %	Accuracy in %	IRR in %	TP in %	AUC in %
Lung cancer radiograph	45	96	100	1.5	98
Noticeable lung cancer	85	98	100	1.5	98
Clearly marked lung cancer	100	98	100	0.9	98

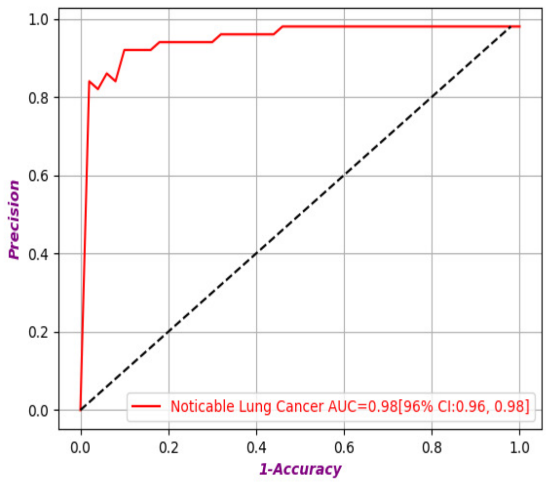
The methodology categorized 4% of CT scans as problematic (3039 of 100 575 radiography for lung cancer radiographs, 3039 of 100535 radiographs for noticeable lung cancers on CT scans, and 3030 of 100500 radiographs for clearly marked lung cancers on CT scans). The algorithm's

International Journal of Recent Development in Computer Technology & Software Applications
Vol. 5, Issue 1 – 2021
ISSN: 2581-6276

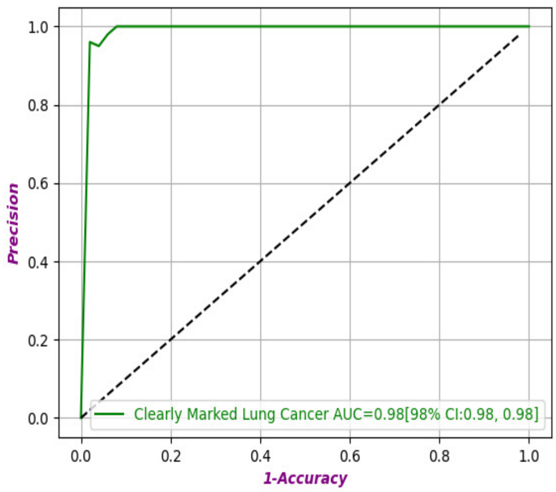
Area under the Curve for lung cancer radiography diagnosis was 0.79 (97 percent CI: 0.74, 0.84). (Figure3a). The system properly diagnosed 40 of the 99 images of malignancy (precision, 45 percent). The algorithm's precision, IRR, and TP were 98 percent, 99 percent, and 1.5 percent, respectively. The method had an AUC of 0.98 (96 percent CI: 0.96, 0.98) in detecting visible lung tumors on chest radiographs (Figure 3b). On 40 of 48 radiography images, visible lung tumors were appropriately identified (precision, 83 percent). For diagnosing visible lung tumors, the system's accuracy, IRR, and TP were 97 percent, 100 percent, and 1.5 percent, correspondingly. The method had an AUC of 0.98 (98 percent CI: 0.98, 0.98) for detecting clearly visible lung tumors on CT scans (Figure 3c). On 29 of 29 CT scans, clearly visible lung tumors were correctly identified (precision, 100 percent). The method's precision, IRR, and TP, correspondingly, were 98 percent, 99 percent, and 0.9 percent. When the multiple ROC were related, the process performed well with enhanced coverage vs noticeable lung cancers on CT scans [AUC = 0.98; 96 percent CI: 0.96, 0.98], P,.002; positive cancer CT scans vs fully noticeable lung cancer on CT scans [AUC = 0.98; 96 percent CI: 0.98, 0.98], P,.002; noticeable lung cancer on chest radiographs vs cancer-positive CT scan.



(a)



(b)



(c)

Figure 3.ROC of Deep Learning algorithm for diagnosis of lung cancer

Discussion

The deep learning method had a 0.99 area under the ROC curve (AUC (96 percent confidence interval: 0.97, 1) and a similar tolerance (95 percent vs 65 percent, P =.25) to radiologist, but a greater false-positive rate (3.2 percent vs 0.4 percent,P, .002). The algorithm's precision, IRR, and true positive rate were similar with those of the physicians at the range when the algorithm's precision mirrored that of the clinicians (0.845).Because of the preceding facts, the applicability to reality of prior deep-learning model diagnoses of CT scan lung cancers was deficient. The precision of detection of identical lung disease in CT images was highly variable, ranging from 25% to 95%, with the most significant and avoidable reasons for issues with identifying or diagnosing lung cancer in CT scans being the cognitive viewpoint of clinicians. In this investigation, the deep learning system significantly beaten earlier research in terms of tolerance (92 percent in the test process and 85 percent in the medical checks), categorizing only 4% of CT scans as having a high likelihood of becoming erroneous. Because the deep learning model demonstrates a reliable and comparable identification efficiency for cancer cases on CT scans and was not susceptible to psychological people who read' inaccurate information, it can significantly minimize diagnosing random errors by small errors or influential factors owing to clinicians' inadequate data and practice.

Conclusion

The scope of this chapter is to find malignant lung nodules in an input lung photo and to evaluate lung cancer and its extent. This study employs unique Deep learning approaches to detect the location of malignant lung nodules. Finally, a deep learning model diagnosed lung cancer lesions on CT scans with similar accuracy to physicians that will be useful for clinicians in large people with low lung cancer frequency. More investigations with a range of nationalities and healthcare contexts will be required to extend the clinical usage of the deep learning model in a surveillance system for the normal community. The prediction accuracy of malignant tumors will be improved in the future and the proposed methodology will be optimized. In particular, more work will be done to grade the radiographs depending on the level of cancer of the lung nodules, which is important for lung cancer diagnosis and therapy in real world applications.

References

1. Bhatt, Chandradeep, Indrajeet Kumar, V. Vijayakumar, Kamred Udham Singh, and Abhishek Kumar. "The state of the art of deep learning models in medical science and their challenges." *Multimedia Systems* (2020): 1-15.
2. Coccia, Mario. "Deep learning technology for improving cancer care in society: New directions in cancer imaging driven by artificial intelligence." *Technology in Society* 60 (2020): 101198.

3. Massion, Pierre P., Sanja Antic, SarimAther, Carlos Arteta, Jan Brabec, Heidi Chen, Jerome Declerck et al. "Assessing the accuracy of a deep learning method to risk stratify indeterminate pulmonary nodules." *American journal of respiratory and critical care medicine* 202, no. 2 (2020): 241-249.
4. S.Sasubilli, A. Kumar, V. Dutt, "Machine Learning Implementation on Medical Domain to Identify Disease Insights using TMS", 2020, Sixth International Conference on Advances in Computing & Communication Engineering Las Vegas USA ICACCE 2020 (22-24 June) ISBN: 978-1-7281-6362-8
5. Raj, R. Joshua Samuel, S. Jeya Shobana, Irina Valeryevna Pustokhina, Denis Alexandrovich Pustokhin, Deepak Gupta, and K. Shankar. "Optimal feature selection-based medical image classification using deep learning model in internet of medical things." *IEEE Access* 8 (2020): 58006-58017.
6. Swarn Avinash Kumar, Harsh Kumar, Vishal Dutt, Himanshu Swarnkar, "COVID-19 Pandemic analysis using SVM Classifier: Machine Learning in Health Domain", Global Journal on Application of Data Science and Internet of Things, 2020, Vol 4 No. 1.
7. Abhishek Kumar, Tvm Sairam, Vishal Dutt, "Machine Learning Implementation For Smart Health Records: A Digital Carry Card", Global Journal on Innovation, Opportunities and Challenges in AAI and Machine Learning Vol. 3, Issue 1-2019
8. S. A. Kumar, A. Kumar, V. Dutt and R. Agrawal, "Multi Model Implementation on General Medicine Prediction with Quantum Neural Networks," 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), Tirunelveli, India, 2021, pp. 1391-1395, doi: 10.1109/ICICV50876.2021.9388575.
9. Khamparia, Aditya, Deepak Gupta, Victor Hugo C. de Albuquerque, Arun Kumar Sangaiah, and Rutvij H. Jhaveri. "Internet of health things-driven deep learning system for detection and classification of cervical cells using transfer learning." *The Journal of Supercomputing* (2020): 1-19.
10. T. Pospisil and A.B. Lee. (f)RFCDE: Random forests for conditional density estimation and functional data. arXiv preprint arXiv:1906.07177, 2019.
11. M.E. Pfetsch and S. Pokutta. IPBoost - non-convex boosting via integer programming. arXiv preprint arXiv:2002.04679, 2020.
12. L. Palagi. Global optimization issues in deep network regression: an overview. Journal of Global Optimization, 73(2):239-277, 2019.
13. S. A. Kumar, H. Kumar, V. Dutt and H. Soni, "Self-Health Analysis with Two Step Histogram based Procedure using Machine Learning," 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), Tirunelveli, India, 2021, pp. 794-799, doi: 10.1109/ICICV50876.2021.9388427.
14. Swarn Avinash Kumar, Harsh Kumar, Vishal Dutt, Pooja Dixit, "Deep Analysis of COVID-19 Pandemic using Machine Learning Techniques", (2020): Global Journal on Innovation, Opportunities and Challenges in AAI and Machine Learning, Vol 4 No 2, [ISSN: 2581-5156].

15. R.K. Mothilal, A. Sharma, and C. Tan. Explaining machine learning classi?ers through diverse counterfactual explanations. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, pages 607-617, 2020.
16. S. A. Kumar, H. Kumar, V. Dutt and H. Soni, "Self-Health Analysis with Two Step Histogram based Procedure using Machine Learning," 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), Tirunelveli, India, 2021, pp. 794-799, doi: 10.1109/ICICV50876.2021.9388427.
17. S. M. Sasubilli, A. Kumar and V. Dutt, "Improving Health Care by Help of Internet of Things and Bigdata Analytics and Cloud Computing," 2020 International Conference on Advances in Computing and Communication Engineering (ICACCE), Las Vegas, NV, USA, 2020, pp. 1-4, doi: 10.1109/ICACCE49060.2020.9155042.
18. M. Miron, S. Tolan, E. G´omez, and C. Castillo. Addressing multiple metrics of groupfairness in data-driven decision making. arXiv preprint arXiv:2003.04794, 2020.
19. A. Lucic, H. Oosterhuis, H. Haned, and M. de Rijke. FOCUS: Flexible optimizable counterfactual explanations for tree ensembles. arXiv preprint arXiv:1911.12199, 2020.
20. Swarn Avinash Kumar, Harsh Kumar, Vishal Dutt, Pooja Dixit, "The Role of Machine Learning in COVID-19 in Medical Domain: A Survey", Journal on Recent Innovation in Cloud Computing, Virtualization & Web Applications, Vol 4 No 1 (2020), [ISSN: 2581-544X]
21. S. R. Swarna, S. Boyapati, V. Dutt and K. Bajaj, "Deep Learning in Dynamic Modeling of Medical Imaging: A Review Study," 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), Thoothukudi, India, 2020, pp. 745-749, doi: 10.1109/ICISS49785.2020.9315990.
22. J. Lin, C. Zhong, D. Hu, C. Rudin, and M. Seltzer. Generalized and scalable optimalsparse decision trees. arXiv preprint arXiv:2006.08690, 2020.
23. R. Raturi and A.Kumar " An Analytical Approach for Health Data Analysis and finding the Correlations of attributes using Decision Tree and W-Logistic Modal Process", 2019, IJIRCCE Vol 7, Issue 6, ISSN(Online): 2320-9801 ISSN (Print) : 23209798.
24. S.Chandrasekaran and A.Kumar Implementing Medical Data Processing with Ann with Hybrid Approach of Implementation Journal of Advanced Research in Dynamical and Control Systems – JARDCS issue 10, vol.10, page 45-52, ISSN-1943-023X. 2018/09/15.
25. Vishal Dutt, Rohit Raturi, Vicente García-Díaz, Sreenivas Sasubilli, "Two-Way Bernoulli distribution for Predicting Dementia with Machine Learning and Deep Learning Methodologies", Solid State Technology, 63(6), pp.: 9528-9546.
26. Bhandary, Abhir, G. AnanthPrabhu, V. Rajinikanth, K. PalaniThanaraj, Suresh Chandra Satapathy, David E. Robbins, Charles Shasky, Yu-Dong Zhang, João Manuel RS Tavares, and N. Sri Madhava Raja. "Deep-learning framework to detect lung abnormality–A study with chest X-Ray and lung CT scan images." *Pattern Recognition Letters* 129 (2020): 271-278.
27. Swarn Avinash Kumar, Harsh Kumar, Vishal Dutt, Himanshu Swarnkar, "Contribution Of Machine Learning Techniques To Detect Disease In-Patients: A Comprehensive Analysisof

Classification Techniques", Global Journal on Innovation, Opportunities and Challenges in AAIand Machine Learning, Vol. 3, Issue 1 -2019, ISSN: 2581-5156.

28. Bala, P. Manju, S. Usharani, R. Rajmohan, and G. Leemaroselin. "Applications of Machine Learning and Deep Learning for maintaining Electronic Health Records." *Global Journal of Internet Interventions and IT Fusion [ISSN: 2582-1385 (online)]* 3, no. 1 (2020).
29. S. Boyapati, S. R. Swarna, V. Dutt and N. Vyas, "Big Data Approach for Medical Data Classification: A Review Study," 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), Thoothukudi, India, 2020, pp. 762-766, doi: 10.1109/ICISS49785.2020.9315870.
30. G. Sasubilli and A. Kumar, "Machine Learning and Big Data Implementation on Health Care data," 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), 2020, pp. 859-864, doi: 10.1109/ICICCS48265.2020.9120906.
31. Swarn Avinash Kumar, Harsh Kumar, Vishal Dutt, Himanshu Swarnkar, "Role of Machine Learning in Pattern Evaluation of COVID-19 Pandemic: A Study for Attribute Explorations and Correlations Discovery among Variables", (2020): Global Journal on Application of Data Science and Internet of Things, Vol 4 No 2, [ISSN: 2581-4370].
32. Balachandar, A., E. Santhosh, A. Suriyakrishnan, N. Vigensh, S. Usharani, and P. Manju Bala. "Deep Learning Technique Based Visually Impaired People Using YOLO V3 Framework Mechanism." In *2021 3rd International Conference on Signal Processing and Communication (ICPSC)*, pp. 134-138. IEEE, 2021.
33. Aarthi, N., K. Abinaya, G. Haripriya, and R. Rajmohan. "Applications of ML/DL for Predicting Epidemic Outbreaks." *Global Journal on Innovation, Opportunities and Challenges in Applied Artificial Intelligence and Machine Learning [ISSN: 2581-5156 (online)]* 4, no. 2 (2020).
34. S.Chandrasekaran and A.Kumar Implementing Medical Data Processing with Ann with Hybrid Approach of Implementation Journal of Advanced Research in Dynamical and Control Systems – JARDCS issue 10, vol.10, page 45-52, ISSN-1943-023X. 2018/09/15.
35. Usharani, S., and S. G. Sandhya. "Detection of ransomware in static analysis by using Gradient Tree Boosting Algorithm." In *2020 International Conference on System, Computation, Automation and Networking (ICSCAN)*, pp. 1-5. IEEE, 2020.
36. Swarn Avinash Kumar, Harsh Kumar, Srinivasa Rao Swarna, Vishal Dutt, "Early Diagnosis and Prediction of Recurrent Cancer Occurrence in a Patient Using Machine Learning", European Journal of Molecular & Clinical Medicine, 2020, Volume 7, Issue 7, Pages 6785-6794.
37. Gopalakrishnan, A., P. ManjuBala, and T. Ananth Kumar. "An Advanced Bio-Inspired Shortest Path Routing Algorithm for SDN Controller over VANET." In *2020 International Conference on System, Computation, Automation and Networking (ICSCAN)*, pp. 1-5. IEEE, 2020.
38. Usharani, S., P. ManjuBala, and M. Martina Jose Mary. "Dynamic Analysis on Crypto-ransomware by using Machine Learning: GandCrabRansomware." In *Journal of Physics: Conference Series*, vol. 1717, no. 1, p. 012024. IOP Publishing, 2021.

39. Vishal Dutt, Sriramakrishnan Chandrasekaran, Vicente García-Díaz, (2020). “Quantum neural networks for disease treatment identification.”, European Journal of Molecular & Clinical Medicine, 7(11), 57-67.
40. Jeyaranjani, J., T. Dhiliphan Rajkumar, and T. Ananth Kumar. "Coronary heart disease diagnosis using the efficient ANN model." Materials Today: Proceedings (2021).

