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ARTIFICIAL NEURAL NETWORK BASED CLASSIFICATION SYSTEM FORLUNG NODULES THROUGH COMPUTED TOMOGRAPHY SCAN

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Abstract

An energy- and area-efficient solution for tolerating the stuck-at faults induced by an endurance problem in secure-resistive main memory. A large number of memory locations with stuck-at faults might be used in the suggested technique to appropriately store the data by using the rotational shift operation and the random properties of the encrypted data encoded by the Advanced Encryption Standard (AES). The suggested method's energy usage is much lower than that of other previously presented approaches because of its straightforward hardware implementation. The error correction code (ECC) and error correction pointer (ECP) are two more error correction techniques that may be used in conjunction with this one. The suggested approach is put into practice in a main memory system based on phase-change memory (PCM) and contrasted with three error-tolerating techniques in order to determine its effectiveness. The findings show that the suggested approach provides 82% energy savings over the state-of-the-art technique for a stuck-at fault incidence rate of 10^{-2} and an uncorrected bit error rate of 2×10^{-3}. More broadly, we demonstrate that the fault coverage of the suggested approach is comparable to the state-of-the-art method using a simulation analysis methodology.

Introduction

Today, lung cancer is one of the deadliest. Medical treatments for lung cancer include surgery, radiation, and chemotherapy. Despite these techniques, lung cancer patients have a 14% 5-year survival rate. Early detection may increase survival rates to 49%, as in other cancers. CT is the most common lung cancer imaging method. CT can easily see nodules and abnormal remnants of various sizes. Lung nodules are benign or cancerous. Solid, unusual malignant nodules may be misdiagnosed as benign. Usually, solid nodules are cancerous. Nodules must be diagnosed early to speed therapy. Medical CAD systems improve pulmonary nodule detection. These devices help doctors make decisions and start therapy early. Some research have examined early lung cancer diagnosis and nodule detection. Filtered X-ray CT pictures to detect lung cancer. Image processing for lung segmentation on X-rays for nodule detection. Invented automated benign nodule detection. CT scans were template-matched using genetic algorithms. Recommended a fuzzy cluster-based CAD system for lung nodule detection. Designed a CT-based CAD system to identify benign lung nodules. Basic image processing and region of interest extraction were utilized. Proposed an automated lung nodule classification CAD system. Literature includes ANN-based CAD. Proposed ANN-based pattern-recognition employing low-dose CT images to reduce false positives in lung nodule computerized identification. A neural-network-based approach for computer-aided lung nodule identification in chest radiographs was provided in another publication. A computer-aided categorization approach for lung CT images was created utilizing ANN. In these investigations, true positive and false positive rates are not high enough for clinical application.

Additionally, these trials do not concentrate on early lung nodule identification. They provide little advice on detecting tiny nodules. An ANN-based CAD system for early benign/malignant lung nodule categorization is proposed in this work. Self-Organizing Maps (SOM) were utilized to segment the tiniest lung nodules in this work. Use GLCM (gray level co-occurrence matrix) to extract features from benign or malignant nodules. Effective classification method ANN is used. Rest of paper organization: The intended CAD system is described in Section 2. Section 3 contains experimental and analytical findings. Last part discusses planned CAD performance assessment and discussions.

The leading cancer killer is lung cancer. Additionally, lung cancer has a greater fatality rate. Lung cancer has a 16% five-year relative survival rate, although early detection of faulty nodules may improve survival. In lung cancer research, computed tomography (CT) is one of the most sensitive technologies for identifying pulmonary nodules, which are spherical, irregular, opaque figures with a diameter up to 30 mm. Early pulmonary nodule diagnosis helps treat lung cancer. A radiologist must evaluate several CT scan pictures, which is tiring. Thus, a computer-aided detection (CAD) system may help radiologists improve scanning efficiency and nodule detection. Nodule detection systems typically include lung volume extraction, nodule candidate identification, and false positive reduction. There are many ways to derive lung volume from a pulmonary CT scan. Global thresholding, optimum thresholding, 3-D-adaptive fuzzy thresholding, rule-based region growth, linked component labeling, graph-cut algorithm, and hybrid segmentation are used to segment lung. Following segmentation, lung volume was retrieved using many approaches and refined to include juxta-pleural nodules.

Literature Survey

A CAD system helps radiologists discover pulmonary nodules early. We provide a hierarchical block classification-based lung nodule identification approach in this work. The suggested CAD system is three-step. Our initial step is to partition input computed tomography images into three-dimensional block pictures and use entropy analysis to choose relevant blocks. The second phase segments and adjusts block pictures to find nodule candidates. The last stage is to categorize nodule candidate photos as nodules or non-nodules. Object feature vectors are extracted from chosen blocks. Support vector machine classifies extracted feature vectors last. Performance of the proposed system is assessed using the Lung Image Database Consortium database. The suggested technique greatly decreased nodule candidate false positives. With 2.27 false positives per scan, it has 95.28% sensitivity. Image processing and CAD technologies have improved radiologists' diagnosis, notably lung nodules. This work describes a technique for analyzing Postero Anterior chest radiographs that splits the lung field and selects low-cardinality, high-sensitivity nodule candidate areas. This research aims to create a CAD method for lung nodule detection in helical X-ray pulmonary computed tomography CT images. We introduce a new template-matching method using a genetic algorithm (GA) to detect nodules in the lung area. The GA efficiently determines target position and selects an appropriate template image from multiple reference patterns for fast template matching. Lung wall template matching (LWTM) was also used to detect lung wall nodules by rotating semicircular models according to the target point's angle on the lung wall contour. We employed 13 feature values to reduce false-positive results after identifying candidates using the two template matching approaches. This research included 557 sectional pictures from 20 clinical patients. Our method accurately recognized 71 of 98 nodules (72%), with 1.1 false positives per sectional picture. Our findings demonstrate that CAD systems can identify nodules in helical CT pulmonary images using our method. The authors created the quoit filter, a mathematical morphological filter, to automatically identify lung cancer potential problematic regions. However, processing speed and extraction accuracy are issues. This study provides variable quoit filtering, where the filter size is flexible due to the pathological shadow, and distance transformation with grey-level weight as preprocessing before the main filtering technique. First, the method's performance is modeled to demonstrate its efficacy. Next, trial applications to photos of 82 real instances (including 21 cancer regions) reveal that all cancer areas were retrieved accurately. It takes less than 1/20 the time of the standard algorithm.

Block Diagram

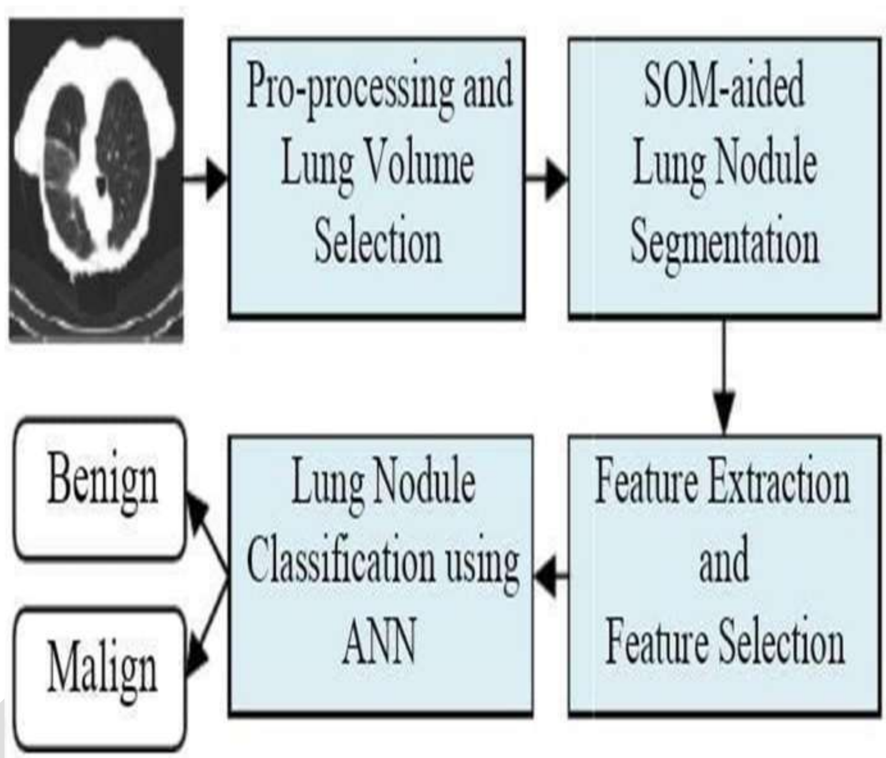
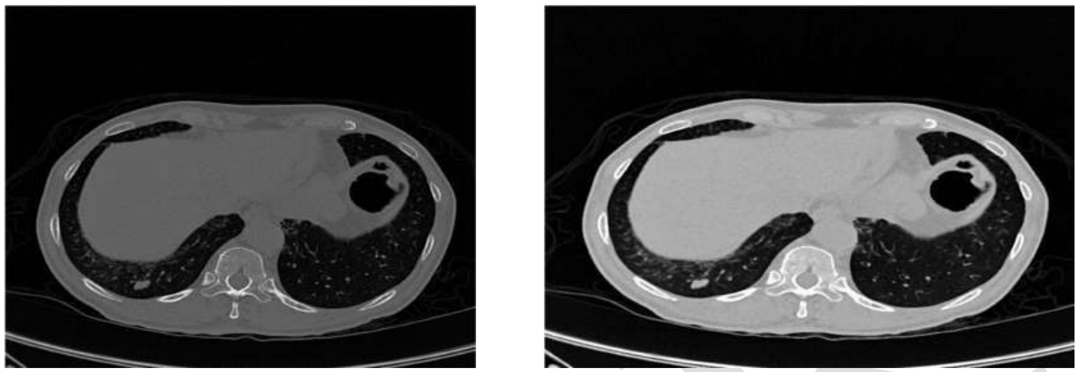


Fig.2.1 Block diagram

- Pro-Processing

Due to noise and bad lighting, interference and other events decrease medical picture quality and contrast. The research examined raw DICOM CT scans for interference. Thus, median filtering image processing reduces "salt and pepper" noise while keeping edges. Grayscale images are contrast-adjusted. Figure 4.2 shows CT lung scans. The medical image enhancement procedure is vital to CAD system analysis, including image analysis, feature identification, and more. Loosing key picture information might hinder subsequent analysis, hence the original structure is kept while enhancing the image. Image pre-processing improves image quality and removes noise in the initial phase of CAD design. 3x3 median filter reduced noise and improved photos. This makes nodules and other locations more visible on CT scans and removes noise. Histogram equalization balanced picture pixel values. Lobe stripping used morphological techniques to remove lung lobes from pre-processed CT images. The remaining side pieces were eliminated using double thresholding. Lung area was acquired.



(a) DICOM raw CT lung image (b) Image after median filtering and contrast
adjustment

Fig.2.2 Lung image in pre-processing stage

Flow Chart

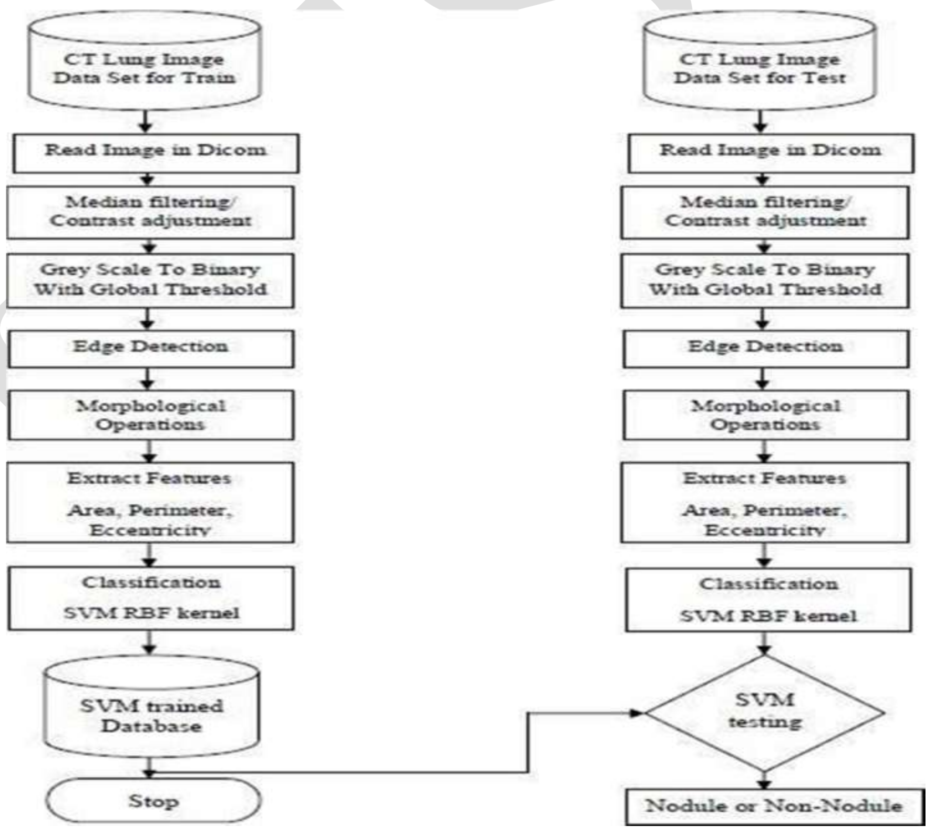


Figure 2.8 The flowchart of implementation of CAD system

Results and its Discussion

The project “Artificial Neural Network based classification system for lung nodulesthrough computed tomography scan" has been implemented and results are discussed below.

Output 1

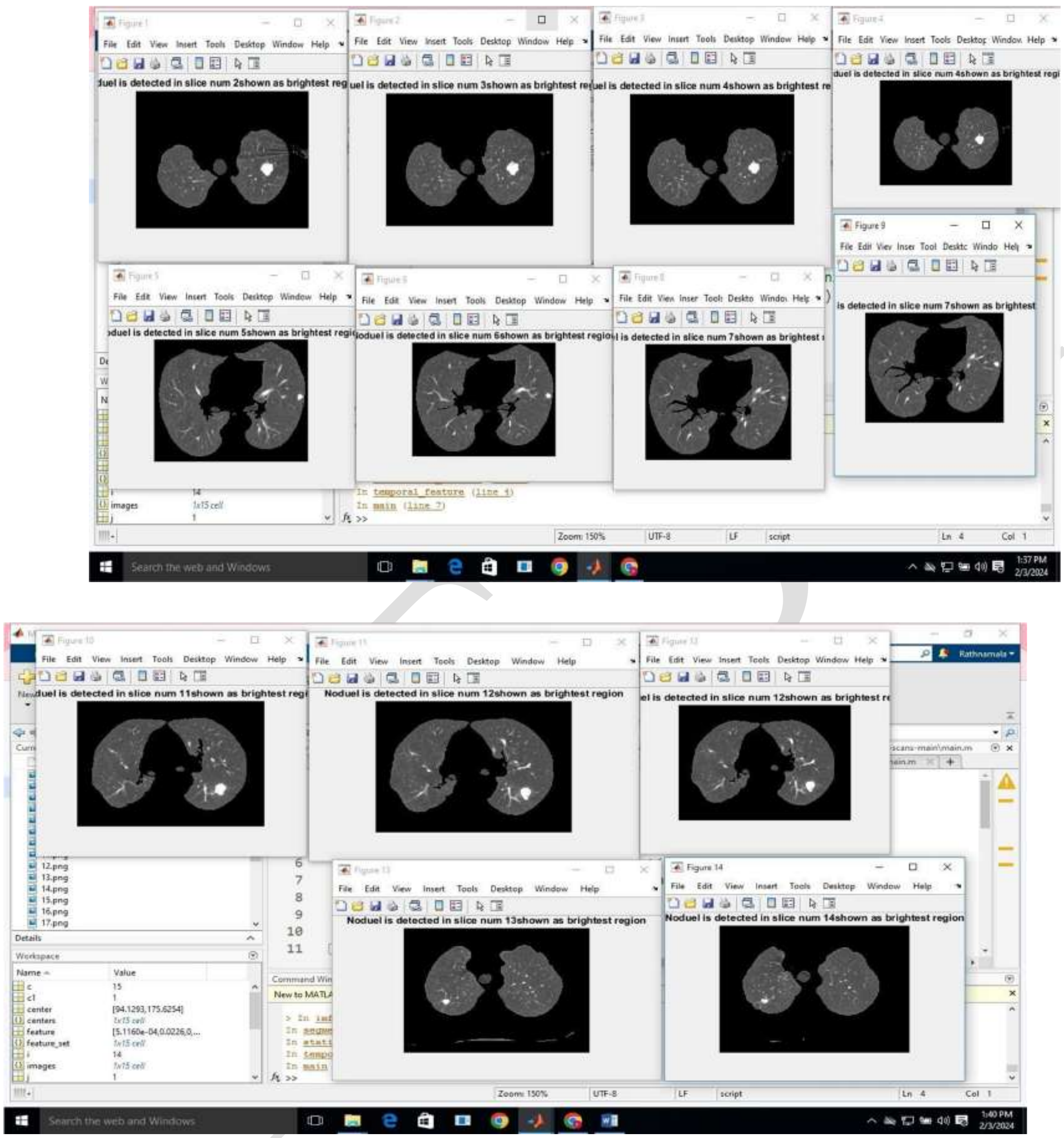


Fig.5.1 Dataset of CT Scan images

Each segmentation technique has its own pros and cons. For some applications it is wiselyto use various segmentation techniques together in order to have better results. For the particular requirements of this implementation, binarization process with global thresholding, edge detection and morphological operations that has major application in image enhancement and segmentation are commonly utilized.

The studied CT lung images have two types of pixels with distinct density. By using global image threshold which is a robust tool for image segmentation, the gray-scale images were converted to binary.

Output 2

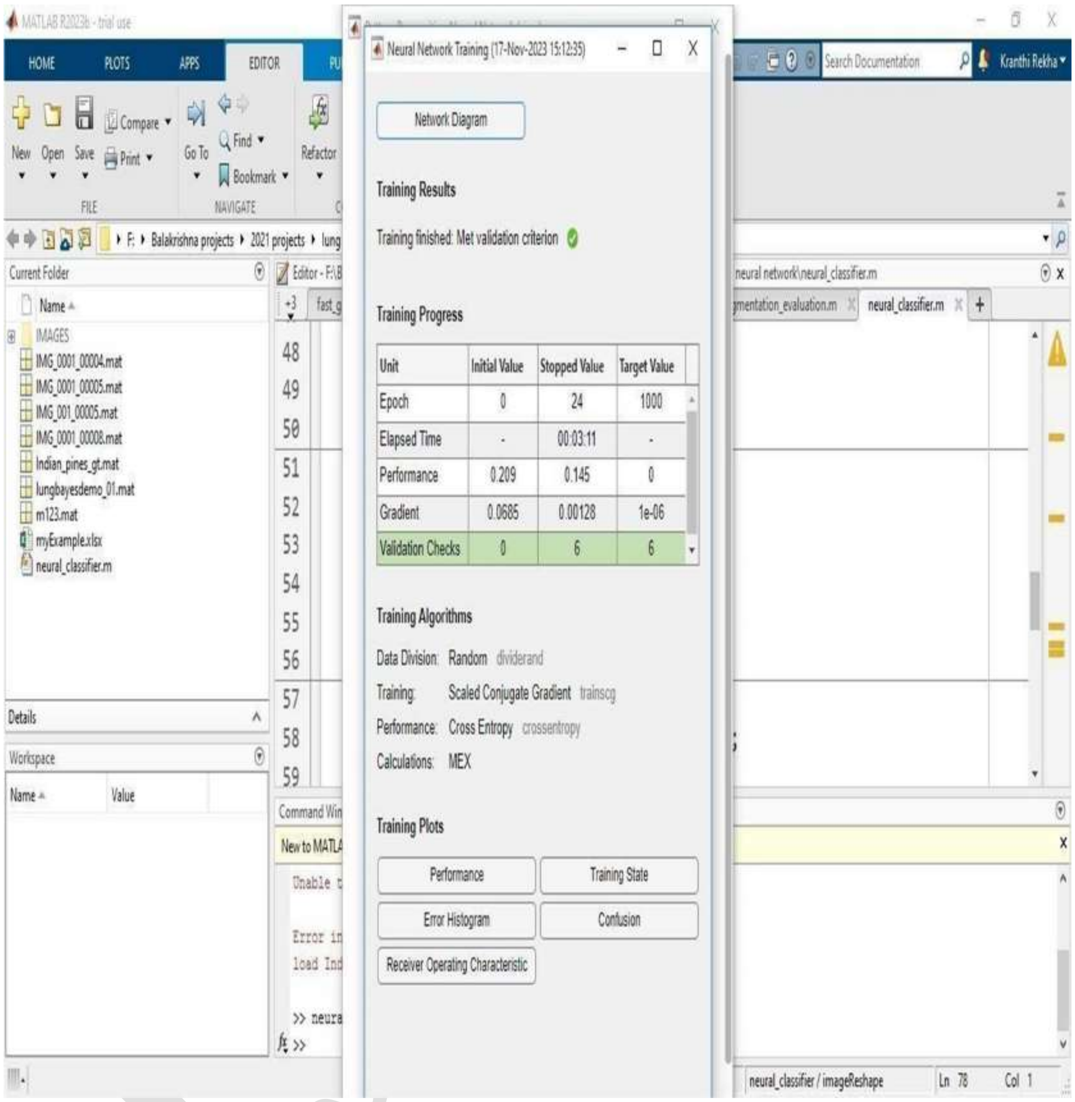


Fig.5.2 Neural Training

LIDC database is used in the training phase. The database subset, which is formed randomly consists of 271 CT lung image scans. The grayscale images are in DICOM format that is the standard for medical images with having a size of 512x512 pixels. Nodule locations as a ground truth information are also provided which were detected bythe radiologist.

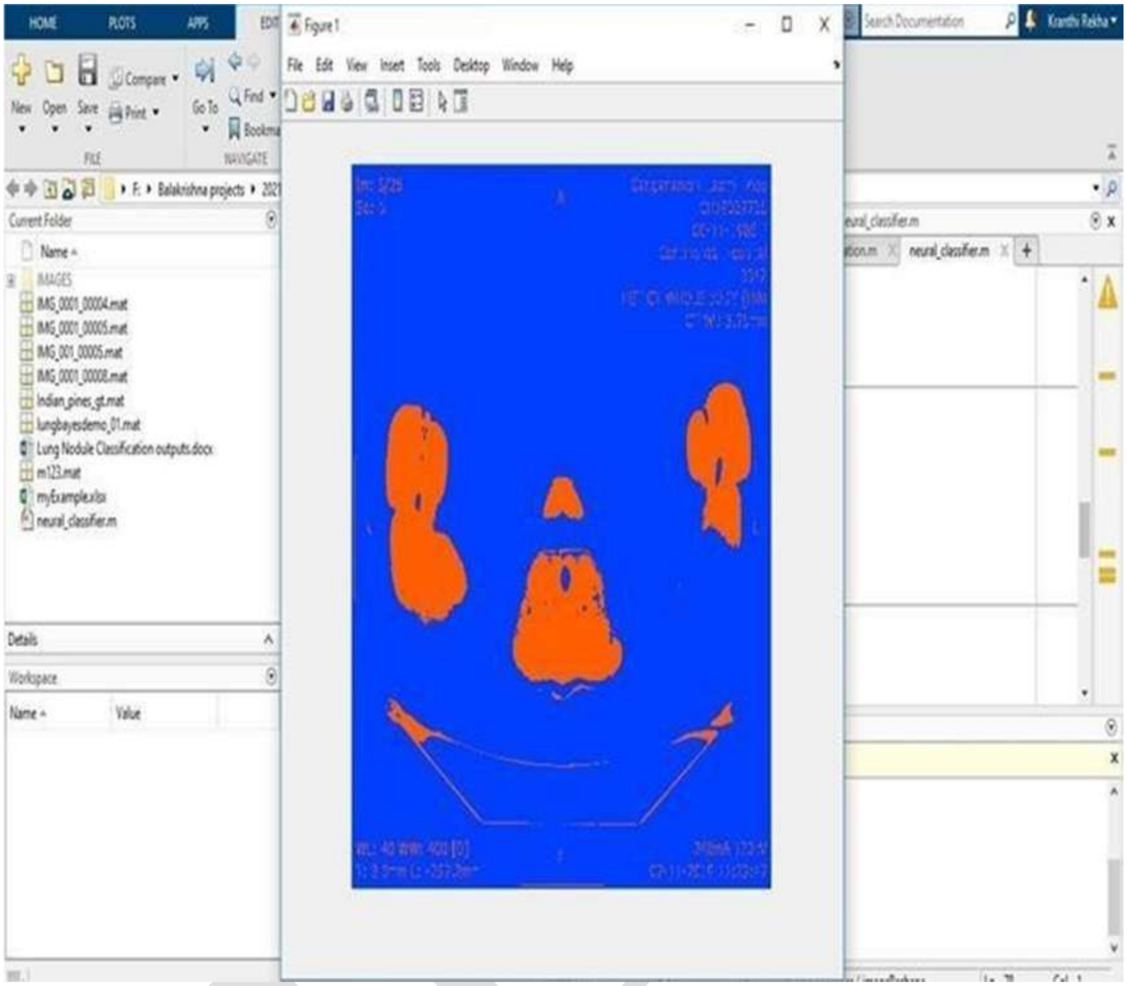


Fig.5.3 Detection of Lung nodules

An image database was created for the designed CAD system by collecting a total of 128CT images from 47 different patients. Detection of lung parts in total image showing where the lung image is there.

Most people find out they have a lung nodule after getting an imaging test in preparation for a procedure or another purpose. The findings are often a surprise. If an imaging test shows a lung nodule, your healthcare provider may recommend active surveillance.

The nodule detection task was performed through faster R-CNN that works at three stages, which are feature extraction, region proposal, and detection. Feature extractions were performed through state-of-the-art CMixNet, and region proposals were performed via U-Net-like encoder–decoder by pixel-wise labeling. The integration of CMixNet with U-Net makes it more robust for nodule feature extraction and generation. The encoder network with CMixNet also implemented batch normalization and dropout. Similarly, in the decoder network, up-sampling/deconvolution operations were performed with CMixNet architecture. Detection was performed through learned features and region proposal by inserting bounding boxes and finally classification.

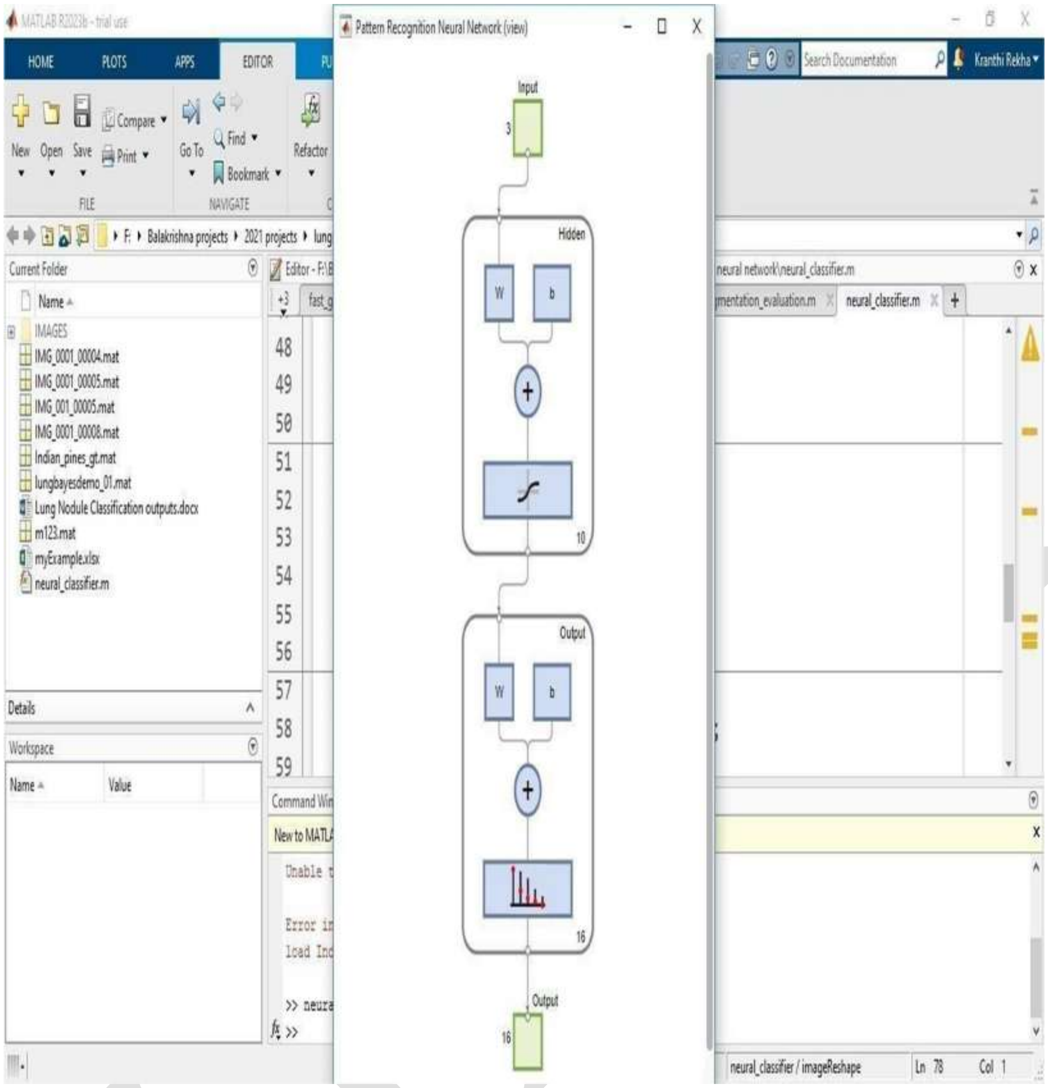


Fig.5.4 Classifier Neural Network

How the classification is done by the neural network and it also show how the confusion matrix varies the other performance graphs. A Classification Neural Network object is a trained, feedforward, and fully connected neural network for classification. The first fully connected layer of the neural network has a connection from the network input (predictor data X), and each subsequent layer has a connection from the previous layer. Each fully connected layer multiplies the input by a weight matrix and then adds a bias vector. An activation function follows each fully connected layer. The final fully connected layer and the subsequent soft max activation function produce the network's output, namely classification scores (posterior probabilities) and predicted labels.

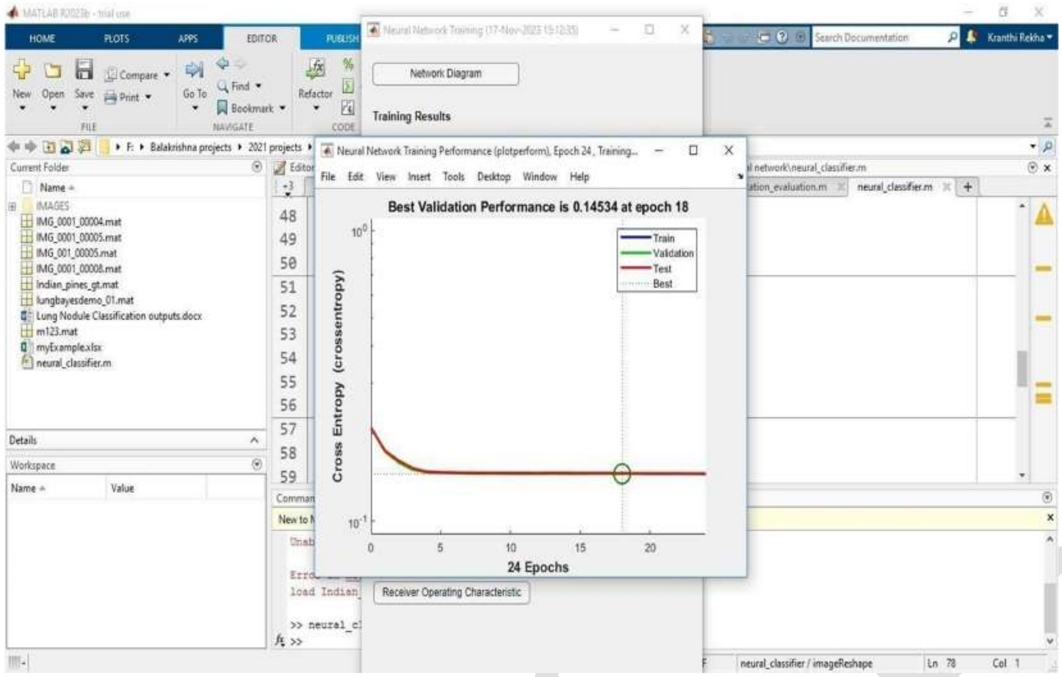


Fig.5.5 Best validation performance

Performance which has decreased from 0.209 to 0.145 so by this we can say that error isless so when error is less the iterations gets stopped.

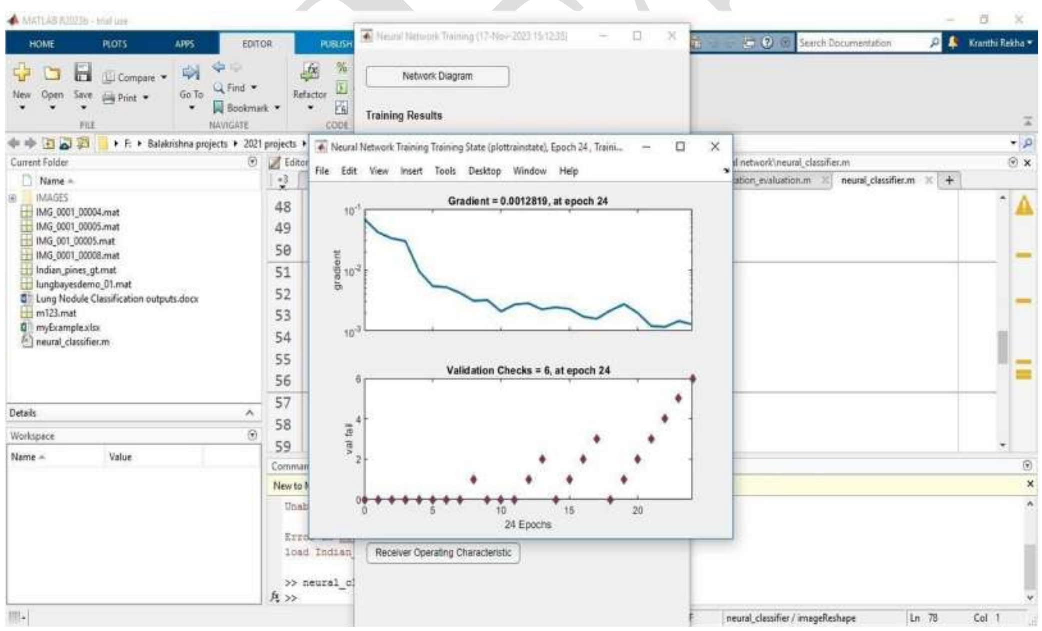


Fig.5.6 Gradient and validation checks

Gradient shows the continuous decrease in the graph.

In Validation checks the increment and decrement is done and where it is constant inevery iteration the particular graph is useful.

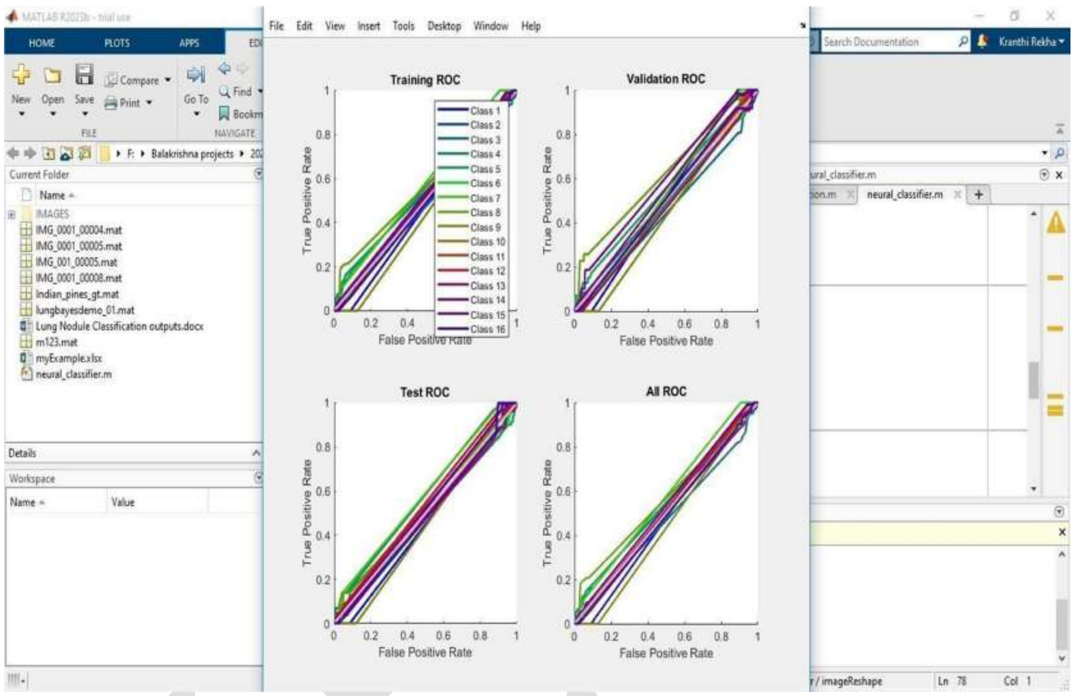


Fig.5.7 Receiver characteristics

Waveforms show error classification performance.

WBAN devices deliver real-time physiological data to doctors' smartphones and PCs. The intelligent system can remotely analyze this information and make smarter judgments based on the electronic healthcare record. Smartphones link body sensor devices to IoT networks and clouds to evaluate massive data for smarter choices. Our suggested study employed sensing devices and smartphone apps to collect patient physiological data and transfer it to the cloud for processing and analysis.

The breathing index using Reuven's Rejiva [online] revealed breathlessness tendencies. Heart rate and fitness data were collected using the Run smartphone app [online]. Wearable sensors assessed blood pressure and a smartphone app recorded body temperature. We employed these sensor devices at Chongqing (CHN.USA) Hygeia Cancer Hospital since they were unavailable throughout the investigation. We employed wearable or implanted monitoring devices and smartphone apps for this investigation. Wearable gadgets collected insomnia data by measuring sleeping patterns. The smartphone software “Finger print thermometer” measured body temperature. BP was monitored with a wearable sensor and weight loss via a health assistant app.

Conclusion and Future scope

This research addressed deep learning-based lung nodule segmentation, detection, and classification advances. CNN is a popular deep learning method for lung illness detection and classification, and CT image datasets are the most used imaging datasets for training networks. The article review used 2014 and subsequent publications. Experimental and clinical trials show that deep learning can outperform radiologists. Deep learning should enhance lung nodule segmentation, identification, and classification. This sophisticated technology helps radiologists understand pictures better. Deep learning has addressed numerous medical difficulties in radiography. It still struggles with large-scale clinical verification, patient privacy, and legal responsibility. Despite these limitations, deep learning is predicted to increase medical demand for accurate diagnosis and treatment due to the medical industry's increasing growth.

This work provides an automated CAD method that correctly classifies CT lung nodules as benign or cancerous. Pre-processing, segmentation, feature extraction, selection, and classification make the suggested CAD system integrated. Early lung nodule identification is possible using CAD's SOM technique. This research used ANN for its excellent classification accuracy (90.63 % accuracy, 92.30 % sensitivity, 89.47 % specification). Deep learning and machine learning AI can handle massive amounts of data and accurately describe pulmonary nodules, promising a fundamental redesign of lung cancer detection. Combinations of convolutional neural networks, machine learning, handcrafted features, computer-aided diagnostics, spectrometry, genetic and molecular alterations improved lung nodule classification and assessment.
sensitivity, specificity, accuracy. Additionally, the machine learning model paired with spectrometry-developed protein marker panels for lung cancer diagnosis and other models employing non-invasive breath testing or public health information improve detection accuracy. Compared to other systems, deep convolutional neural networks improved lung nodule classification and detection. Combining artificial intelligence with radiologists may create a cost-effective and time-saving lung cancer screening method. In the future, models must be validated to be useful in ordinary healthcare.

Future Scope

Further research and studies are to be conducted and validation of theproposed models of convolutional neural networks has to be performed. Validation ofthe proposed models is required for the practical application of these in the screeningprocedure of lung cancer and thereby increasing the detection in earlier stages. More research and trials are to be conducted utilizing the technological advancements and thedoctors have to take up the challenge to improvise and implement them.

This study extensively surveys papers published between 2014 and 2022. Demonstrate that deep learning-based lung imaging systems have achieved high efficiency and state- of-the-art performance for lung nodule segmentation, detection, and classification using existing medical images. Compared to reinforcement and supervised learning techniques, unsupervised deep learning techniques (such as CNN, Faster R-CNN, Mask R-CNN, and U-Net) are more popular methods that have been used to develop convolutional networks for lung cancer detection and false-positive reduction.

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