
IJITCE
ISSN 2347- 3657
International Journal of
Information Technology & Computer Engineering
www.ijitce.com
Email : ijitce.editor@gmail.com or editor@ijitce.com

International Journal of Information Technology & Computer Engineering

ISSNNO: ISSN 2347–3657

Volum Volume 10,Issue 4 ,2022

CLASSIFICATION OF LUNG CANCER NODULES TO MONITOR PATIENTS HEALTH USING NEURAL NETWORK TOPOLOGY

ARUNA SRI[1], M.A.HARITHA[2], M.A.HARIKA[3]

Article Info

Received: 03-07-2022 Revised: 17 -08-2022 Accepted: 12-09-2022

ABSTRACT:

Lung cancer is one of the major causes of cancer-related deaths due to its aggressive nature and delayed detections at advanced stages. Early detection of lung cancer is very important for the survival of an individual, and is a significant challenging problem. Generally, chest radiographs (X-ray) and computed tomography (CT) scans are used initially for the diagnosis of the malignant nodules; however, the possible existence of benign nodules leads to erroneous decisions. At early stages, the benign and the malignant nodules show very close resemblance to each other. In this paper, a novel deep learning-based model with multiple strategies is proposed for the precise diagnosis of the malignant nodules. Due to the recent achievements of deep convolutional neural networks (CNN) in image analysis, we have used two deep three-dimensional (3D) customized mixed link network (CMixNet) architectures for lung nodule detection and classification, respectively. Nodule detections were performed through faster R-CNN on efficiently-learned features from CMixNet and U-Net like encoder–decoder architecture. Classification of the nodules was performed through a gradient boosting machine (GBM) on the learned features from the designed 3D CMixNet structure. To reduce false positives and misdiagnosis results due to different types of errors, the final decision was performed in connection with physiological symptoms and clinical biomarkers. With the advent of the internet of things (IoT) and electro-medical technology, wireless body area networks (WBANs) provide continuous monitoring of patients, which helps in diagnosis of chronic diseases—especially metastatic cancers. The deep learning model for nodules' detection and classification, combined with clinical factors, helps in the reduction of misdiagnosis and false positive (FP) results in early-stage lung cancer diagnosis. The proposed system was evaluated on LIDC-IDRI datasets in the form of sensitivity (94%) and specificity (91%), and better results were obatined compared to the existing methods

INTRODUCTION

Lung cancer is one of the deadliest cancers worldwide. However, the early detection of lung cancer significantly improves survival rate. Cancerous (malignant) and noncancerous (benign) pulmonary nodules are the small growths of cells inside the lung. Detection of malignant lung nodules at an early stage is necessary for the crucial prognosis [1].

ASSISTANTPROFESSOR[1], UG SCHOLAR [2&3]

DEPARTMENT OF CSE, MALLA REDDY ENGINEERING COLLEGE FOR WOMEN,MAISAMMAGUDA, DHULAPALLY KOMPALLY, MEDCHAL RD, M, SECUNDERABAD, TELANGANA 500100

Early-stage cancerous lung nodules are very muchsimilar to noncancerous nodules and need a differential diagnosis on the basis of slight morphological changes, locations, and clinical biomarkers [2]. The challenging task is to measure the probability of malignancy for the early cancerous lung nodules [3]. Various diagnostic procedures are used by physicians, in connection, for the early diagnosis of malignant lung nodules, such as clinical settings, computed tomography (CT) scan analysis (morphological assessment), positron emission tomography (PET) (metabolic assessments), and needle prick biopsy analysis [4]. However, mostly invasive methods such as biopsies or surgeries are used by healthcare practitioners to differentiate between benign and malignant lung nodules. For such a fragile and sensitive organ, invasive methods involve lots of risks and increase patients' anxieties. The most suitable method used for the investigation of lung diseases is computed tomography (CT) imaging [5]. However, CT scan investigation has a high rate of false positive findings, with carcinogenic effects of radiations. Low-dose CT uses considerably lower power radiation contact than standard-dose CT. The results show that there is no significant difference in detection sensitivities between low-dose and standard-dose CT images. However, cancer-related deaths were significantly reduced in the selected population that were exposed to low-dose CT scans as compared to chest radiographs, which is depicted in the National Lung Screening Trial (NLST) database [6]. The detection sensitivity of lung nodules improves with sophisticated anatomical details (thinner slices) and better image registration techniques. However, this increases the datasets to very large extent. Depending upon the slice thickness, up to 500 sections/slices are produced in one scan [7]. An experienced radiologist takes approximately 2–3.5 min to observe a single slice [8]. The workload of a radiologist increases significantly to screen a CT scan for the possible existence of a nodule. In addition to section thickness of the CT slices, detection sensitivity also depends on nodule features such as size, location, shape, adjacent structures, edges, and density. Results show that only 68% of the time lung cancer nodules are correctly diagnosed when only one radiologist examines the scan, and are accurately detected up to 82% of the time with two radiologists. The detection of cancerous lung nodules at an early stage is a very difficult, tedious, and time-consuming task for radiologists. Screening a lot of scans with care requires plenty of time by the radiologist, meanwhile it is very much error-prone in the detection of small nodules [9]. In this situation, a tool is needed to assist radiologists by reducing reading time and detection of missed nodules, and allowing for better localization. Computer-aided detection (CAD) systems were initially designed to reduce the workload of radiologists and increase nodule detection rate. However, the latest generation of CAD systems also helps in the screening process by differentiating between benign and malignant nodules [10]. With the recent advances in deep neural networks, especially in image analysis, CAD systems are consistently outperforming expert radiologists in both nodule detection and localization tasks. However, results from various researchers show a wide range of detection from 38–100%, with a FP rate from 1–8.2 per scan by the CAD systems [11][14][15]. The classification between benign and malignant nodules is still a challenging problem due to very close resemblance at early stages. Benign and malignant nodules have considerable feature overlaps, but still have to be differentiated on the basis of morphology and location at early stages. Benign nodules are usually located at the

International Journal of Information Technology & Computer Engineering
ISNNO: ISSN 2347–3657
Volum Volume 10,Issue 4 ,2022

peripheral, with smooth surfaces and triangular shapes filled with fat and calcium, while malignant nodules often show speculations with edges, lobulated, vascular convergence, cystic air spaces, pleural indentations, bubble-like lucencies, and sub-solid morphology. Malignancy is also related with size and growth of the nodules [12]. The three different categories (benign, primary malignant, and metastatic malignant) of lung nodules are shown in Figure 1

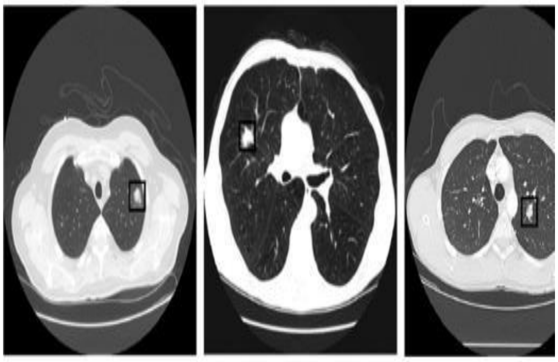


Fig: Categories of lung nodules in a CT scan; benign, primary malignant, and metastatic malignant (from left to right)

Various types of errors can occur during the screening process. These are scanning errors, which lead to failure in capturing the lesion area, recognition error related to the failure in identifying the lesion, and decision-making error, which happens due to incorrect understanding of the benign and malignant lesions and the normal structures. In the majority of patients, these errors lead to delayed and wrong diagnoses, which are the main cause of mortality. Almost 4% of radiological reports comprehend diagnostic errors on a daily basis, and around 30% of abnormal radiological findings are missed. To counteract these errors, multiple strategies (deep learning-based CT scan analysis with clinical and physiological findings) have been used in connection for the detection and classification of early-stage lung nodules[11][12] [13]. In our prior study, which is mentioned at the end of Section 2, we used a deep learning-based model for the diagnosis of early-stage lung cancer by CT scan analysis. However, due to the close resemblance of benign and maliganat nodules at early stages and various types of scanning errors, a large number of false positive results are reported in CT scan analysis techniques. To reduce false positive results, better deep learning-based models for nodule detection and classification have been developed in connection with clinical and physiological settings. A number of modifications have been done in our previous deep learning models to learn the nodules' features in better way. Classification results of deep learning model were evaluated, in connection with clinical and physiological findings, to reduce the false positive results. The MixNet architecture used in previous work was modified to learn nodules' features at a finer level. The most popular modern CNN architectures are residual network (ResNet), densely connected network (DenseNet), dual path network (DPN), and mixed link network (MixNet). ResNet is the winner of the ImageNet Large Scale Visual Recognition Competition (ILSVRC) 2015 (Image Classification, Localization, Detection). ResNet introduces skip connection (or shortcut connection) to fit the input from the previous layer to the next layer, without any modification of the input. Skip connection enables a deeper network, and finally ResNet became the winner of ILSVRC 2015 in image classification, detection, and localization, as well as the winner of MS COCO 2015 detection and segmentation. DenseNet paper got the best paper award of computer vision pattern recognition (CVPR) in 2017. DPN (Dual Path Network) is the combination ResNet and DenseNet. Mixed link networks have also shown that both dense connections and residual connections belong to a common topology. These methods utilize these interpretations to design hybrid networks that incorporate the core idea of DenseNet with that of ResNet. These works demonstrate that inclusion of addition and concatenation-based connections improves classification accuracy, and is more effective than going deeper or wider. With the rapid growth of the internet of things (IoT) and medical sensor devices, patients can be examined distantly and continuously by physicians through wireless body area networks (WBANs). WBANs are one of the key applications of IoT that provides tele-monitoring of patient health ubiquitously. The purpose of an IoT-based healthcare system is to connect physicians, patients, and nurses via smart devices. In WBANs, various implantable, wearable, and invadable sensing devices are placed on the patient’s body for continuous remote monitoring of the vital parameters. This is known as medical IoT, which provides the advantages of recording and analyzing patient data for diagnosis. These technological advances have upgraded pulmonary cancer detection and Figure 1. Categories of lung nodules in a CT scan; benign, primary malignant, and metastatic malignant (from left to right). Various types of errors can occur during the screening process. These are scanning errors, which lead to failure in capturing the lesion area, recognition error related to the failure in identifying the lesion, and decision-making error, which happens due to incorrect understanding of the benign and malignant lesions and the normal structures. In the majority of patients, these errors lead to delayed and wrong diagnoses, which are the main cause of mortality. Almost 4% of radiological reports comprehend diagnostic errors on a daily basis, and around 30% of abnormal radiological findings are missed. To counteract these errors, multiple strategies (deep learning-based CT scan analysis with clinical and physiological findings) have been used in connection for the detection and classification of early-stage lung nodules [13]. In our prior study, which is mentioned at the end of Section 2, we used a deep learning-based model for the diagnosis of early-stage lung cancer by CT scan analysis. However, due to the close resemblance of benign and maliganat nodules at early stages and various types of scanning errors, a large number of false positive results are reported in CT scan analysis techniques. To reduce false positive results, better deep learning-based models for nodule detection and classification have been developed in connection with clinical and physiological settings. A number of modifications have been done in our previous deep learning models to learn the nodules' features in better way. Classification results of deep learning model were evaluated, in connection with clinical and physiological findings, to reduce the false positive results. The MixNet architecture used in previous work was modified to learn nodules' features at a finer level. The most popular modern CNN architectures are residual network (ResNet), densely connected network (DenseNet), dual path network (DPN), and mixed link network (MixNet). ResNet is the winner of the ImageNet Large Scale Visual Recognition Competition (ILSVRC) 2015 (Image Classification, Localization, Detection). ResNet introduces skip connection (or shortcut connection) to fit the input from the previous layer to the next layer, without any modification of the input. Skip connection enables a deeper network, and finally ResNet became the winner of ILSVRC 2015 in image classification, detection, and localization, as well as the winner of MS COCO 2015 detection and segmentation. DenseNet paper got the best paper award of computer vision pattern recognition (CVPR) in 2017. DPN (Dual Path Network) is the combination ResNet and DenseNet. Mixed link networks have also shown that both dense connections and residual connections belong to a common topology. These methods utilize these interpretations to design hybrid networks that incorporate the core idea of DenseNet with that of ResNet. These works demonstrate that inclusion of addition and concatenation-based connections improves classification accuracy, and is more effective than going deeper or wider. With the rapid growth of the internet of things (IoT) and medical sensor devices, patients can be examined distantly and continuously by physicians through wireless body area networks (WBANs). WBANs are one of the key applications of IoT that provides tele-monitoring of patient health ubiquitously.

The purpose of an IoT-based healthcare system is to connect physicians, patients, and nurses via smart devices. In WBANs, various implantable, wearable, and invadable sensingThis is known as medical IoT, which provides the advantages of recording and analyzing patient data for diagnosis. These technological advances have upgraded pulmonary cancer detection and classification, using CT scan images, with the help of numerous computer-assisted detection systems (CADe) [14]. With the innovation of IoT, medical data is accessible via distant sensors over the internet. These technologies have enabled the health sector to acquaint with new methods for the diagnosis and detection of lung cancer. In this paper, automated lung nodule detection and classification using deep learning with multiple strategies is proposed. The proposed system works on three-dimensional (3D) lung CT scans, along with physiological symptoms and the clinical biomarkers, to reduce false positive results and ultimately prevent invasive methods. Two deep 3D modern convolutional networks were designed for nodule detection and classification, respectively [23]. Faster R-CNN with CMixNet and U-Net-like encoder–decoder was designed for nodule detection [15]. For the classification of the nodules, the gradient boosting machine (GBM) [16] with 3D CMixNet was used. Our designed framework for nodule detection and classification on the publically available data set LIDC-IDRI outperforms the other state of the art deep learning methods. Supreme false positive reduction was achieved through combining multiple strategies on the suspicious results of the deep learning model.

RELATED WORK

Although the first computer-aided detection (CAD) system for lung nodule detection was designed in the late 1980s, these attempts were not appealing due to inadequate computational resources for advanced image analysis techniques at that time. After the invention of the graphical processing unit (GPU) and convolutional neural networks (CNN), the performance of computer-based image analysis and decision support system got a high boost. A lot of deep learning-based medical image analysis models have been proposed by researchers, and a few of the most relevant lung nodule detection and classification methods are mentioned here. Setio et al. proposed a 3D fully convolutional neural network for FP reduction in lung nodule classification [17]. A 3D network was used to analyze the 3D nature of the CT scans to reduce wrong diagnosis, and weighted sampling was used to improve results. Ding and Liao et al. used 3D Faster R-CNN for nodule detection to reduce false positive (FP) results of lung cancer diagnosis [18]. Faster R-CNN shows very good results for object detection. It was used with very deep modern CNN architecture, the dual path network (DPN), to learn the features of the nodules for classification [19]. Jiang Hongyang et al. designed group-based pulmonary nodule detection using multi patches scheme with Frangi filter to boost the performance [20]. Images from the two groups were combined and a four channel 3D CNN was proposed to learn the features marked by the radiologist. Their CAD system's results show sensitivity of 80.06% with 4.7 FP for each scan, and sensitivity of 94% with an FP rate of 15.1. Zhu Wentao et al. proposed automated lung nodule detection and classification models using 3D DPN with 3D faster R-CNN and gradient boosting machine (GBM) by learning spatial features of lung nodules [18]. After preprocessing of the whole chest CT scan, the lung volume was segmented. The segmented lung volume was analyzed by 3D faster R-CNN with DPN and U-Net-like encoder–decoder architecture for nodule detection. After detecting the nodules, suspected nodule regions were cropped to learn the finer level features of the nodules to classify with DPN and gradient boosting machine. The model shows a detection accuracy of 87.5% with an error rate of 12.5%. Masood et al. proposed deep fully convolutional neural network (DFCNet) for the detection and classification of pulmonary lung nodules in a CT image [14]. Initially the nodule was classified aseither benign or malignant; after that, the malignant nodule was further classified into four sub-classes on the basis of the CT image and metastasis information obtained from the medical IoT network. Gu Yu et al. proposed 3D deep CNN with multiscale prediction strategies for the detection of lung nodules from segmented images [13]. The 3D CNN performs much better with richer features than 2D CNN. In addition to 3D CNN, a multiscale lung nodule prediction strategy was applied for the small nodules with cube clustering techniques. Zhao J et al. proposed a new method for lung segmentation and nodule detection by combining the features from CT and PET images [4]. They used a dynamic threshold-based segmentation method for lung parenchyma from CT scans and identified doubtful areas through PET scans. After that, they performed watershed-based segmentation techniques to find the suspected areas of nodules in the CT images. Later, a support vector machine was used to classify the nodules in the CT images through textual features and, lastly, PET images were used to validate the method. Dr. Silvestri and his research team have proposed proteomic

International Journal of
Information Technology & Computer Engineering
ISSNNO: ISSN 2347–3657
Volum Volume 10,Issue 4 ,2022

classifiers, along with nodule features, to differentiate between small size benign and malignant lung nodules [3]. They have achieved very good results on 8–30 mm nodule sizes with a reduction of 40% in biopsies on benign nodules. In [11], the authors proposed 3D-CNN for the classification of the volumetric benign and malignant lung nodules to reduce the false positive results in an automated lung nodule detection setup in the CT scans. After the popularity of convolutional neural networks (CNNs) in image analysis, different types of connectivity patterns were proposed by researchers to increase the performance of deep CNNs[16][17][18]. Up until now, in the deep CNNs, dense topology structures ResNet, DenseNet [21], and DPNs performance is superior as compared to other ones, but there is still room for connection improvements in these topologies [22[23]]. The MixNet architecture has improved connection structures with better features of extraction and reduced parameter redundancy [23]. In our previous work [24], we used MixNet for the first time for lung nodule detection and classification with GBM on publically available LUNA16 and LIDC-IDRI datasets, and achieved very good results of detection (94%) and specificity (90%). In these datasets, only the nodules of sizes greater than 3 mm were annotated by the three to four expert radiologists. However, in the case of an individual radiologist's examination of a CT scan, nodules of sizes less than 6 mm are usually missed. CT scan analysis techniques are facing a lot of false positive results in the early stage of lung cancers diagnosis. Therefore, a multi-strategy-based approach is needed for early-stage lung cancer detection.

EXISTING SYSTEM

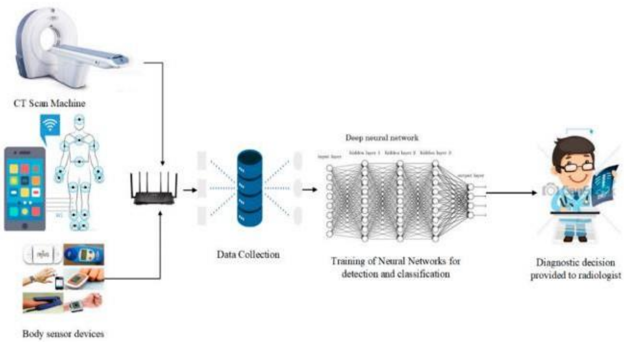
In existing paper, a picture handling procedures has been utilized to recognize beginning time lung malignant growth in CT examine pictures. The CT filter picture is pre-prepared pursued by division of the ROI of the lung. Discrete waveform Transform is connected for picture pressure and highlights are extricated utilizing a GLCM. The outcomes are encouraged into a SVM classifier to decide whether the lung picture is carcinogenic or not. The SVM classifier is assessed dependent on a LIDC dataset.

Disadavantages:

1. The CT filter picture is pre-prepared pursued by division of the ROI of the lung.

2. Discrete waveform Transform is connected for picture pressure and highlights are extricated utilizing a GLCM.

PROPOSED SYSTEM



International Journal of Information Technology & Computer Engineering
ISNNO: ISSN 2347–3657
Volum Volume 10,Issue 4 ,2022

Fig: Overview structure of the proposed lung nodule detection and classification system

The proposed model applies a range of algorithms to the different stages of image processing. In this proposed model, first the CT scan image is pre-processed and the ROI (region of interest) is separated in preparation for segmentation.[17] At the segmentation stage, Discrete Wavelet Transform (DWT) is applied and the feature is extracted by using a GLCM (Gray level co-occurrence matrix) such as correlation, entropy, variance, contrast, dissimilarity and energy. After the feature extraction stage, classification is carried out by an SVM (support vector machine) for classification of cancerous and non-cancerous nodules.The proposed automated lung nodule detection and classification system works on multiple strategies to decrease FP results. The system performs decisions based on physiological symptoms, CT scan analysis, and clinical biomarkers. UN-attempted physiological symptoms lead to lung cancer prognosis with family history about lung cancer. Deep learning-based CT scan analysis techniques outperform radiologists in the detection of lung nodules, especially of nodule sizes of

MODULES:

Upload Lung Cancer Dataset

Read &split Dataset To Train & Test

Execute SVM Algorithms

Execute K-Means Algorithm

Predict Lung Cancer

Accuracy Graph

Advantages:

1. The classification is the major portion where the cancerous and non-cancerous is identified with the pre trained model.

CONCLUSION

In the principal period of the venture the Region of Interest in a picture is distinguished. The Identified district is situated in an item. The highlights in the picture are distinguished by utilizing some picture handling system. In second period of the task the component removed information is then used to arrange the picture is destructive or not utilizing a portion of the SVM – bolster vector machine grouping. At that point some boosting calculation is utilized to expand the exactness of the instrument.In existing paper, a picture handling procedures has been utilized to recognize beginning time lung malignant growth in CT examine pictures. The CT filter picture is pre-prepared pursued by division of the ROI of the lung. Discrete waveform Transform is connected for picture pressure and highlights are extricated utilizing a GLCM. The outcomes are encouraged into a SVM classifier to decide whether the lung picture is carcinogenic or not. The SVM classifier is assessed dependent on a LIDC dataset. In future the advanced level of algorithm is used to increase the level of prediction while we are in process to include the Extreme gradient boosting Algorithm to use the data set more effectively.

REFERENCES

1. M. Debois, —TxNxM1 : the anatomy and clinics of metastatic cancer.Boston,‖ Kluwer Academic Publishers, 2006.

2. J.M. Fitzpatrick, & M. Sonka, —Medical imaging 2003: image processing. USA: SPIE Society of PhotoOptical Instrumentation Engineers,‖ 2003.

3. C. M. Haskell, & J.S. Berek, — Cancer treatment. Philadelphia: W.B. Saunders, 2001

4. K.T.Manivannan, —Development of gray level co-occurrence matrix based support vector machines for particulate matter characterization,‖Retrieved fromhttp://rave.ohiolink.edu/etdc/view?acc_num=toledo1341577486, 2012.

5. Sathish Kumar R, R. Logeswari, N. Anitha Devi, S. DivyaBharathy Efficient Clustering using ECATCH Algorithm to Extend Network Lifetime in Wireless Sensor Networks. International Journal of Engineering Trends and Technology. 45. 476-481. 10.14445/22315381/IJETT-V45P290 – March 2017

6. C. Charalambous, Conjugate gradient algorithm for efficient training of artificial neural networks, IEEE Proceedings 139 (3) (1992) 301–310.

7. B. H. Boyle, —Support vector machines : data analysis, machine learning, and applications,‖ Retrievedhttp://public.eblib.com/choice/publicfullrecord.aspx?p=3021500, 2011.

8. A.A. Abdulla, S.M. Shaharum, Lung cancer cell classification method using artificial neural network, Information Engineering Letters 2 (March) (2012) 50–58.

9. Sathish Kumar R , Nive tha M, Madhu mita G &Santhoshy P. Image Enhancement using NHSI Model Employed in Color Retinal Images. International Journal of Engineering Trends and Technology. 58. 14-19. 10.14445/22315381/IJETT-V58P203-April 2018.

10. D. Harini, & D. Bhaskari, —Image retrieval system based on feature extraction and relevance feedback,‖ ACM, 2 Penn Plaza, Suite 701, New York,NY 10121-0701, 2012.

11. P. Kshirsagar and S. Akojwar, "Classification & Detection of Neurological Disorders using ICA & AR as Feature Extractor", Int. J. Ser. Eng. Sci. IJSES, vol. 1, no. 1, Jan. 2015.

12. Pravin Kshirsagar, Dr.SudhirAkojwar, —Classification and Prediction of Epilepsy using FFBPNN with PSO‖, IEEE International Conference on Communication Networks, 2015.

13. P. Kshirsagar, S. Akojwar, Nidhi D. Bajaj , —A hybridised neural network and optimisation algorithms for prediction and classification of neurological disorders‖ International Journal of Biomedical Engineering and Technology ,vol. 28,Issue 4,2018.

14. P. Kshirsagar and S. Akojwar, "Novel approach for classification and prediction of non linear chaotic databases," 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), 2016, pp. 514-518, doi: 10.1109/ICEEOT.2016.7755667,2016

15. Kshirsagar, P.R., Akojwar, S.G., Dhanoriya, R, ― Classification of ECG-signals using artificial neural networks‖, In: Proceedings of International Conference on Intelligent Technologies and Engineering Systems, Lecture Notes in Electrical Engineering, vol. 345. Springer, Cham (2014).

16. P. Kshirsagar and S. Akojwar, ―Optimization of BPNN parameters using PSO for EEG signals,‖ ICCASP/ICMMD-2016. Advances in Intelligent Systems Research. Vol. 137, Pp. 385-394,2016

17. Pravin Kshirsagar, Nagaraj Balakrishnan & Arpit Deepak Yadav ―Modelling of optimised neural network for classification and prediction of benchmark datasets‖ , Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, 8:4, 426-435, DOI: 10.1080/21681163.2019.1711457,2020

18. Dr. Sudhir Akojwar, Pravin Kshirsagar, Vijetalaxmi Pai ―Feature Extraction of EEG Signals using Wavelet and Principal Component analysis‖, National Conference on Research Trends In Electronics, Computer Science & Information Technology and Doctoral Research Meet, Feb 21st & 22nd ,2014.

19. S. Akojwar and P. Kshirsagar, ―A Novel Probabilistic-PSO Based Learning Algorithm for Optimization of Neural Networks for Benchmark Problems‖, Wseas Transactions on Electronics, Vol. 7, pp. 79-84, 2016.

20. Sudhir G. Akojwar, Pravin R. Kshirsagar, ― Performance Evolution of Optimization Techniques for Mathematical Benchmark Functions‖. *International Journal of Computers*, **1**, 231-236,2016.

21. Pravin Kshirsagar And Sudhir Akojwar ―Hybrid Heuristic Optimization for Benchmark Datasets‖, International Journal of Computer Applications (0975 – 8887) Volume 146 – No.7, July 2016

22 .Kshirsagar, P., Akojwar, S, ―Classification of human emotions using EEG signals', *Int. J. Comput. Sci.*, 2016, 146, (7), pp. 17– 23

23. Pravin Kshirsagar et.al (2016), ―Brain Tumor classification and Detection using Neural Network‖, DOI: 10.13140/RG.2.2.26169.72805.