

Lung Disease Classification and Identification using Deep Learning Techniques

simran shivhare, HOD dr.manish Dixit,
Madhav institute of technology and science,Gwalior, M.P. INDIA
simranshivhare656@gmail.com , dixitmits@mitsgwalior.in,

Abstract: Machine learning is a subfield of artificial intelligence that uses a wide range of statistical, probabilistic, and optimization techniques. These methods allow computers to "learn" from previous examples and find patterns that are hard to spot in large, noisy, or complicated data sets. Learning by machine is a key strategy for making complex algorithms that can work on their own and are completely objective. This makes it perfect for analysing high-dimensional and multimodal biomedical data. Machine learning is an important part of the modern medical systems we have today. Many lives can be saved and stress on the system can be eased if diseases are found earlier and more accurately. Lung problems are one of the most common reasons why people die. During this investigation, we will suggest and evaluate the convolution neural network that was made to classify ILD patterns. ILD patterns can have one of seven different results: healthy, ground glass opacity (GGO), honeycombing, consolidation, reticulation, or micro nodules. Another choice is to use both GGO and reticulation. For training and testing the CNN, we first used a deep CNN that was made for the problem at hand. Lastly, we put into groups how well CNNs did at analysing lung patterns, which showed that they had a 91% success rate. We suggested that a deep convolutional neural network (CNN) be used to divide lung CT image patches into seven different groups, including six different ILD patterns and healthy tissue. The method is easy to train on different types of lung patterns, and its effectiveness could be improved even more. Randomizing the weights at the beginning makes the results for the same input slightly different. This is because the weights are not always the same. This means that the number of normal and non-pathological images in the training data is skewed. This is another important issue in medical image analysis. Rare diseases are an extreme example of this because they can be missed if there aren't enough training examples. Even though there is a risk of overfitting, the effect of this data imbalance can be lessened by using data augmentation to create more training images of unusual or atypical data. In addition to looking at data-level

approaches, algorithmic modification strategies and cost-sensitive learning have also been looked at.

Keywords: Lung diseases, Chest CT images, Active contour models, Spatial interdependence matrix, Feature extraction, Image segmentation

I Introduction

The lungs, which are very important, make it possible for the body to expand and relax in order to take in oxygen and get rid of carbon dioxide. This is how the body takes in oxygen and gets rid of carbon dioxide. Lung diseases are a type of respiratory disease that affect the many organs and tissues that help us breathe. This can lead to a number of problems, such as problems with the airways, lung tissue, and circulation in the lungs. Some respiratory diseases, like the common cold and flu, only cause mild pain and trouble breathing, while others, like pneumonia, tuberculosis, and lung cancer, can be fatal and cause severe acute breathing problems [1]. According to the results of a study called "The Global Impact of Respiratory Disease," which was done by the Forum of International Respiratory Societies, 10.4 million people had mild or severe symptoms of tuberculosis, and 1.4 million of those who had the disease died [2]. The Forum of International Respiratory Societies was in charge of the study. Lung cancer kills an astonishing number of people every year. During the time the poll was done, it was said that more than 1.6 million people had died. The "Pneumonia and Diarrhea Progress Report 2020" from the Johns Hopkins Bloomberg School of Public Health says that pneumonia is one of the most common respiratory infections and that it killed 1.23 million children under the age of 5 around the world in [3]. If any of the above diseases are found in their early stages, not only will the chance of survival be much higher, but it may also be possible to keep people from dying. X-rays of the chest and CT scans are two common types of tests used to find out if these diseases are present [4]. For the scanned photos to be looked at and the infections to be found, qualified professionals must be present. Official numbers from the Ministry of Health of

the Union show that there is a shortage of 76.1 percent of doctors working in rural Community Health Centers (CHCs). Deep learning strategies are used to get around this problem, which makes it possible to try something new. Deep learning is a branch of artificial intelligence that combines traditional machine learning with representation learning to make the most accurate programmes possible. It is a part of the field of machine learning. This tool has been getting a lot of attention lately because it can read data from pictures, process those pictures, and give results based on data it has already learned [5]. By looking at the images that make up a dataset, deep learning models can learn features and patterns. Then, these models can use the features they have learned to classify new test images they have never seen before. Researchers from all over the world have already done a lot of studies, and the results of many of them are good news. These works can help support existing ways of doing things or open the door to new ones that weren't possible before they were made. These new ideas can help quickly and accurately identify diseases and put them into groups. They can also help quickly get amazing results in the fight against infectious diseases that kill people.

LUNG DISEASES Most cases of tuberculosis, which is an infectious disease, are caused by a type of microbe called Mycobacterium tuberculosis. Most of the time, the bacteria get into the body through the lungs and the respiratory system [4]. Lung cancer is always listed as one of the world's most deadly diseases [8]. Also, if it is found and treated quickly, it can be completely cured. Er et al. [4,] say that pneumonitis is an infection or inflammation of the lungs that is usually caused by a virus or bacteria. [Needs citation] Another way to get pneumonia is to breathe in vomit or other foreign matter. This is an additional risk. Er et al. [4,] say that asthma is a long-term condition that is marked by repeated bouts of shortness of breath and wheezing. [Needs citation] When someone has asthma, the lining of the bronchial tubes swells up. This causes the airways to narrow, which makes it harder for air to get in and out of the lungs. COPD is a disease that can be prevented and treated. It is characterised by a restriction in airflow that can't be completely fixed [4]. Also, the airflow usually gets worse over time. This is because the lungs have an abnormal inflammatory response to toxic particles or gases, which is usually caused by smoking cigarettes.

PROBLEM IDENTIFICATION When someone has a lung disease, it's hard for them to breathe. In the United States, millions of people have lung diseases. When all types of lung disease are added up, lung disease is the third leading cause of death in the United States. People use the

term "lung disease" to describe a wide range of conditions that affect the lungs. Even though there is a computer system to find pneumonia, it does not find all lung diseases that can be seen on a chest X-ray. Still, there is a computer system that can tell if someone has pneumonia. The information from the patient's chest X-ray, along with some other information, was used in this research to figure out what was wrong with the patient's lungs.

MOTIVATION :Changes in the world are happening so quickly that they are putting more and more stress on people's health. Changes in the climate, the environment, and the way people live their lives that are not good all contribute to more people getting sick. The lung is one of the organs that is hurt by this. Chronic obstructive pulmonary disease (COPD), which is mostly caused by smoking and pollution, killed almost 3 million people in the year 2020, while asthma killed 400,000 people. People can have many different lung diseases, but this is just one example of the kinds of diseases that we might be able to save people from if we find them sooner. Thanks to improvements in technology, machines, and computer power, diseases, especially lung diseases, can be found earlier and more accurately. This could not only save the lives of a lot of people but also take some pressure off the system. The number of people has grown, but the health care system has not grown at the same rate. With the power of computers and the large amount of data that is now available to the public, now is a good time to help solve this problem. The goal is to make a bigger difference in the community by making health care less expensive.

II IRELATED WORK

CNNs, which are very good at classifying images, are now thought to be one of the best ways to analyse medical images. In the next sections, we'll look at the Pre-Trained, Functional, and Sequential CNN models, which are some of the most recent versions of this type of network. In their study about how to diagnose tuberculosis, Liu et al. showed how CNN-trained models can be used in three different ways. In each of these three methods, CNN architectures are used to pull out features, and the support vector machine (SVM) is used to train those features. In the second proposal, on the other hand, the co reference resolution (CR) is used to pull out features, and then the SVM classifier is used to train those features. In the third idea, these two methods are combined to make what is called a classifier ensemble. There are a total of 138 X-ray images in the Montgomery dataset, while there are a total of 662 X-ray images in the Shenzhen dataset.

These trained models help cut down on processing time, but they aren't very accurate, so they can't be used for medical diagnosis. The method that Amit Kumar Jaiswal, Prayag Tiwari, Sachin Kumar, and Deepak Gupta came up with is called the RCNN. It is a model based on a deep neural network that can get both global and local information. In this method, division is done pixel by pixel, and it is expected that this method will work better on the radiograph dataset when it is tested.

This method finds the infected areas and makes a heat map to help people who are looking at the results understand the information better. But they have a group of ResNet50 and ResNet101 models, both of which are Mask RCNN models. Even though training these models takes more GPU processing resources, the results are less biased than expected. Elshennawy and Ibrahim each gave a talk about four different models. CNN and LSTM-CNN are two of these four models that were trained from scratch. ResNet152v2 and MobileNetV2 are two examples of models that had already been trained. The first steps were taken by the CNN and LSTM-CNN models. They came up with a plan to build a deep learning neural network model from the bottom up, with the goal of using chest X-ray pictures to diagnose pneumonia in a patient who was showing signs of the disease [6]. One of its flaws is that it has a huge architecture with hundreds of millions of trainable parameter weights [7, 8]. Other problems include the fact that it is so big. For this kind of model, you need a lot of computer power and processing power. Naik and Edla [9] made a way for computed tomography (CT) images to classify and identify lung nodules.

They did this by using different methods of deep learning. So that the diagnosis didn't take too long, the CT scans needed a computer-aided detection system that could tell if the lung nodule was good or bad. Also, this system needed the most exact measurements possible. When compared to other methods, the results of the deep learning algorithms used to classify the lung nodule are good. How well the mutations were built into the deep learning architecture was directly related to how quickly the classification system got better at its job. Deep learning was used to find the early stages of a cancerous lesion as well as new effects on the classification of nodules [10].

III DATASE

A From the Kaggle repository, you can download a set of medical photos that make up a dataset. In this research, the new CNN models of sequential and functional models were used to put this dataset into practise. Using the new CNN models, these models were used to put together this

dataset. Four different modelling algorithms were used in the study that was suggested. In the sections that follow, you'll learn more about each of these topics.

IV PROPOSED METHODOLOGY

Recently, a lot of X-ray lung data was made public on Kaggle and the UCI Machine Learning Repository. This was followed by lung disease data that had been labeled. The proposed method can classify Seven types of lung disease: ground glass opacity (GGO), micro nodules, consolidation, reticulation, honeycombing, and a combination of GGO and reticulation. It does this by taking features from segmented CT images and using deep learning to do so.

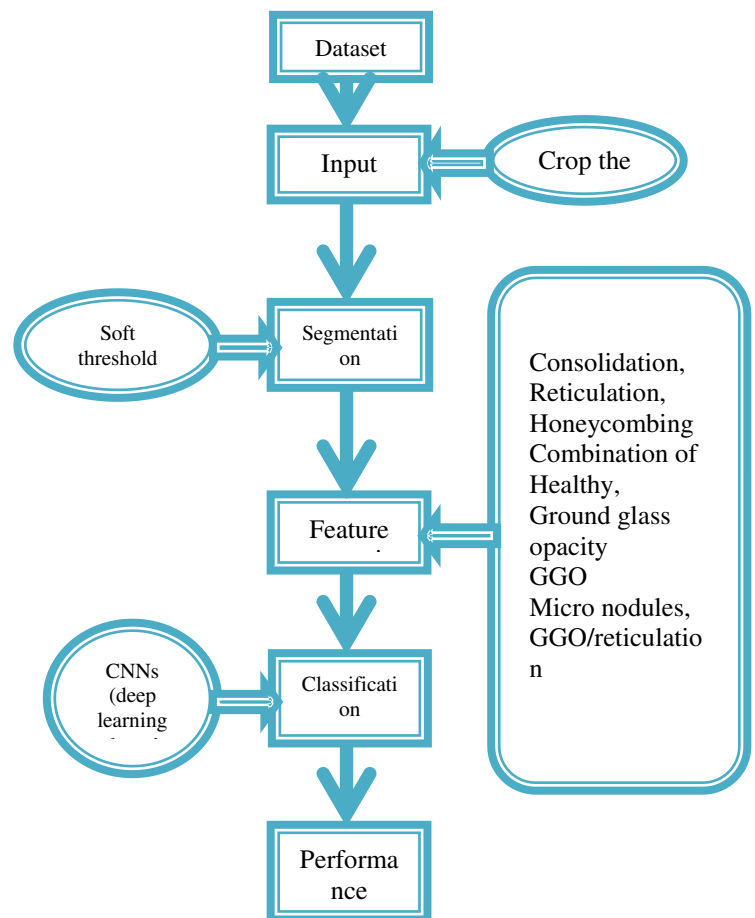


Fig.1 Flow diagram

Figure 1 shows a picture of how the process works. The first thing we'll talk about is how computed tomography (CT) gets digital images, and then we'll talk about how the

lungs are divided up. In the last part of this presentation, we talk about the plan for figuring out which lung diseases are present.

Preprocessing and Data Augmentation.

The photos in the datasets are all different sizes and resolutions. Still, the CNN models need images to be a certain size for them to work properly. So, every image in the dataset was resized so that it had a resolution of 224 pixels by 224 pixels. By making the input image smaller, it's easier to run images faster, which makes the model faster for the task it's linked to.

Data augmentation is a common method of support that is used to greatly increase the amount of training data. This is done by making small changes to a picture at every step of the training process. This work uses five different variations: horizontal flip, zoom, shear, rotation, and rescale. Because of this method, the CNN model can be trained on more data than was originally in the dataset. This is very important for getting very accurate results. Figure 3 shows how a single example photo can be used to make a lot of different things.

Functional Model. The flexibility offered by the functional model is superior to that of the other algorithms. It is able to build connections between any two layers that are in opposition to the others and move forward in a sequential manner. Because of this, we are able to design networks that are more intricate and advanced [13]. After passing through the initial layer, the input continues on through the rest of the architecture as designed. In contrast to the model that has been retained, this technique also begins training from the very beginning. As the suggested functional model consists of two convolution layers with a window size of 7 7 and another layer with a 1 1 window placed on top of a 3 3 window. Following the individual processing of the input by each of the two convolution layers, the results of those two layers are appended together and then sent on to a total of five 3 x 3 convolution layers. It was decided to use the Te Adam optimizer with a learning rate of 0.0001.

Pretrained Model. This is the easiest way to group pictures, and it's also the one that people use most often. Instead of training a model from scratch, this method uses weights that have already been trained on a large set of photos [14, 15]. In the end, this means that the required images can be sorted better. This method is also called

"transfer learning" because the weights that have already been learned are transferred and used in the process of classifying. In general, training on this model takes less time and gets better and more accurate results than training on other models.

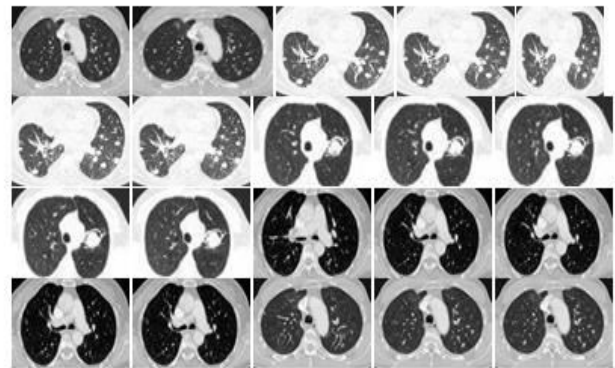


Fig 2 Dataset

A train-validation-test framework is used to judge the different ways to classify ILD patches. After the methods had been trained on the training set, which was where most of the training took place, the validation set was used to fine-tune them.

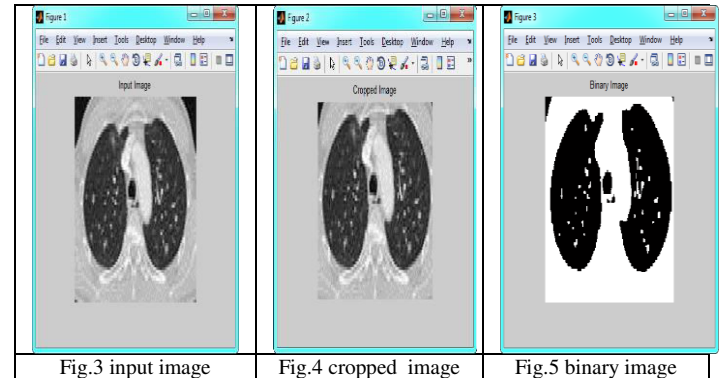


Fig.3 input image

Fig.4 cropped image

Fig.5 binary image

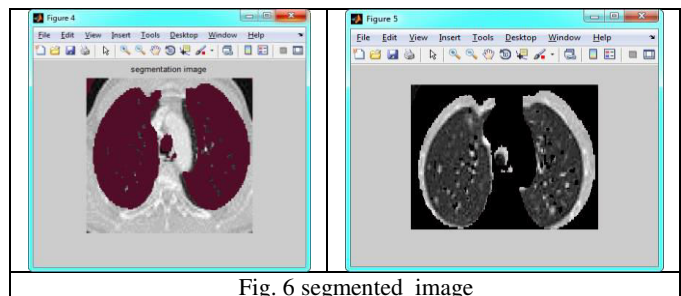


Fig. 6 segmented image

V CLASSIFICATION RESULT

The statistical information in the database. (H: Healthy, GGO: Ground Glass Opacity, Micronodules, Cons:

Consolidation, HC: Honeycombing, R: Reticulation) challenge taken into account, which is the classification of ILD patterns in this case. ILD patterns in CT images can be told apart by their local textural features, whereas random objects in colour pictures are made up of complex, high-level structures with a set orientation. It's not easy to come up with a formal definition of texture, even though most people understand the idea of texture intuitively. Since the two networks were made to classify colour images with 224 by 224 patches, we had to rescale the 32-patch data to 224 by 224 to make it work with our data. Also, we made three channels by taking into account three different HU windows, as described in [3]. Then, we tried to teach AlexNet to work with our own data from scratch. But because of how big these networks are, they need to be trained with a lot of data. About 91% accuracy was reached, and noisy low-detail filters from the first convolution layer were used. The network is too big for the problem we have, both in terms of its size and its scale. We tweaked the AlexNet that had already been trained (on Image Net), which is currently the most common way to use it on other problems. This let us get around the problem of not having enough data. It's possible that the size of the data set used is more important than the type of data used. On the other hand, if you look at the filters in the first layer. In the end, we looked at the pre-trained (on ImageNet) VGG-Net that had been tweaked. This was needed because starting from scratch with a network that big would need even more data than AlexNet did. Compared to AlexNet, the network was able to improve by about 2%. This is likely because the kernels are smaller, which makes it possible to use more convolution layers. Even so, the result is less than what was expected.

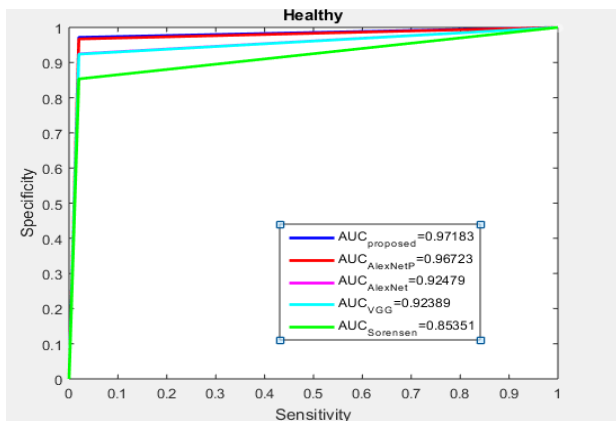


Fig.7 Healthy class graph

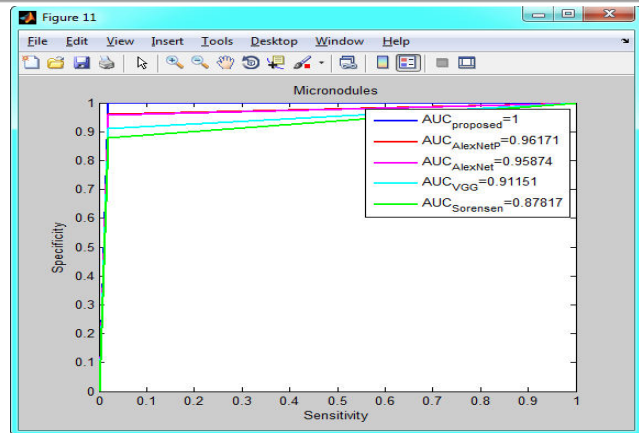


Fig.8 micronodules class graph

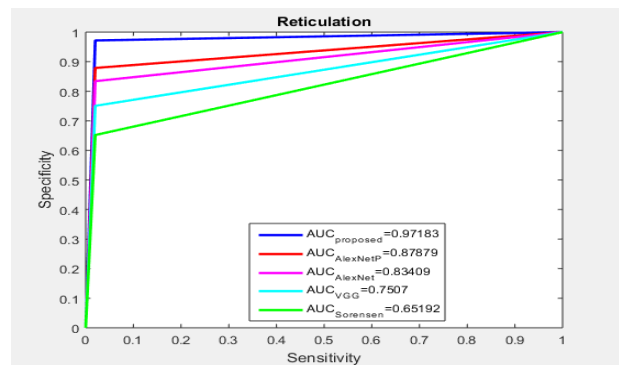


Fig.9 reticulation class graph

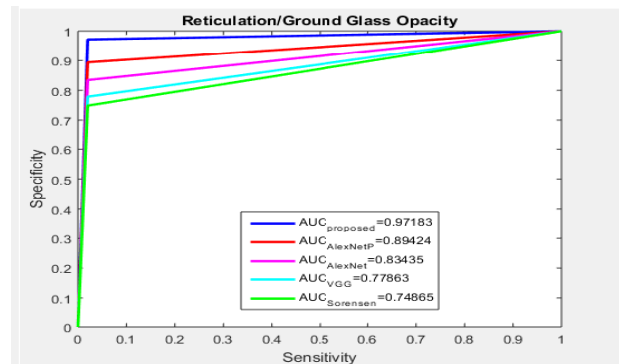


Fig.10 reticulation / ground glass opacity class graph

For the analysis of AlexNet, AlexNetP, VGG-Net, the method by [13], and the proposed CNN, the area under the curve (AUC) was calculated. The 95% confidence interval was shown, which was based on [14]. Based on the comparison, it was found that the suggested approach had the highest AUC in all seven categories. In order to find out if the differences in AUC are statistically significant or not, the analysis was done on a class-by-class basis and the

average was shown for all classes (one vs all). The area under the curve (AUC) and the 95% confidence interval for each ROC are shown on a graph. When it comes to the more difficult patterns, like consolidation, reticulation, honeycombing, and reticulation/GGO, here are some comparisons: It was found that there wasn't a big difference between the proposed method and the pre-trained version of AlexNet for the rest of the patterns (healthy, GGO, and micro nodules), and for GGO, there wasn't a big difference between the proposed method and VGG-Net either). In the end, it was decided that the proposed strategy was statistically significantly better after averaging its performance over all of the classes that were looked at.

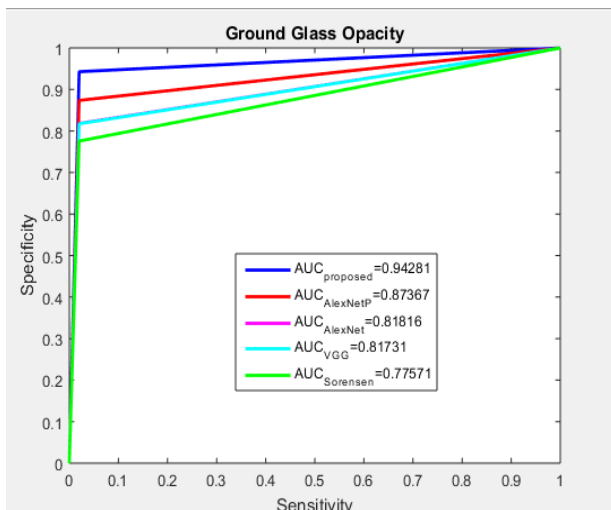


Fig.11 Ground Glass Opacity Class Graph

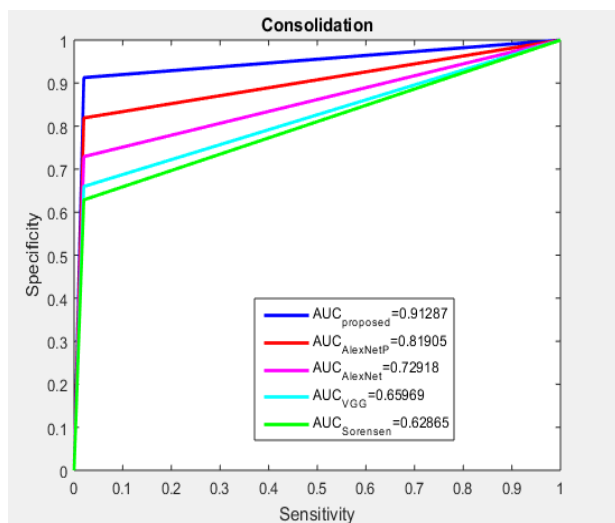


Fig.12 Consolaidation

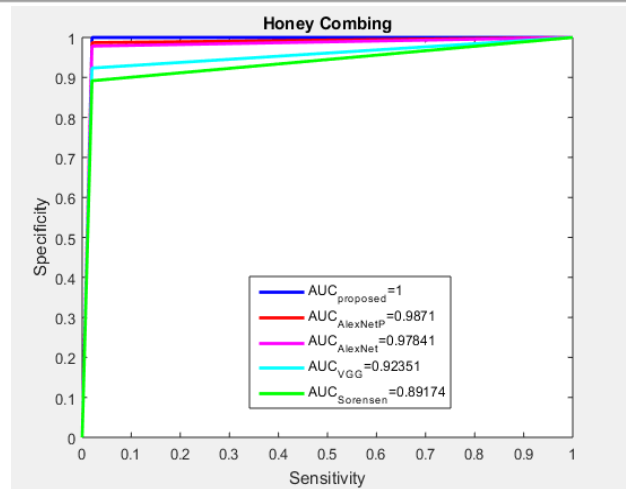


Fig.13 Consolaidation

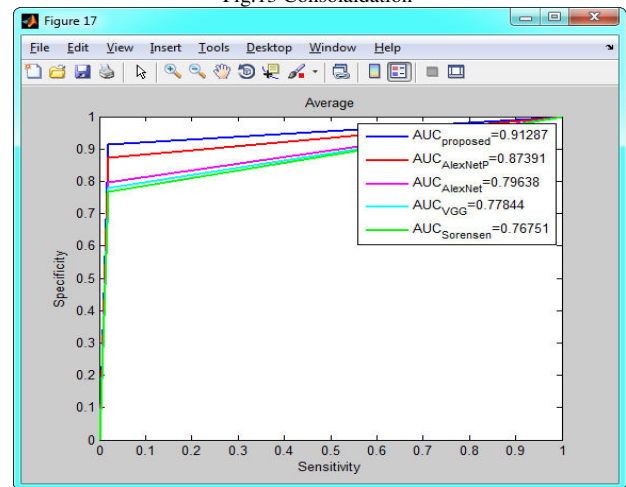


Fig.14 Honey Combing Class Graph

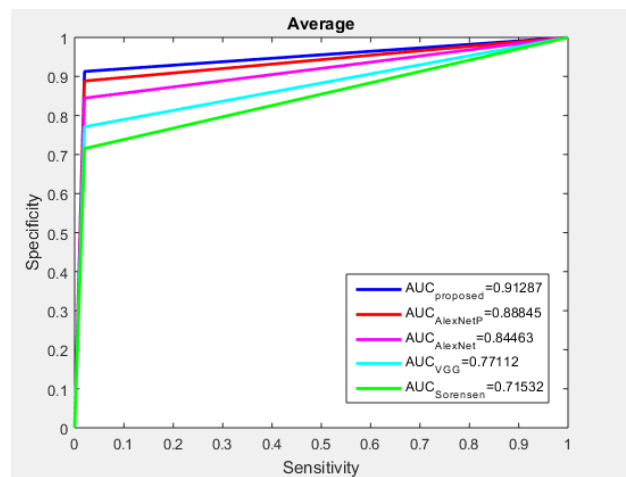


Fig..15 Sensitivity graph

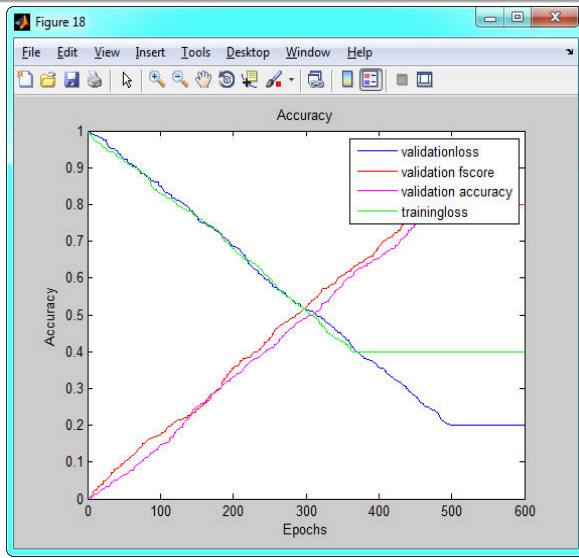


Fig16 Accuracy graph

In Deep Learning, an epoch is a type of hyper parameter that must be defined before a model can be trained. One epoch is when a full dataset is run through the neural network in both forward and backward directions just once..For example, if we divide a dataset with 2,000 training instances into 500 batches, then the results of four iterations will fully cover one epoch.

Table. 1 The proposed method for the seven considered classes.

VI CONCLUSION

We proposed a deep CNN to classify lung CT image patches into 7 classes, including 6 differentILD pattern sand healthy tissue. The method can be easily trained on additional textural lung patterns while performance could be further improved. The slight fluctuating of the results, for the same input, due to the random initialization of the weights. Data or class imbalance in the training set is also a significant issue in medical image analysis. this refers to the number of images in the training data being skewed towards normal and non-pathological images. Rare diseases are an extreme example of this and can be missed without adequate training examples. This data imbalance effect can be ameliorated by using data augmentation to generate more training images of rare or abnormal data, though there is risk of over fitting. Aside from data-level strategies, algorithmic modification strategies and cost sensitive learning have also been Analysis

Table 1: comparison result with existing result

Techniques	Accuracy
Existing system - VGGNet-16[1]	82%
Proposed system – AlexNet	99.99%

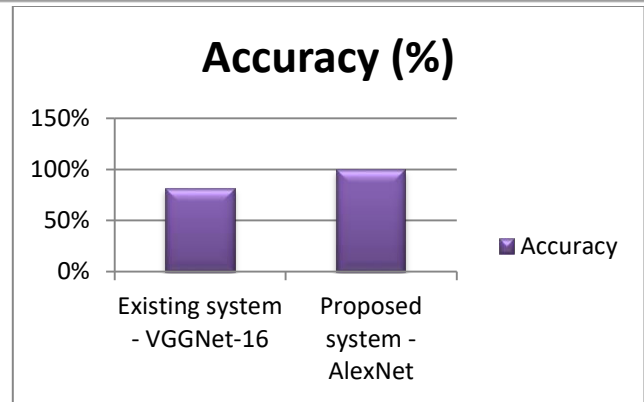


Fig.17 comparison result with existing result

References

1. Ines Chouat; Amira Echtioui; Rafik Khemakhem; Wassim Zouch; Mohamed Ghorbel; Ahmed Ben Ham Lung Disease Detection in Chest X-ray Images Using Transfer Learning 2022 6th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP) 24-27 May 2022 10.1109/ATSIP55956.2022.9805892
2. Syed MS Islam Hassan Mahmood Adel Ali Al-Jumaily ; Scott Claxton Deep Learning of Facial Depth Maps for Obstructive Sleep Apnea Prediction Published in: 2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI) DOI: 10.1109/ICMLDE.2018.00036 Sydney, Australia,
3. Yaniv Bar Idi tDiamant Lior Wolf ; Sivan Lieberman Date of Conference: 16-19 Chest pathology detection using deep learning with non-medical training DOI: 10.1109/ICIECS.2018.8276011
4. Ho-Shon Sarvnaz Karim Len Hamey Modality Classification and Concept Detection in Medical Images Using Deep Transfer Learning: 10.1109/IVCNZ.2018.8634803 Teleconference Location: Auckland, New Zealand, New Zealand
5. JahanzaibLati fChuangbai Xia Medical Imaging using Machine Learning and Deep Learning Algorithms: A Review 2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)10.1109/ICOMET.2019.8673502 Sukkur, Pakistan,
6. Nirmala Singh Sachchidanand Singh Object classification to analyze medical imaging data using deep learning Published in: 2017

-
- International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS) DOI: 10.1109/ICIIECS.2017.8276099 Conference Location: Coimbatore, India
7. J.selvakumar , A.Lakshmi, T.Arivoli, “Brain Tumor Segmentation and Its Area Calculation in Brain MR images using K-Mean Clustering and Fuzzy C-Mean Algorithm” , IEEE-International Conference On Advances In Engineering, Science And Management (ICAESM -2012) March 30, 31, 2017
 8. Sudipta Roy, Samir K.Bandyopadhyay, “Detection and Quantification of Brain Tumor from MRI of Brain and it’s Symmetric Analysis”, IJICTR, Volume 2 No. 6, June 2012.
 9. Krishna Kant Singh , AkanshaSingh,“A Study Of Image Segmentation Algorithms For Different Types Of Images”, IJCSI International Journal of Computer Science Issues, Vol. 7, Issue 5,September 2018
 10. Qurat-Ul-Ain, L.G., Kaz mi, S.B., Jaffar, M.A ., Mirza, A.M.: ‘ Classification and segmentation of brain tumor using texture analysis’ , Recent Adv. Artif. Intell. Knowl. Eng. Data Bases, 2015 10, pp. 147 –155
 11. 2 Khalid, N.E.A., Ibrahim, S., Haniff, P.N.M.M.: ‘MRI brain abnormalities segmentation using K-nearest neighbors (k-NN) ’, Int. J. Comput. Sci. Eng. (IJCSE), 2011, 3, (2), pp. 980 –990
 12. 3 Aslam, H.A., Ramashri, T., Ahsan, M.I.A.: ‘A new approach to image segmentation for brain tumor detection using pillar K-means algorithm ’, Int. J. Adv. Res. Comput. Commun. Eng., 2013, 2, (3), pp. 1429 –1436
 13. Maity, A., Pruitt, A.A., Judy, K.D.: ‘Cancer of the central nervous system’ (Clinical Oncology, 2008, 4th edn.)
 14. Ricci, P.E., Dungan, D.H.: ‘Imaging of low and intermediate-grade gliomas ’, Semradonc, 2001, 11, (2), pp. 103 –112
 15. Rajini, N.H., Narmatha, T., Bhavani, R.: ‘Automatic classification of MR brain tumor images using decision tree ’. Special Issue of Int. J. of Computer Applications on Int. Conf. on Electronics, Communication and Information Systems (ICECI 12) 2012, pp. 10 –13
 16. Armstrong T.S., Cohen, M.Z., Weinbrg, J., Gilbert, M.R.: ‘Imaging techniques in neuro oncology ’ Semoncnur, 2004, 20, (4), pp. 231 – 239
 17. Bandyopadhyay, S.K.: ‘Detection of brain tumor- a proposed method ’, J. Global Res. Comput. Sci., 2011, 2, (1), pp. 55 –63
 18. Anbeek, P. Vincken, K.L., Viergever, M.A.: ‘Automated MS-lesion segmentation by K-nearest neighbor classification’, Midas J. MS Lesion Segmentation (MICCAI 2008 Workshop), 2008
 19. D. Yu and L. Deng, “Deep learning and its applications to signal and information processing,” IEEE Signal Processing Magazine, vol. 28, no. 1, pp. 145–154, 2011
 20. Deng, Platt Li Xavier Glorot, Antoine Bordes Domain Adaptation for Large-Scale Sentiment Classification: A Deep Learning Approach vol. 15 no. 1, pp. 132–136, 2011
 21. Gravier, Garg[Dandan Mo, L. Stochastic gradient learning in neural networks: A survey on deep learning: one small step toward AI vol. 28, no. 4 , pp. 130–134, 2012.