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PULMONARY IMAGE CLASSIFICATION WITH APPROPRIATE NEURAL NETWORK SELECTION AND ENSEMBLE LEARNING

Siddavatam Siva Jyothi Academic Consultant, Dept of CSE, YV University, Kadapa
Dr. A. Rama Mohan Reddy Professor, Dept of CSE, Krishna Teja Institutes,Tirupathi

Abstract

Classification at a medical diagnosis is a complex process that is extremely error prone. Since medical imaging is a major contributor to the overall diagnostic process, the Chest X-ray film is the most widely used and common method of clinical examination for pulmonary nodules. However, the number of radiologists obviously cannot keep up with this outburst due to the sharp increase in the number of Infectious Diseases, which is also a major potential source of diagnostic error. The existing system using inception-v3 transfer learning model to classify pulmonary images, and augmented the data of pulmonary images, then used the fine-tuned Inception-v3 model based on transfer learning to extract features automatically, and used different classifiers (Softmax , Logistic, SVM) to classify the pulmonary images. In the proposing system the classification of Pulmonary Images and the performance can be increased by the study of appropriate neural network selection and by using ensemble learning.The ensemble technique performs better on benchmark datasets than other state-of-the-art methods.

Keywords: Prediction, Classification Technique, Pulmonary Image Technique, Inception v3, Deep Convolution Neural Network, Data Augmentation, Ensemble Learning , Machine Learning,

I. INTRODUCTION

Now a days machine learning is widely used for various diseases prediction accurately with provided and trained datasets.This paper provides is a study of Predictive Analysis of Pulmonary nodules Disease Based onstudy of appropriate neural network selection and by using ensemble learning.

As our proposed pulmonary image classification based neural network selection using VGG_16 Model, Inception_v3, ResNet50 and VGG19.Nodule detection is an acute pulmonary infection caused by bacteria, viruses, or fungi that infects the lungs, producing inflammation of the air sacs and pleural effusion (fluid in the lung). It is the cause of over 15% of all deaths in children under the age of five.[21]. Lung infections are more common in undeveloped and underdeveloped countries, where overcrowding, pollution, and unsanitary environmental circumstances worsen the problem, and medical resources are limited. As a result, early detection and treatment can help prevent the disease from progressing to the point of death. The use of computed tomography (CT), magnetic resonance imaging (MRI), or radiography (X-rays) to examine the lungs is commonly employed for diagnosis[23,24,25]. X-ray imaging is a non-invasive and painless method of obtaining information. Figure 1 displays an example of a lung X-ray with a damaged and a healthy lung. Infiltrates, or white patches on the Lung X-ray Chest X-ray exams for infection identification, on the other hand, are vulnerable to subjective variability [2, 3]. As a result, an automated technique for detecting Nodules Infection is necessary. We created a method based on deep learning methods for dealing with such automation difficulties in this research. The most extensively used and common type of clinical assessment for pulmonary nodules is a chest X-ray film.

However, due to the fast increase in the number of infection diseases, which is also a major potential source of diagnostic error, This explosion is definitely outpacing the amount of radiologists available. As of January 2020, infectious diseases had killed more than half a million Americans, out of a total of two and a half million deaths worldwide, according to the Centers for Disease Control and Prevention.. (CDC) [15].

What was initially assumed to be a respiratory virus began to express itself in other parts of the body, with a long list of symptoms ranging from arrhythmia, heart attacks, blood clots, liver and kidney damage, rashes, and more. Despite this, respiratory problems are still the most common symptom of infectious diseases. In terms of diagnosis, thoracic radiography's specificity for infectious diseases is debatable, and its usefulness for frontline prescreening is also debatable. Several radiology organizations, such as the American College of Radiography[6,7,8], advise against utilizing clinical radiography to diagnose pulmonary causes. Nonetheless, a few researchers believe that a lung scan examination might be utilized as a primary tool for screening various locations, and that it could provide essential information for diagnosis and, in particular, the management of respiratory tract infections. We contributed a better investigation and established a novel Protocols to measure ML models when using heterogeneous data sources, particularly with a large number of patient cases, because to the limits of Strategies for ensuring that the ML models' visual features are particularly documenting the locations of lung anomalies rather than bright objects like medical equipment or hard tissue; Algorithms for tracking the position of a feature in a CXR image processing task and evaluating [22] the relationship with essential factors linked to a variety of viral diseases in the lungs.

The following is the outline for this paper. We begin by reviewing current studies in order to identify potential flaws in employing neural networks to process radiography pictures[9,14]. Then, using the open-access benchmark dataset Infectious Diseases as a case study, we present protocols and strategies for evaluating deep learning models for segmentation and classification.

Deep learning is a powerful artificial intelligence technology that can help solve a variety of difficult computer vision problems [4, 5, 6]. For diverse picture categorization issues, deep learning models, notably convolutional neural networks (CNNs), are widely used. However, such models work best when they are given a huge amount of data to work with. Such a large volume of labelled data is challenging to obtain for biomedical image classification challenges because it requires professional doctors to classify each image, this is a time-consuming and costly task. A workaround for overcoming this barrier is transfer learning. In this strategy, a model trained on a big dataset is re-used and the network weights determined in this model are employed to solve a problem with a small dataset. For biological image classification tasks, CNN models trained on a large dataset like ImageNet [7], which contains over 14 million images, are widely utilized.

Ensemble learning is a popular method for combining the decisions of multiple classifiers to produce a final prediction for a test sample. It is done so that discriminative information from all of the base classifiers may be captured, resulting in more accurate predictions. The most often used ensemble approaches in the literature were average probability, weighted average probability, and majority voting. In the average probability-based ensemble, each member base learner gets equal priority. However, for a certain situation, one base classifier may be superior than others at capturing information. Assigning weights to all of the base classifiers is thus a more effective technique[11]. The most extensively used and common type of clinical assessment for pulmonary nodules is a chest X-ray film. However, because to the fast increase in the number of infectious diseases, which is also a major potential source of diagnostic error, the number of radiologists clearly cannot keep up with this eruption. The deep learning method is the most suited method for dealing with such automation issues. Previously, experts offered a framework for conducting ML research in medicine[23,29]. In order to evaluate the existing ML algorithm in Lung Infectious Disease [8] prediction, systematic review and meta-analysis, which are the foundations of modern evidence-based medicine, must be undertaken.

II LITERATURE SURVEY

Marcin Wozniak , DawidPołapproposed a method to perform computer aided diagnosis the goal of this study is to investigate the possibilities of using deep learning algorithms to diagnosis respiratory diseases images by using firefly algorithm, artificial bee colony algorithm ,artificial ant colony, cuckoo algorithm, practical swarm algorithm and extraction is carried out by bim tissue keypoints and aggregated key points ,In the images of lung illnesses like pneumonia, lungs sarcoidosis and cancer medical experts search for tissues that have changed structure. These types of changes are visible in x-ray images with a solid structure similar to bone tissues, which are not permeable to x-ray radiation and therefore visible in images. Schematic Tissue Key-Area's position detection in x-ray image is performed by the proposed BIM approach over the input image [1]

S.Mukherjee et al. [2] proposed a method for autonomously detecting lung nodules based on geometric parameters. The x-ray pictures are used to classify benign and malignant pulmonary nodules based on shape factors such as roundness, eccentricity, diameter, and aspect ratio**.**Noise Removal using Bilateral Filtering then Image Binarization and Segmentation and classification is carried out by using Bayesian classifier [2]

Woniak et al. [3] proposed a probabilistic neural network-based lung cancer classification system. This method is basic, yet it has a decent classification effect and can detect nodules with low contrast. The following probabilistic neural network was used to extract features from a lung image:. As a result, a vector is generated, the elements of which show how close the input is to single classes in Mahalanobisdistance.. By using this vector, the pattern layer computes a probability vector whose components define the belonging to the different classes. Finally, the output layer selects the largest value of the probability vector to predict the target class, determining whether an input vector belongs to that class.

Here, to create and apply feature extraction methods and algorithms, most of these methods require required professional knowledge or a significant amount of time and effort. With the progressive advancement of deep learning research, the technology that can be employed with photos has also made a qualitative leap. [4] by using a variety of datasets to train a certain domain and a variety of model architectures.

Long and Wang proposed a method To address the problem of domain adaptation in transfer learning [5] they introduced a unique Deep Adaptation Network (DAN), which extends Deep Convolutional Neural Network [30] to domain Adaptation. This architecture optimizes the transferability of features from the task-specific layers of the neural network. In a replicating kernel Hilbert space, mean-embedding matching of multi-layer representations across domains can considerably increase feature transferability. While an unbiased estimate of the mean embedding naturally leads to a linear time approach, which is particularly desirable for deep learning from large-scale datasets, an efficient multi-kernel selection strategy boosts embedding matching effectiveness even more.

The usage of multiple classifier systems (or ensemble systems) and then merging the results of their outputs is one of the suitable ways for improving classification accuracy. The "creation of ensemble" and "combination of class label" are the two main components of a multiple classifier system.[6]

III. EXISTING ANALYSIS

To create and apply feature extraction methods and algorithms, most of these methods require required professional knowledge or a significant amount of time and effort. The technology that can be applied to photos has evolved qualitatively as a result of the progressive advancement of deep learning research, giving rise to the notion of medical picture categorization based on deep learning. Deep learning does not demand any medical or engineering technology qualities, nor does it necessitate any medical-related specialist knowledge. To categories pulmonary pictures, the existing system uses the inception-v3 transfer learning model. On the JSRT database, the neural network model based on transfer learning outperforms the original DCNN model in pulmonary image categorization. Then, automatically extract features from pulmonary images using the fine-tuned Inception-v3 model based on transfer learning.

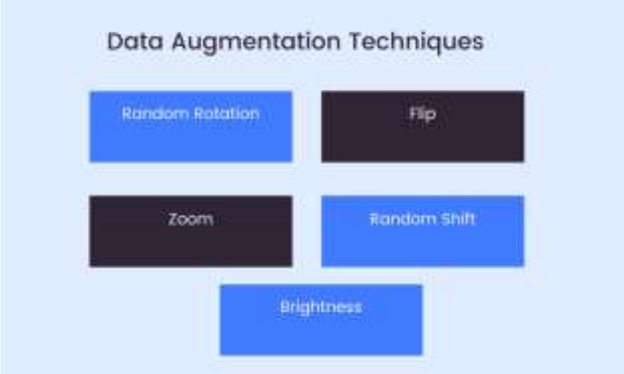

Figure 5: Existing Data augmentation method used for pulmonary Analysis

Data Augmentation

As a result, only professional radiologists can label these data, and it requires complex skilled radiologists to spend more time observing images over and over. As a result of the paucity of professionals, medical imaging data will unavoidably suffer from a lack of data. The Z-score standardization approach was used to normalize the data in order to avoid dimensional effects. Zero-phase Component Analysis was also used to whiten the data (ZCA). The fundamental goal of Z-Score is to convert data with diverse magnitudes into data with the same magnitude. When compared to other methods of normalizing, The Z-score can speed up the gradient decline.The two types of whitening are Principal Component Analysis (PCA) and ZCA whitening.. CA whitening is the singular value decomposition of the data in the specified data set's covariance matrix, while ZCA whitening is the transformation of the data acquired by PCA whitening back to the original space. When compared to PCA, ZCA ensures that data dimensions have the same variance, guaranteeing that the whitened data is as close to the original as possible. As a result, ZCA was chosen as a whitening agent.

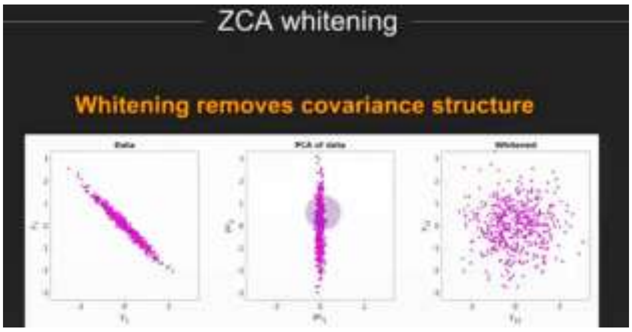

Figure 6: ZCA whitening Removes covariance

Figure 7: SCA Whitening Activity using Data Augmentation Procedure

TRANSFER LEARNING

As a result, deep learning based on transfer learning emerges as a cost-effective method of training. The practise of transferring trained model parameters to a new model to aid in its training is known as transfer learning. As a result, the learning efficiency of the new model can be boosted and improved. The 247 Lung Xray pictures in the JSRT database utilised in this article are insufficient when compared to the amount of data required by the neural network model. As a result, the Inception-v3 model was chosen as a transfer learning framework because it has been trained on ImageNet datasets (nearly 1 million copies of 1000 categories of picture data) and works well on small data sets. To improve the model's accuracy,

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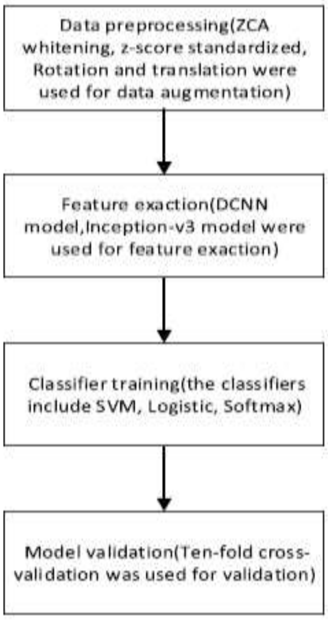


Figure 8: Flow Diagram Showing Flow Architecture of Existing system

V. PROPOSED METHODOLOGY

We created an ensemble framework of several classifiers in this study. Using a weighted average ensemble technique, in which the weights assigned to the classifiers are produced using a novel scheme, as detailed in the sections below. Using Ensemble learning in the Proposing system, the categorization of Pulmonary Image and performance may be improved. The following are the study's primary contributions.

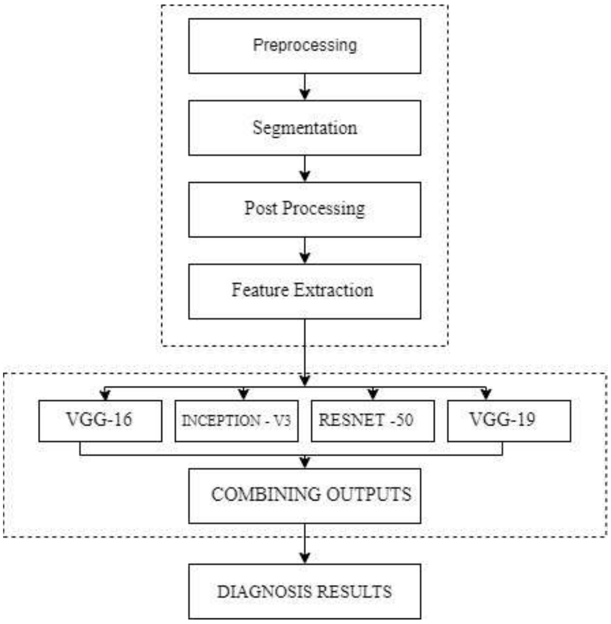
An ensemble architecture was designed to improve the performance of the base CNN learners in the categorization of lung nodules. A weighted average ensemble approach was used for this purpose.

The evaluation measures were combined to calculate the weights assigned to the classifiers: accuracy, recall, f1-score, and AUC. We employed a hyperbolic tangent function to set the weights instead of relying exclusively on the accuracy of classifiers or the results of tests.

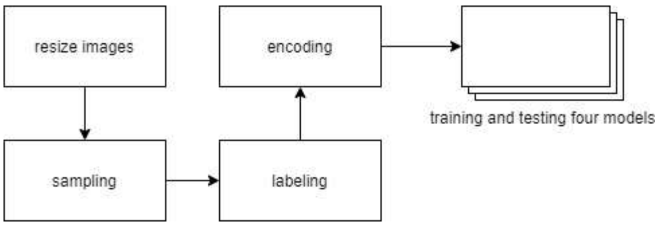
The proposed model was tested on the JSRT dataset [4] and two publicly available chest X-ray datasets. The results outperform those of state-of-the-art methods, demonstrating that the method is viable for usage in the real world. Ensemble learning is the process of creating and combining many models, such as classifiers or experts, to solve a given computational intelligence problem. Ensemble learning is frequently used to improve the performance of a model (classification, prediction, function approximation, etc.) or to lessen the risk of an unintentional poor model selection.

Dataset:A laser digitizer with a 2048x2048 matrix size (0.175-mm pixels) and a 12-bit grey scale digitized 154 conventional chest radiographs with a lung nodule (100 malignant and 54 benign nodules) and 93 radiographs without a lesion for the database (no header, big-endian raw data). Additional information in the database includes the patient's age, gender, and diagnosis (malignant or benign).),

The proposed system is depicted in Fig. 2 as a systematic overview. In brief, the system accepts lung CT scans as input and processes them using two key techniques: image processing and classification. In the first module, noise is removed from photos, segmentation is performed, backgrounds are removed, and the interested items and their features are extracted from raw images. The remaining potential objects are categorized in the second module based on their attributes extracted during the feature extraction phase, allowing lung cancers to be diagnosed. Among suspicious items, the system would be able to differentiate between nodule and non-nodule. This classification is based on a committee of three different classifiers comprising VGG-16,INCEPTION-V3,RESNET-50,and VGG-19 .



1) **Preprocessing:**Image preprocessing is a technique for removing main noise and image distortion from CT scans while simultaneously enhancing key characteristics.. By using some image enhancement methods



Stages of preprocessing

Resize images: When adjusting the aspect ratio of images, image resizing is a new and effective way for image resizing that keeps image content and does not create visible distortion. here we change the image into(224,224,3)ratio

Sampling: we use to down-sampling and up-sampling to make the classes into equal number of images. Before sampling Lung Nodule 154 images and non-Nodule 93 images. After sampling Lung Nodule 250 Non- Nodule 250

Following, the steps of the proposed system have been described, respectively.

Labeling and Encoding: the labelling of images are carried out by lung-nodule into LN and non-nodule into NN. And thereafter the LN and NN is encoded in to the binary form, where (0,1) is non-nodule and vice-versa

Feature Extraction: Further work is needed to extract specific features from raw images in order to identify suspected objects as nodule or non-nodule in two-dimensional images.A nodule id called cancer nodule if its size is more than 30 mm diameter

Classification module:

- The usage of numerous classifier systems (or ensemble systems) and then merging the results of their outputs is one of the suitable ways for improving classification accuracy. The majority of multiple classifier systems have two primary components: “creation of an ensemble” and “combination of class labels”.in the first part of this module, four different classifiers VGG_16 Model, Inception v3, ResNet50, and VGG19 work using numerical data derived from feature vectors, and the final result is generated using the majority vote method based on the outputs of each classifier.

The study was performed by using 247 images including both men and women collected by JSRT the extracted features from The ensemble system uses suspected items as inputs, which are normalized between zero and one. Lung lesions(nodules) in these images are marked as nodule or non-nodule by radiologists.

Creating an ensemble:

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Machine learning is a hot topic in research and industry, with new methodologies developed all the time. Even professionals find it difficult to keep up with new techniques due to the speed and complexity of the field, which can be overwhelming for rapid analysis. The following are various methods used from machine learning for pulmonary disease analysis.

- VGG_16 Model
- Inception_v3
- ResNet50
- VGG19

VGG_16 Model

K. Simonyan and A. Zisserman of the University of Oxford introduced VGG 16 as a convolutional neural network model in their article "Very Deep Convolutional Networks for Large-Scale Image Recognition." ImageNet is a database of images, a dataset with over 14 million images divided into 1000 classes, the model achieves 92.7 percent top-five test accuracy. The NVIDIA Titan Black GPUs were used to train VGG16 for weeks.

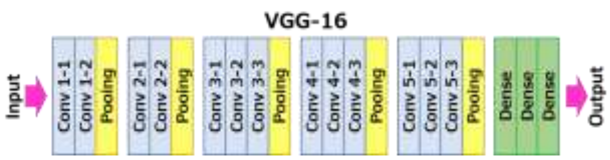

Figure 1: Architecture showing VGG 16 Input and Output Activity

ResNet-18

He et al. [23] presented the ResNet-18 model, which is based on a residual learning framework that boosts deep network training efficiency. Unlike the original unreferenced mapping in monotonically progressive convolutions, the residual blocks in ResNet models permit the optimization of the overall network, which increases model accuracy. Identity mapping is performed by these residuals or "skip connections," which does not add parameters or increase computing complexity. The design of the ResNet-18 model is depicted below. ResNet, short for Residual Networks, is a well-known neural network that serves as the foundation for many computer vision tasks. In 2015This model was chosen as the winner of the ImageNet competition. ResNet was a game-changer because it allowed us to successfully train extraordinarily deep neural networks with 150+ layers. AlexNet, the ImageNet 2012 winner and the model that appears to have sparked interest in deep learning, featured only eight convolutional layers,There were 19 layers in the VGG network, 22 layers in Inception or GoogleNet, and 152 layers in ResNet 152. ResNet-50 is a condensed version of ResNet 152 that is widely used as a jumping off point for transfer learning. ResNet's Strength — Skip Connection The concept of skip connection was first presented by ResNet. The skip connection is depicted in the diagram below. The graphic on the left shows convolution layers being stacked one on top of the other. On the right, we continue to stack convolution layers as previously, but now we additionally include the original input in the convolution block's output. This is referred to as a skip connection.

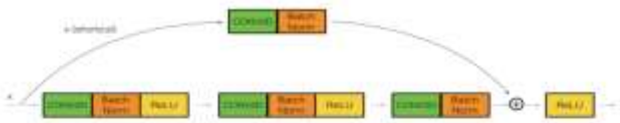

Figure 2: Architecture showing ResNet18 Connectivity and flow activity

Inception-v3 model

The Inception-v3 model has been trained on ImageNet datasets (about 1 million copies of 1000 categories of picture data) and performs well on tiny data sets. The model's structure is re-tuned, and the last three layers are removed to make it more suitable for our experiment.

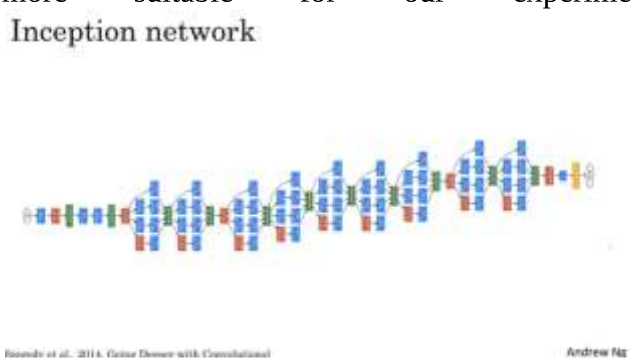

Figure 3: Architecture showing Inception v3 Model Connectivity with input and out process

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VGG-19

VGG-19 is a deep convolutional neural network with 19 layers.. You can use the ImageNet database to load a pretrained version of the network that has been trained on over a million photos. The network can categorise photographs into 1000 different object categories, such as keyboards, mouse, pencils, and other animals. The picture input size for the network is 224 224 pixels. VGG19 is a little better than VGG16, although it takes up a little more RAM.

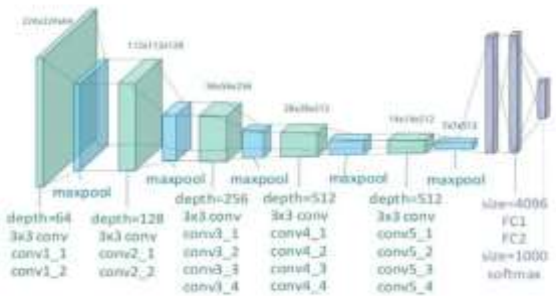

Figure 4 : Architecture showing vgg_19 Flow activities

Combining various models yields an ensemble-based system (henceforth classifiers). As a result, multiple classifier systems or simply ensemble systems are sometimes used to describe these systems. The use of an ensemble-based system makes statistical sense in a variety of situations, which are outlined below. However, in order to truly comprehend and apply the value of using multiple classifier systems, you must first grasp what they are and how they work.it may be helpful to consider the psychological context of this otherwise statistically solid reasoning We employ a similar strategy in our daily lives, before making a decision, we seek the counsel of numerous specialists.For example, before agreeing to a medical procedure, we usually seek the advice of multiple doctors, as well as the individual decisions of several professionals. The main goal is to lower the chances of opting for an unnecessary medical procedure, a subpar product, an inexperienced employee, or even a poorly written and deceptive article. Machine learning is a trendy topic in both academia and industry, with new approaches being created on a regular basis. Even professionals find it difficult to keep up with new techniques due to the speed and complexity of the field, which can be overwhelming for rapid analysis.

COMBINING OUTPUTS

In the second part of each ensemble system, the decisions of all these classifiers are combined to create an ensemble output. The most common combination method is Majority voting, though many more powerful techniques such as: Naïve Bayes,Decision,Templates,Dempster,Shaferminim um, Sum,Maximum, Mean rule, and product rule have also been proposed and in many instances may provide even higher classification performance. In this study, each base classifiers has its own opinion and identifies suspended objects as nodule or non-nodule. Then, majority voting techniques is used to combine the results of base classifiers. According, lung nodule among all suspected objects is detected through proposed system

SYSTEM PERFORMANCE MEASUREMENTS

This study was performed by using the 247 images including both men and women collected by jsrt(Japanese society of Radiological Technology).The proposed system detects suspected objects in each image as nodule or non-nodule. In fact, the collected dataset is divided into two categories (positive and negative). There are a variety of metrics that may be used to assess the success of categorization methods that are regularly employed in automatic medical diagnosis systems. TP is the number of accurate predictions for a positive instance; FN denotes the number of erroneous predictions for a negative instance; For a positive instance, FP signifies the number of incorrect predictions; for a negative instance, TN denotes the number of accurate predictions. We could generate the measures below to evaluate the system's performance based on these indicators.

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a) ***Accuracy (Acc)*:**The ratio of properly identified instances to total test examples is is said to be accuracy

b) ***Specificity(sp)***is a metric that counts how many negatives the classifiers properly identify. Specificity is calculated by dividing the number of truenegative outcomes by the sum of truenegative and false positive findings.

c) ***Precision(prc)*** measure describes the number of predicted nodules that are actually linked to the prone state.

d) ***F-measure*** is a combination of precision and sensitivity. A high $F_{measure}$ value indicates a high level of precision and sensitivity.

confusion matrix

A confusion matrix is a table that lists the actual and predicted categories in a classification system. The data in the matrix is commonly used to assess a system's performance. The confusion matrices for base classifiers and ensemble systems are shown here.

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results
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	model	Test-Accuracy	Sensitivity	specificity
0	VGG-16	0.953333	0.925000	0.985714
1	Inception_v3	0.963333	0.966443	0.960265
2	ResNet50	0.936667	0.882759	0.858065
3	VGG--19	0.966667	0.948718	0.986111
4	Average ensemble	0.973333	0.930730	0.947539

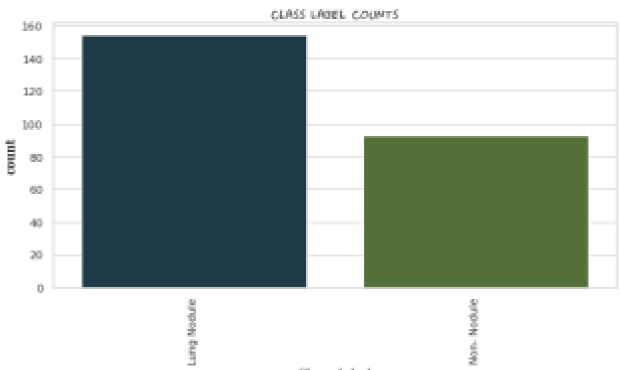

Chart 1: Chart Showing Lung Nodule and Non Nodule comparison

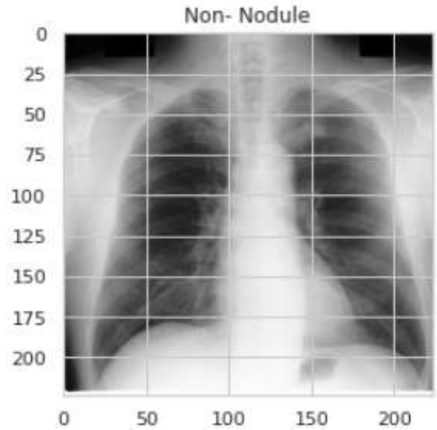

Figure 10: Xray Showing Non Nodule Image with pulmonary readings to be noted.

Chart 2: Heatmap displaying Non Nodule and Lung Nodule Comparisons using VGG 16

Chart 3: Line Chart displaying Train and Test Accuracy Comparisons using VGG 16

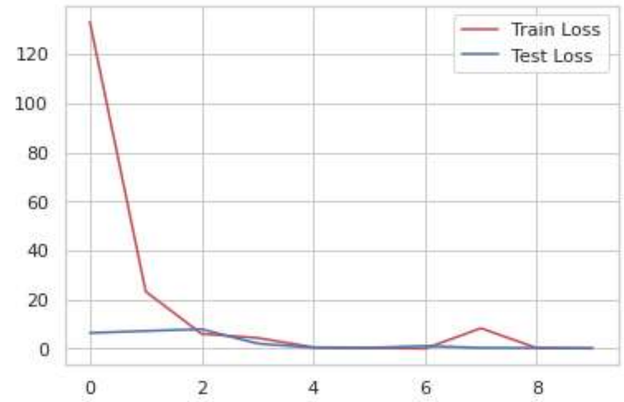

Chart 5: Line chart Displaying Train and Test Loss Comparisons using Inception v3

Chart 6: Heatmap Displaying Non Nodule and Lung Nodule Comparisons using RSSNet50

Chart 4: Heatmap Displaying Non Nodule and Lung Nodule Comparisons using Inception V3

Receiver operating characteristic curves obtained by the proposed ensemble method on the two pulmonary nodules chest X-ray datasets used in this researchAt the principal level stage, the dataset is first cleaned and processed using preprocessing techniques using panda's package. The counterplot of sex and target attributes group is shown in Table 2. After that, using the data visualization procedure, the data frame attributes are shown

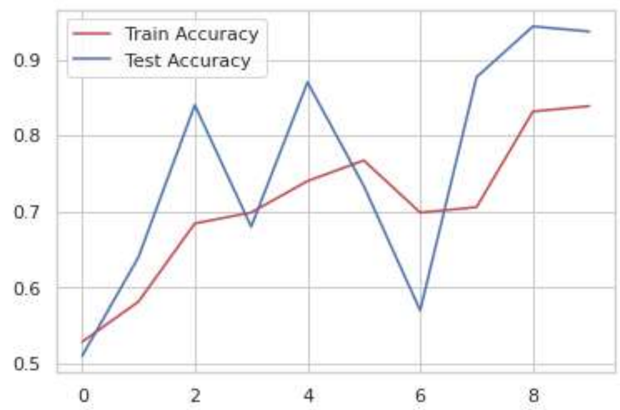

Chart 7: Line Chart Describing Train Accuracy and Test Accuracy Comparison.

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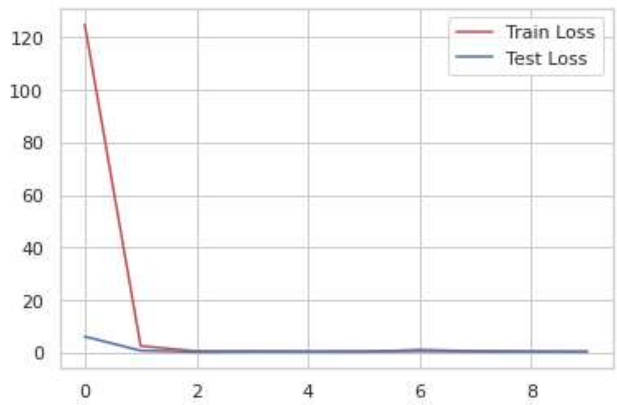

Chart 8: Line chart Describing Train and test loss Accuracy Comparison

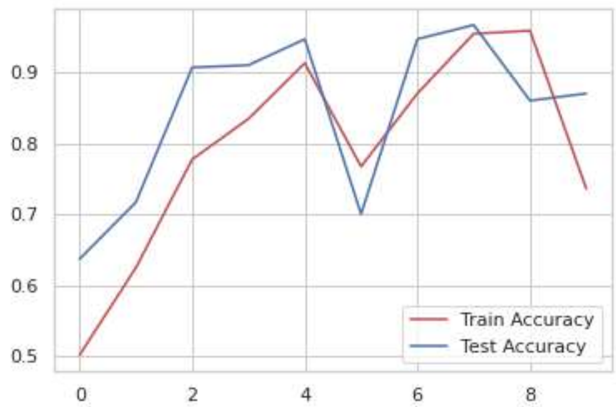

Chart 8: Line chart Describing Train and test Accuracy AccuracyComparison using vgg19

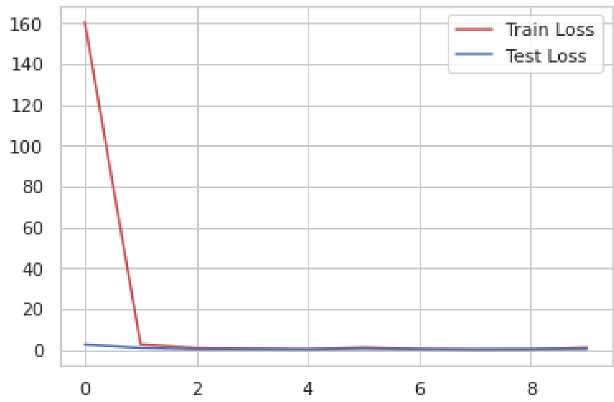

Chart 9: Line chart Describing Train and test loss Accuracy Comparison using vgg19

Chart 9: Heatmap Displaying Non Nodule and Lung Nodule Comparisons using vgg19

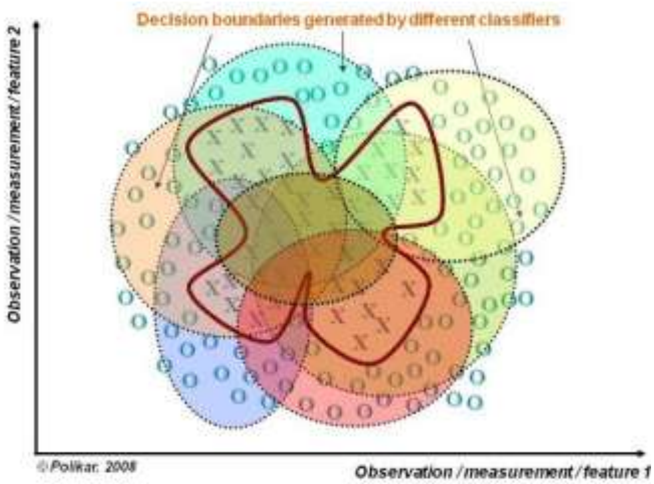

Fig 9: Classification Using Ensemble Learning

Feature extraction method	Classification model	Sensitivity	Specificity	Accuracy
Automatic Localization of Heart and Lung Shadows [30]	SVM	77.1 %	76.4%	76.80%
Hand-crafted feature with oriented gaussian derivatives filter [31]	Fuzzy clustering method (FCM)	92.79%	97.07%	94.70%
Watershed segmentation [32]	SVM	55.74 %	35.81%	59.80%
Hand-crafted feature with a simple multiscale method [1]	SVM	97.74 %	99.37%	98.50%
DCNN model	Softmax	92.91%	78.39%	84.70%
DCNN model	Logistic	94.30%	79.31%	85.80%
DCNN model	SVM	91.11%	77.27%	83.30%
Fine-tuning Inception-v3 model	Softmax	94.71%	80.09%	86.40%
Fine-tuning Inception-v3 model	Logistic	95.41%	77.78%	85.10%
Fine-tuning Inception-v3 model	SVM	92.96%	79.83%	85.70%
our model	Ensemble learning	93.7%	94.75%	97.33

Table 1: Comparison Of Experimental Results of Existing System

4. Experimental results and analysis

The proposed model accuracy is compared with the existing ML models which were depicted in Table were vgg-16 shows 0.9 test accuracy, 0.925

sensitivity, 0.98 specificity. Inception v3 shows 0.96 test accuracy, 0.96 sensitivity, 0.96 specificity. Resnet50 shows 0.93 test accuracy, 0.88 sensitivity, 0.85 specificity. vgg-19 shows 0.96 test accuracy, 0.94 sensitivity, 0.98 specificity and Average ensemble shows 0.97 test accuracy, 0.93 sensitivity, 0.94 specificity. The graphical representation of proposed method accuracies s shown in given table 2.

Performance Table

```
In [ ]: results
Out[ ]:
```

	model	Test-Accuracy	Sensitivity	specificity
0	VGG-16	0.953333	0.925000	0.985714
1	Inception_v3	0.963333	0.966443	0.960265
2	ResNet50	0.936667	0.882759	0.858065
3	VGG--19	0.966667	0.948718	0.986111
4	Average ensemble	0.973333	0.930730	0.947539

Table 3: Result of ensemble model showing their test, sensitivity and specificity comparions.

VI. CONCLUSION

Experiments on the jsrt database are used to test the effectiveness of the proposed ensemble system for lung nodule diagnosis. Image processing techniques such as pre-processing, post-processing, and feature extraction were used in the first phase. The categorization phase was then provided specific features of the items of interest, In the classification phase, these features were used as inputs for each single classifiers (VGG_16,Inception_v3,ResNet50,VGG19) and ensemble system. Then, majority voting method was applied to combine results of base classifiers in committee. In order to assess the efficacy of the suggested hybrid intelligent technique, Table 2 shows that the suggested ensemble system has the best performance among base classifiers independently. Also, the confusion matrix was calculated for each base classifiers and proposed ensemble system to prove priority of ensemble learning. In conclusion, our proposed CAD system is a highly promising method, providing high performance in the identification of pulmonary nodules from x-ray images which may be used as a second opinion for physicians in the diagnosis of pulmonary nodule.

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