Journal of
Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.776773

LUNG TUMOR DETECTION USING DEEP CNN ARCHITECTURE WITH THE FINAL LAYER AS MACHINE LEARNING: CT SCAN IMAGES

Ms. Seema Rathod1* and Dr. Lata Ragha2†
1*Department of Computer Science and Engineering, Lokmanya Tilak College of Engineering, Navi Mumbai University, Mumbai, 400709, Maharashtra, India.
2Department of Computer Engineering, Lokmanya Tilak College of Engineering, Fr. C. Rodrigues Institute of Technology, Mumbai, 400709, Maharashtra, India.
*Corresponding author(s). E-mail(s): omseemarathod@gmail.com; Contributing authors: lata.ragha@fcrit.ac.in;
†These authors contributed equally to this work.

Abstract
Lung inflammation is caused by the development of cancer cells. As the frequency of cancer rises, men and women are dying at a higher rate. With malignancy, cancerous cells multiply uncontrollably in the lobes. It is impossible to prevent lung cancer, but we can lower its associated risks. Early detection of lung can- cer can considerably improve a patient's chances of survival. Patients with lung disease are more likely to be chain smokers. Several classification methods were applied to assess lung cancer prediction, such as the Deep CNN algorithm and Deep CNN, with the Final Layer as Machine learning. The first Deep CNN model defined this accuracy. However, the second model, Deep CNN+SVM, is the best mode2 defined. The accuracy is 98.61%. The primary purpose of this research paper is to identify lung cancer early. Throughout this publication, we identified two models: model 1 and model 2. Depending on this technique, Model 1 provides a new categorization method. With such a 98.61% accuracy, the support vector machine is the most accurate, whereas model 2 is the most accurate compared to model 1, which has a 98.4% accuracy.
Keywords: CT, Deep CNN, Lung cancer, Machine Learning, SVM

1 Introduction

Cancer is easily spread throughout the body because the cells are immature and grow faster; there is a probability that the later version of the cells will make the same mis- take as the host cells [1]. This causes the cells increased farm to be more juvenile, with higher growth and dispersion. According to the Indian Council of Medical Research (ICMR) and the National Cancer Registry Program (NCRP), the total number of can- cer deaths reported in India in 2020 would be 14 lakh. Furthermore, cases will reach 16 lacks by the end of 2025. In addition, around 10 million new cases of malignancy were recorded globally in 2020, according to data from the World Health Organization (WHO). The breast, lung, colon, rectum, prostate, skin, and stomach contributed to this. In addition, the most prevalent malignancies that resulted in death in 2020 were lung cancer (1.8 million fatalities), colon and rectum cancer (935 000 fatalities), liver cancer (830 000 fatalities), stomach cancer (769 000 fatalities), and breast cancer (769 000 fatalities). Six hundred eighty-five thousand people died.

Tobacco use, a poor diet, an inactive schedule, and pollution are the leading causes of cancer on a broad scale. However, according to the numbers supplied above by rival agencies, lung cancer was responsible for most cancer deaths. The leading cause of lung cancer risk is cigarette smoking. Smoking is to blame for around 80% of lung cancer deaths in the US every year. Following the detection of tumors in the lung, a medical process known as excision is used to diagnose aggressiveness. Tissue samples are classified into four varieties based on their medical applications: bone marrow biopsy, endoscopic biopsy, needle biopsy, skin biopsy, and surgical biopsy [2]. In either procedure, a tiny quantity of tissues or an entire lump is removed and submitted for examination. Selected are used to determine if the test is cancerous or normal. We can heal cancer only if it is diagnosed in an early stage. Also, we have defined two models that are model1 and model2 At. Lastly, to operate the Variable categorization in the CNN Model2, we combined all of the Lung cancer photos into one set of data and all of the regular patient lung cancer photos into one dataset so that we could conduct the Variable categorization in CNN using the Final Layer as Support Vector Machine (SVM) to create a machine learning algorithm model.

2 Literature Survey

Hexuan Li, Hu, and associates [3]. Its network model is created by fusing DenseNet with the hybrid attention mechanism module. The parallel deep learning algorithm that utilized a hybrid attention mechanism attained an accuracy of 94.61% when it came to the photo recognition of lung cancer. These findings are based on the overall results of the testing.

Wang, Xi, Chen, and colleagues [4] suggested a semi-supervised learning method in this paper to solve the full slide cancer picture classification with minimal annotation effort. The author tested the method on a TCGA open lung disease WSIs dataset before creating the most extensive fine-grained lung cancer WSI dataset, SUCC, for thorough analysis.

Jue Jiang et al. [5], In this study, the authors suggest using two different neural network models to differentiate lung tumors from CT scans by merging many residual channels with varying degrees of quality. The findings demonstrate that the classifica- tion technique has improved across several datasets. For classifying lung nodules, the MV-KBC model exhibited an accuracy of 91.60% and an AUC of 95.70%.

Sarfaraz Hussein and colleagues [6] With Computer-Aided Diagnosis (CAD) tech- niques, risk characterization of cancers from radiological images may be more precise and quicker. To characterize tumors, this work develops both supervised and unsu- pervised learning techniques. This paper proposed a new 3D CNN architecture based on Graph Organizational culture model Sparse for the supervised learning approach. Multithread learning and evaluating CT scans for lung nodule characterization.

N. Mohanapriya and colleagues [7] Lung cancer is a potentially fatal disease affecting people of both genders today. In CT imaging, DCNN categorizes benign and malignant lung cancers. The LIDC database was used to test the recommended designs. When the findings of the DCNN classifier were compared to those of other classifiers, such as the Artificial Neural Network Simulation, it became clear that the DCNN classifier performed significantly better.

The better contrast of PET scans and the superior spatial resolution of CT images are used in this work by Ju, Wei, and colleagues [8] to merge the two modalities successfully. The random variable and graph cut methods are combined to address this separation challenge. A random walk activation method on PET and CT images provides object seeds for graph cut segmentation.

Qi, Song, and their friends [9], This paper present a unique method for co- segmenting tumors in PET and CT images leveraging the advantages of the function- ality data and anatomical structure data from each modality. To obtain the optimal solution, which determines the tumor volume concurrently in both modalities, one maximum flow problem may be resolved.

Rekka Mastouri, in addition to their collaborators [10] This method focuses on a few aspects of the information mining algorithms used to make patient-specific projections about the progression of lung tumors. Ideas for information extraction can aid the characterization of lung tumors.

Hongyang Jiang et al. [11], Neural network technique is used in this method because the characteristics are picked at random and neural networks improve the study's validity. The proposed strategy falls short when dealing with low-quality imagery because the algorithm cannot identify tumor cells.

A.R. Talebpour and colleagues [12] The suggested methodology uses CAD frame- works to handle complex tasks. Because of its intricate structure, the program's performance deteriorates. After preprocessing, the suggested approach will do a manual investigation.

S. Kalaivani and colleagues [13] The K symbol categorizes information into two types (generous and dangerous). Pre-processing, extraction of features, and extraction methods are used in the proposed method to detect breast cancer cells. The suggested method's prediction accuracy in picking relevant attributes is low. Sukhjinder. Kaur et al. [14] utilized information accumulation strategies such as neural networks and SVM to conduct rehabilitative image mining, information preparation, division, inclusion extraction, and grouping. Vinitha, D., et al.[15] The recommended approach detects tumor cells in the early stages; however, if the tumor grows more significantly than 3 mm, the suggested method will not respond. The likelihood of correctly diagnosing tumors using the suggested method is minimal.

Sathyan H and others [16] Using an SVM classifier, the proposed technique col- lects and groups characteristics from tumor cells. The suggested strategy, on the other hand, considers additional characteristics and criteria for detecting tumor cells. S. Kalaivani et al. [17] suggested a method based on genetic research. Identifying inher- ited variables and beneficial compounds is critical in developing a unique lung tumor growth prevention technique. The recommended method employs K-Means clustering via methods for data mining, and the pixel enhancement procedure is lengthy.

J. Alam and colleagues [18] Provide several information accumulation approaches in a few distinct lung illness datasets to improve lung cancer progression predic- tion. The author also suggests enhancing and expanding current tools for predicting lung tumor growth. The proposed method is rarely used because complex operations degrade system performance.

Sairamya and associates [19]. In the concluding part, acceptable means of the deleted characteristics were developed for analysis criteria for the standard-based clas- sifier for tumor applicants. The recommended method identifies tumor cells but does not accurately describe the size or stage of the tumor.

Kaya Y et al. [20] used specific upgrading channels and a pre-programmed principle-based classifier to portray a mechanized lung tumor location in delicate area CT images. This technique's degree of categorizing cancer cells is small sufficient, similar to the duration required for handling the photos.

Using predictive information mining calculations to analyze computations, Jaiswal et al. [21] presented an approach for forecasting reply optimism in lung tumor development patients. This strategy may be found in their paper.

Tiwari et al. [22] investigated the parameterization measurement for the position of a brain tumor. The considerable detail was evaluated using volumetric and area characteristics in light of two characterization classes, such as planned recurrence and Asymmetric Factor analysis, and three characterization classes, such as Linear SVM, Gaussian SVM, Cosine KNN, Complex, and regression models. A strategy for organizing the process of obtaining features was developed by Sairamya et al. [23]. This method uses the GLC grid to extract characteristics, including vitality, entropy, variance, dissimilarities, and founder.

The GLCM separation strategy, which arranges many pixel intensity values in an example, was utilized by G. Battista et al. [24]. The writers then referred to con- cepts such as connection, skewness, imperativeness, entropy, homogeneity, smoothness, variance, standard deviation/n, root mean square, and mean.

G. Bhat et al. [25] eliminated vital features, such as volatility, differentiation, and vitality, which enhance efficacy and can be easily examined for order. Highlights such as region, edge, and circularity were extracted by G. Kaur et al. [26]. Ganeshan B et al. [27] extracted geometric and content highlights. Geometric features such as size, area, circular width, and disproportionality are extracted using a double Mask. Gray Level differentiates content features such as homogeneity, moment, entropy, skewness, distinction, and liveliness.

3 Proposed System

The block diagram of the system is shown in Fig. 1.

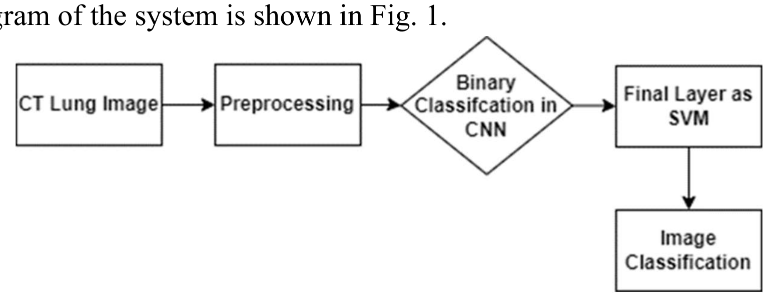

Fig. 1: Block diagram of the proposed system

3.1 Dataset

Four distinct forms of lung cancer, including adenocarcinoma, extensive cell carcinoma, normal, and squamous cell carcinoma, were represented by lung cancer picture samples on the Kaggle websites. The data folder, which is the primary folder, contains each staging folder. Three folders, i.e., train, test, and valid, can be found under the Data folder. The train stands for the training set, the test for the testing set, and the valid for the validated datasets. To perform binary classification in CNN utilizing the last layer as SVM to build a machine learning algorithm model, we integrated all lung cancer pictures and all traditional diagnostic lung cancer images into one dataset. A dataset sample of the dataset is shown in Fig. 2.

3.2 Data Set Preprocessing

Pre-processing is the procedure that consists of all the steps necessary to convert incoming data into a format that can be used for feature extraction. The supplied image must be resized, noise reduced, centered, and given character input. This step is essential since improperly pre-processed input images might compromise feature extraction. The lung CT images are already size adjusted and centered in the current work.

3.3 Feature Extraction

In the proposed research, the model is used to extract features from the lung CT scans that are used as input. Lung CT scans that have been processed in the past are taken into consideration by the hybrid model that has been developed. As an activation function, the Sigmoid function has been utilized in the past. The function determines the output probability for each sample CT image submitted to the function as input. The outputs from the last hidden layer with trainable weights and bias terms are combined linearly to provide the input for the following layers. A vector

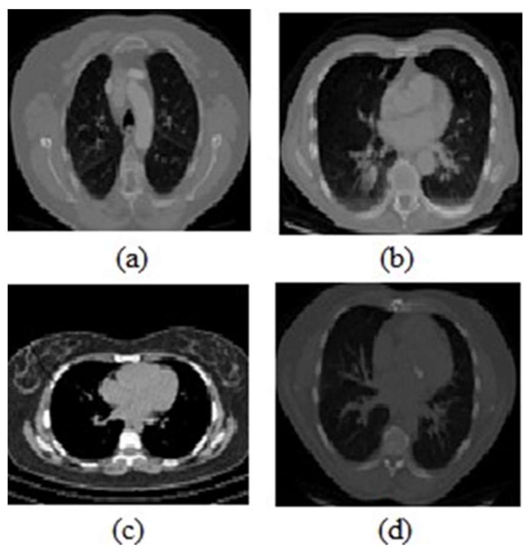

Fig. 2: Dataset sample images of (a) adenocarcinoma, (b) large cell carcinoma, (c) Normal, (d) squamous cell carcinoma consisting of a single column is produced from the feature map and then used. The SVM classifier receives this one-column feature vector with distinct properties as input for the recognition experiment.

3.4 Training and Classification

To detect lung cancer, CNN Convolutional Neural Network employs the fundamental technique of combining convolutional layers into a single layer. Its hybrid convolutional neural network outperforms the other approaches, and we employed the final layer as SVM by employing the gradient descent as Hinge and optimizers as Adam. Compared to other algorithms, it is also relatively fast and can retrieve more information from images.

The strategy that has been developed utilizes aspects that are advantageous from both CNN and SVM classifiers. A convolutional neural network (CNN) with a super- vised learning process consists of many fully connected layers. CNN can learn invariant local features exceptionally well and work in a manner analogous to that of humans. It can obtain the most discriminating information from lung CT scans that have not been processed. Using a 3x3 kernel/filter, the technique that has been described can pull out the features that are the most easily discernible from the raw input photos. In the convolutional layer, the input neuron from the input layer is convolved with a mxm filter to produce an output with dimensions (n-m+1) (n-m+1). The output of one layer is used as the input for the layer that follows it. The effective sub-regions of

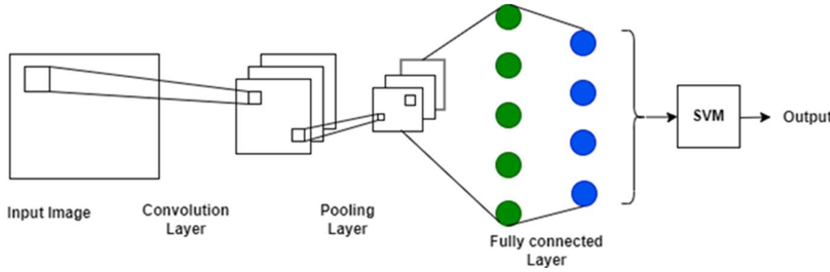

Fig. 3: The architecture of the proposed Hybrid CNN-SVM Model

the CT raw pictures are determined using CNN's receptive field feature, which uses these images.

SVM is a type of machine that attempts to represent multi-dimensional datasets. This machine operates in a space where a hyperplane separates data items from differ- ent classes. On untested data, the SVM classifier can reduce the generalization error. The hyperplane separating the two sets of points is sometimes called the "optimal hyperplane." It is generally agreed that SVM performs poorly on noisy data, although it has shown promise for binary classification. Because of its shallow architecture, SVM might make it challenging to learn in-depth characteristics.

In this study, the hybrid CNN-SVM model is presented. In this model, the SVM acts as a binary classifier and substitutes the softmax layer used by CNN. CNN is an algorithm that extracts features, while SVM is a binary classifier. Figure 3 depicts the architecture of the hybrid CNN-SVM model that was proposed before.

The model comprises an SVM classifier and a straightforward CNN framework. A 305x430x3 matrix of normalized lung CT images from the dataset is used as the CNN input layer's input. In the convolutional layers, we use convolutional filtering that is 3X3 in size and a stride size of 2. The distinguishing qualities of the input image are quantified and retrieved by the two feature map layers as values. The CNN is trained after it has been run through several epochs and has continued to run until the training process converges. The SVM classifier serves as this application's last layer of the CNN. The third layer properties of the lung CT are used as input for the SVM classifier. The initial step in training the SVM classifier is automatically using these newly developed training image attributes. After that, the trained SVM classifier determines which lung CT corresponds to the test.

4 Results

In this approach, two experiments are carried out; in the first experiment, the data is trained with simple CNN algorithms. The hybrid CNN-SVM approach trains the data in the second experiment.

Accuracy and loss parameters are used to assess the proposed system's outputs. How closely a measurement resembles a known or reference value in terms of accuracy. When choosing the appropriate algorithm to utilize moving forward, the accuracy of the results is crucial. The quality of the research's findings increases with accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \tag{1}$$

In this formula, TP stands for True Positives, TN for True Negatives, FP for False Positives, and FN for False Negatives. The datasets for training and validation are used during the experiment's 30 epochs of operation. Because the training was only run a few times in the beginning, the accuracy was low. The precision grew as the number of epochs rose. Table 1 displays the absolute accuracy determined using the Hybrid CNN-SVM method and the Simple CNN algorithm on the dataset of Chest CT-Scan pictures.

Table 1: Comparative analysis of simple CNN and Hybrid CNN-SVM algorithms in terms of accuracy

Model	Training Accuracy	Validation Accuracy
Simple CNN	0.9815	0.981504
Hybrid CNN-SVM	0.9840	0.98397

The final result shows that hybrid CNN-SVM has performed better than a simple CNN Model regarding training and validation accuracy. The training progress graphs of the simple CNN and hybrid CNN-SVM algorithms are shown in Fig.4 and Fig.5.

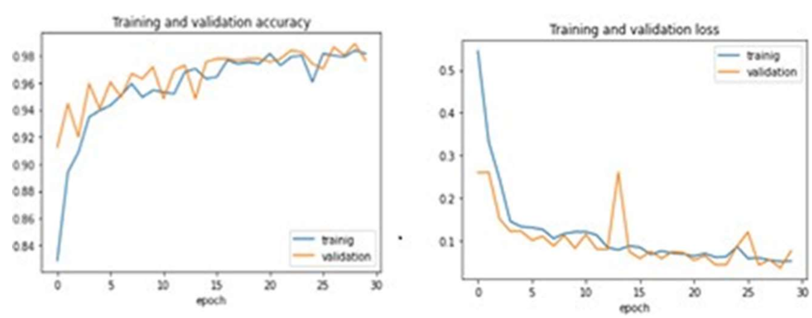

Fig. 4: Training progress graph of simple CNN algorithm on lung cancer CT image dataset (a)accuracy (b)loss

It can be observed from Fig.4 and Fig.5 that training and validation of the accuracy of the classifier increased rapidly as the epoch increased while the loss decreased. In the case of hybrid CNN-SVM, there is a small gap between the training and validation accuracy. This means the model overcomes the effect of the overfitting and underfitting problems.

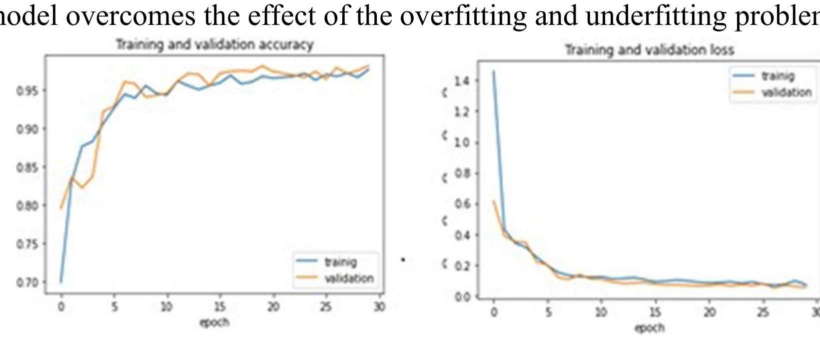

Fig. 5: Training progress graph of hybrid CNN-SVM algorithm on lung cancer CT image dataset (a)accuracy (b)loss

5 Conclusion

This work presents a hybrid CNN-SVM approach to classify lung CT images into normal and cancerous. Since accuracy is the ultimate goal of any computer-aided detection system, this was the objective. The process was used for the dataset of chest CT scan pictures, a widely used and openly available collection of CT scans. The method was evaluated on 315 photos, with a training classification accuracy rate of 98.40% and validation accuracy of 98.39%. It proves how effective the recommended hybrid CNN-SVM and its features are.

The researchers want to test the approach with various datasets for future studies. The accuracy may be even higher by using more photos during the process. This approach may also be used to interpret PET, X-ray, and X-beam pictures. All of these photographs need to be accessible for inspection. The medical staff will be able to utilize the best photographs to find lung cancer by researching and evaluating the predictions of various types of images.

Compliance with Ethical Standards

Funding

No funding has been received for this research work.

Author Identifying Information

Department of Computer Science and Engineering, Lokmanya Tilak Col- lege of Engineering, Navi Mumbai University, Mumbai, India

Ms. Seema Rathod

Department of Computer Engineering, Lokmanya Tilak College of Engi- neering, Fr. C. Rodrigues Institute of Technology, Mumbai, India

Dr. Lata Ragha

Corresponding author

Correspondence to Ms. Seema Rathod.

Conflict of Interest

The authors of this paper hereby declare that there is no conflict of interest.

References

[1] Rathod, S., Ragha, L.: Analysis of CT Scan Lung Cancer Images using Machine Learning Algorithms (2022)

[2] Rathod, S., Ragha, L.: Using Weakly Supervised Machine learning Algorithms for Classification and Analysis of CT Scan Lung Cancer Images (2022)

[3] Hu, H., Li, Q., Zhao, Y., Zhang, Y.: Parallel deep learning algorithms with hybrid attention mechanism for image segmentation of lung tumors. IEEE Transactions on Industrial Informatics 17(4), 2880–2889 (2021) https://doi.org/10.1109/TII. 2020.3022912

[4] Wang, X., Chen, H., Gan, C., Lin, H., Dou, Q., Tsougenis, E., Huang, Q., Cai, M., Heng, P.-A.: Weakly supervised deep learning for whole slide lung cancer image analysis. IEEE Transactions on Cybernetics 50(9), 3950–3962 (2020) https: //doi.org/10.1109/TCYB.2019.2935141

[5] Jiang, J., Hu, Y.-C., Liu, C.-J., Halpenny, D., Hellmann, M.D., Deasy, J.O., Mageras, G., Veeraraghavan, H.: Multiple resolution residually connected feature streams for automatic lung tumor segmentation from ct images. IEEE Transac- tions on Medical Imaging 38(1), 134–144 (2019) https://doi.org/10.1109/TMI. 2018.2857800

[6] Hussein, S., Kandel, P., Bolan, C.W., Wallace, M.B., Bagci, U.: Lung and pan- creatic tumor characterization in the deep learning era: Novel supervised and unsupervised learning approaches. IEEE Transactions on Medical Imaging 38(8), 1777–1787 (2019) https://doi.org/10.1109/TMI.2019.2894349

[7] Mohanapriya, N., Kalaavathi, B., Kuamr, T.s.: Lung tumor classification and detection from ct scan images using deep convolutional neural networks (dcnn). In: 2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), pp. 800–805 (2019). https://doi.org/10.1109/ICCIKE47802. 2019.9004247

[8] Ju, W., Xiang, D., Zhang, B., Wang, L., Kopriva, I., Chen, X.: Random walk and graph cut for co-segmentation of lung tumor on pet-ct images. IEEE Trans- actions on Image Processing 24(12), 5854–5867 (2015) https://doi.org/10.1109/ TIP.2015.2488902

[9] Song, Q., Bai, J., Han, D., Bhatia, S., Sun, W., Rockey, W., Bayouth, J.E., Buatti, J.M., Wu, X.: Optimal co-segmentation of tumor in pet-ct images with context information. IEEE Transactions on Medical Imaging 32(9), 1685–1697 (2013) https://doi.org/10.1109/TMI.2013.2263388

[10] Mastouri, R., Neji, H., Hantous-Zannad, S., Khlifa, N.: A morphologi- cal operation-based approach for sub-pleural lung nodule detection from ct images. In: 2018 IEEE 4th Middle East Conference on Biomedical Engineer- ing (MECBME), pp. 84–89 (2018). https://doi.org/10.1109/MECBME.2018. 8402411

[11] Jiang, H., Ma, H., Qian, W., Gao, M., Li, Y.: An automatic detection system of lung nodule based on multigroup patch-based deep learning network. IEEE Journal of Biomedical and Health Informatics 22(4), 1227–1237 (2018) https: //doi.org/10.1109/JBHI.2017.2725903

[12] Talebpour, A.R., Hemmati, H.R., Hosseinian, M.Z.: Automatic lung nodules detection in computed tomography images using nodule filtering and neural net- works. In: 2014 22nd Iranian Conference on Electrical Engineering (ICEE), pp. 1883–1887 (2014). https://doi.org/10.1109/IranianCEE.2014.6999847

[13] Kalaivani, S., Chatterjee, P., Juyal, S., Gupta, R.: Lung cancer detection using digital image processing and artificial neural networks. In: 2017 International Conference of Electronics, Communication and Aerospace Technology (ICECA), vol. 2, pp. 100–103 (2017). https://doi.org/10.1109/ICECA.2017.8212773

[14] Roy, K., Chaudhuri, S., Burman, M., Ganguly, A., Dutta, C., Banik, S., Banik, R.: A comparative study of lung cancer detection using supervised neural network, pp. 1–5 (2019). https://doi.org/10.1109/OPTRONIX.2019.8862326

[15] Khdair, H., Dasari, N.M.: Exploring machine learning techniques for coronary heart disease prediction. International Journal of Advanced Computer Science and Applications 12(5), 1227–1237 (2021) https://doi.org/10.14569/IJACSA. 2021.0120505

[16] Sathyan, H., Panicker, J.V.: Lung nodule classification using deep convnets on ct images. In: 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT), pp. 1–5 (2018). https://doi.org/10.1109/ ICCCNT.2018.8494084

[17] Kalaivani, S., Chatterjee, P., Juyal, S., Gupta, R.: Lung cancer detection using digital image processing and artificial neural networks. In: 2017 International Conference of Electronics, Communication and Aerospace Technology (ICECA), vol. 2, pp. 100–103 (2017). https://doi.org/10.1109/ICECA.2017.8212773

[18] Alam, J., Alam, S., Hossan, A.: Multi-stage lung cancer detection and prediction using multi-class svm classifie. In: 2018 International Conference on Computer,

Communication, Chemical, Material and Electronic Engineering (IC4ME2), pp. 1–4 (2018). https://doi.org/10.1109/IC4ME2.2018.8465593

[19] Sairamya, N.J., Thomas George, S., Subathra, M.S.P., Kumar, N.M.: Computer- aided diagnosis of epilepsy based on the time-frequency texture descriptors of eeg signals using wavelet packet decomposition and artificial neural network. In: Cognitive Informatics and Soft Computing, pp. 677–688. Springer, Singapore (2019)

[20] Sairamya, N.J., Thomas George, S., Narain Ponraj, D., Subathra, M.S.P.: Auto- mated detection of epileptic seizure using histogram of oriented gradients for analysing time frequency images of eeg signals. In: Smart and Innovative Trends in Next Generation Computing Technologies, pp. 932–943. Springer, Singapore (2018)

[21] Jaiswal, A.K., Banka, H.: Local pattern transformation based feature extraction techniques for classification of epileptic eeg signals. Biomedical Signal Processing and Control 34, 81–92 (2017) https://doi.org/10.1016/j.bspc.2017.01.005

[22] Tiwari, A.K., Pachori, R.B., Kanhangad, V., Panigrahi, B.K.: Automated diag- nosis of epilepsy using key-point-based local binary pattern of eeg signals. IEEE Journal of Biomedical and Health Informatics 21(4), 888–896 (2017) https: //doi.org/10.1109/JBHI.2016.2589971

[23] Sairamya, N.J., George, S.T., Ponraj, D.N., Subathra, M.S.: Detection of epileptic eeg signal using improved local pattern transformation methods. Cir- cuits Syst. Signal Process. 37(12), 5554–5575 (2018) https://doi.org/10.1007/ s00034-018-0829-1

[24] Battista, Sassi, Zompatori, Palmarini, Canini: Ground-glass opacity: interpreta- tion of high resolution ct findings. Radiol Med 106(5-6), 425–442 (2003)

[25] Bhat, G.M., Biradar, V.G., Sarojadevi, H.: Artificial neural network based cancer cell classification (ann – c3). (2012)

[26] Nanglia, P., Kumar, S., Mahajan, A.N., Singh, P., Rathee, D.: A hybrid algorithm for lung cancer classification using svm and neural networks. ICT Express 7(3), 335–341 (2021) https://doi.org/10.1016/j.icte.2020.06.007

[27] Ganeshan, B., Abaleke, S., Young, R., Chatwin, C., Miles, K.: Texture analysis of non-small cell lung cancer on unenhanced computed tomography: Initial evidence for a relationship with tumour glucose metabolism and stage. Cancer imaging : the official publication of the International Cancer Imaging Society 10, 137–43 (2010) https://doi.org/10.1102/1470-7330.2010.0021