A COMPARATIVE ANALYSIS FOR EARLY DIAGNOSIS OF LUNG CANCER DETECTION AND CLASSIFICATION BY CT IMAGES PROCESSING USING RESNET-50 MODEL OF CNN

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Abstract

Cancer is the leading cause of death in the world, with lung cancer having the greatest mortality rates since 1985. Recognizing with higher accuracy and predicting the type of Lung Cancer at the earliest possible stage will help patients have a better chance of surviving. This paper compares various automated algorithmic method for detecting lung cancer at an early stage using computed tomography (CT) images. CT Scan is the most effective imaging approach as compared to other diagnostic techniques because it may reveal every suspected and unsuspected lung cancer nodule and provides an exhaustive image of the tumour in the body. Lung cancer datasets such as LIDC Dataset, ELCAP Public Lung Image Dataset, LUNA-16 Challenge Kaggle Dataset, AAPM Dataset, etc. The process of detection followed as per our research follows Image Pre-Processing, Image Segmentation, Feature Extraction, and Neural System identification. This paper majorly focuses on a comparative analysis of various approaches for detecting lung cancer and analysing the recent best technique. Resnet-50 transfer learning model when used for lung cancer detection might increase the accuracy of lung cancer detection as it has given impressive accuracy when used with covid-19 detection, breast cancer detection and several other similar systems. It might also help in the prediction of the cancer at an early stage making it easier for patients to diagnose and treat the lung cancer disease.

Keywords: Lung Cancer Detection, Computer Tomography (CT), ResNet-50, CNN, Type Classification

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1. Introduction

Lung cancer is one of the most serious diseases in the world today, and it has been the leading cause of mortality in the last few decades, with an estimated 1.8 million fatalities each year [26]. Furthermore, lung cancer death rates are expected to continue to grow, with 17 million people dying from the disease globally by 2030 [1].

Exposure to substances such as asbestos or radon at home or at work, inhaling tobacco smoke and the use of other tobacco products are some of the causes of lung cancer [2]. Tobacco and alcohol are also some of the causes of lung cancer, accounting for around 19% of all fatalities globally [3]. Increase in the air pollution level, previous radiation therapy and family history of lung cancer are also some of the causes of lung cancer. Even the relatively new Covid-19 epidemic has caused a slew of problems for lung cancer patients, who are particularly susceptible to illness [4]. During the Covid-19 outbreak, the lungs of those who contracted the virus were harmed, making them vulnerable to other diseases such as lung cancer [5]. The most common indications of lung cancer are respiratory infection, cough, shortness of breath, chest pain and weight loss [6].

Only 23.7 % of those with lung cancer survive five years [27]. The main reason for such a high fatality rate is that the sickness is discovered later in the course of the disease, which result in delayed treatment. If lung cancer is found early enough, survival rates might reach 50-70% [3].

Lung cancer can be classified mainly into two types namely, Small Cell Lung Cancer and Non-Small Cell Lung Cancer. The Non-Small Cell Lung Cancer comprises of 80-85% while the Small Cell Lung Cancer comprises of the remaining 15-20% of the overall occurrence of lung cancer worldwide [3][29]. Since Non-Small Cell Lung Cancer comprises of such a high percentage, in this paper we have focused mainly on the prediction of non-small cell lung cancer.

Lung cancer is primarily explored using X-ray or Computer Tomography (CT) screening, which is a time-consuming and tedious task for a radiologist and can be inaccurate. False positive rates of up to 54 % have been reported in studies of lung cancer screening based on human expert analysis [7]. The screening procedure necessitates a high level of concentration, skill and experience.

MRI (Magnetic Resonance Imaging), CT (Computed Tomography), PET (Positron Emission Tomography), Chest X-ray, and other diagnostic techniques have been used to detect lung cancer, however chest CT scan images were chosen due to low noise and resilience in tumor size finding [6]. CT scans contain critical clinical image data that helps in the identification and treatment of lung cancer in its initial stages [8]. CT scans have low noise and contain critical image data that can be used for diagnosis. Hence, our research uses CT Scan Images for the prediction of Lung Cancer. The Kaggle Data set of CT scan images was used in our research which comprised of training set of 70%, testing set of 20%, validation set of 10% [28].

To prevent lung cancer and diagnose it at an early stage, doctors need computer-aided advanced technology to help them, including Image Processing, Machine Learning, and Artificial Intelligence. These strategies can be used as engineering solutions to process medical field data for the goal of detecting and diagnosing lung cancer [9]. In the literature, there are 8 separate research on image processing approaches for early-stage cancer detection. However, the impact ratio of early-stage cancer diagnosis has not been up to the mark and can be improvised. The neural network helps to improve the detection of cancer cells in normal tissues, making it a useful tool for detecting lung cancer at an early stage [7].

As a result, prognosis-based systems frequently employ techniques such as Artificial Neural Networks, SVM, Decision Trees, autoencoders, Fuzzy Logic and other similar image processing methodologies. This research will investigate a deep learning-based categorization method motivated by the success of these systems in related disciplines [10]. A variety of studies proposes that the methodology developed for these systems includes dataset collection, pre-processing, lung segmentation, feature extraction and classification [11].

For this research study, we have focused on prediction of Lung Cancer using ResNet-50. ResNet-50 has given high accuracy when applied to other systems such as Breast Cancer Detection [12], COVID-19 detection [13], Poultry Disease Recognition [14], etc. Inspired by the success of ResNet-50 in the above-mentioned systems, we have planned to use ResNet-50 for Lung Cancer Detection using CT Scan Images.

Literature Survey

Numerous research has been proposed and implemented for detection of lung cancer, corona virus and similar problems using different CAD systems. These predictions used either the X-ray images, CT Scan images, MRI images, etc for the diagnosis of respective diseases using different approaches of Image Processing and Machine/Deep Learning.

Lung CT images were utilized to diagnose lung cancer in this study. The Median Filter was used to reduce salt and pepper noise from CT images from the Lung Image Database Consortium (LIDC) Dataset. The Gaussian Filter was applied after the Median Filter to decrease noise and smooth the image. The pre-processed CT images were segmented using the Watershed

Segmentation method. The feature extraction procedure includes extracting features like Area, Perimeter, and others from cancer nodule segmentation CT scan images. Using SVM as a classifier, the study determines if Lung Cancer nodules are benign or malignant with an accuracy of 92% [15].

The dataset contains 000 T1-weighted contrast-enhanced pictures from three patients. This study looked at three batches of images, each of which contained only 26 images. These photos were first enhanced, and then a Median Filter was used to decrease noise. For the Image Segmentation procedure, Otsu's technique based on thresholding was employed to segment the pre-processed CT images. The feature extraction of the fundamental geometric feature from the segmented images follows after Image Segmentation. SVM was used to classify the images as malignant or benign with 95% accuracy [16].

Lung cancer was diagnosed using CT scan images with image dimensions of 512x512 pixels. The pre-processing consisted of applying the Median Filter to remove the noise from the CT images as well as removal of some undesirable characteristics. Manual segmentation was employed to divide photos into small pieces using ImageJ and Adobe Photoshop CS6 to aid the feature extraction process, which included the extraction of various geometric features. KNN (k-Nearest Neighbor) divided the data into two classes in the form of a vector with an accuracy of 98.15% [17].

In addition to detection, the prediction of Lung Cancer was also done in this research. This study made use of the UCI machine learning dataset, which included 500 contaminated Lung CT jpeg images. As part of the pre-processing phase, the selective median filter is used to remove noise. Following pre-processing, threshold and marker-controlled watershed were used to split the images for the Image Segmentation method. The Grey Level Co-occurrence Method (GLCM) technique was utilized to extract several characteristics useful in lung cancer prediction. The system has a cancer detection accuracy of 97% and a cancer prediction accuracy of 87% [1].

The TCIA and Kaggle Datasets were used in this research, which contained 1595 and 1018 photos, respectively. The Median filter was used for Image smoothening & noise removal as part of the pre-processing. The images were then segmented into discrete segments using the U-Net Convolutional Network. Following image segmentation, Gaussian Naive Bayes was used to extract continuous numerical parameters such as Diameter, Spiculation, MeanHU, and Eccentricity. Multi class SVM classifiers were used to classify Lung Cancer Images. The system has a precision of 62.31% in [18].

Classification of lung nodules in CT scans using three-dimensional deep convolutional neural networks with checkpoint ensemble method is described. The LUNA16 Challenge Kaggle Dataset, which included 888 CT Scan Images, was used for the research. To overcome the data skewness issue, the pre-processing used Sampling and Augmentation approaches. The Free Response Receiver Operating Characteristic (FROC) is used for evaluation of performance along with Competition Performance Metric (CPM). The max average sensitivity, CPM of the system was 91% [19].

ELCAP Public Lung Image Dataset, which included 200 photos of cancerous and non-cancerous lung nodules was used for the detection. These images were pre-processed to convert them to greyscale images. These greyscale images were converted to binary image (0,1) using the Image Binarization technique with a threshold value of 175. Image segmentation was employed after pre-processing to remove unnecessary information from the image and detect things such as lines and curves. Area, Perimeter & Eccentricity are some of the features extracted after the Feature Extraction process. The SVM was employed as a classifier to determine whether the images were benign or malignant [20].

Decision Level Fusion technique was utilized to detect the Lung Cancer, using 22,489 CT images from the American Association of Physicists in Medicine (AAPM). These images were in the Digital Imaging and Communication in Medicine (DICOM) format, with a pixel depth of 16 bits and a matrix size of 512x512 pixels. The nodule patch was cropped using the coordinate information (x, y, z) from the nodule's Region of Interest (ROI). DICOM pictures are pre-processed for contrast enhancement utilizing the basic image pre-processing techniques. The characteristics of each DCNN are extracted and utilized to train the SVM and AdaBoostM2 classifiers. The classification is then performed based on the probability ratings of each class. The prediction accuracy in this study for VGG-19, ResNet-101 & ResNet-50 was 80.90%, 86.28% and 81.42%, respectively using SVM Classifier [21].

A transfer convolutional neural network for fault diagnosis based on ResNet-50 was proposed in this research study. The Cohn-Kanade Dataset, which included 593 sequences from 123 subjects and 2502 images, was used. The time-domain fault signals were used to generate the RGB images. After that, the RGB photos were scaled to 224x224. Several Transfer Learning Models, including Resnet-50, VVG-16, and others, were used to train the data. The greatest accuracy of the system with Resnet-50 was 98.96%, VVG-16 was 97.38%, VVG-19 was 96.07%, and Inception-V3 was 93.97%, respectively [22].

Malaria Cell Image Classification was done using infected and uninfected cell images. The Data Set was obtained from the National Library of Medicine (NLM) and included 27,558 images. Pre-processing included resizing the photos to 224x224 for uniformity. After pre-processing and before training the network, the model must be compiled. A few parameters, including as the optimizer, loss function, and metrics to be calculated throughout the training, must be declared. In this study, Stochastic Gradient Descent (SGD) was utilised as an optimizer to set the learning rate of the neural model. The trained model was 95.91% accurate [23].

Breast Cancer was diagnosed utilizing Histopathological imaging in this study. The ImageNet Dataset, which contained 7909 histopathological images, was used for the prediction. Data pre-processing included data mounting, data resizing, data encoding, data shuffling, data visualization, data creation, and data reshaping. To mount the data and use it as a virtual disc, Google Drive was employed. Data scaling was used for deleting unwanted features from the image collection. Using data encoding, the textual material was converted into numerical numbers. Data shuffling was used to redistribute the data in the training dataset. Data Generation was used for batch generation of tensor image data with real-time data augmentation. To adapt the input form for our preprocessed dataset, the input layer of ResNet-50 is adjusted via data reshaping. Following the pre-processing of the images, feature learning was conducted. In this study, Resnet-50 transfer learning model was applied which generated 99.10% accuracy [12].

During the covid pandemic, the number of cases increased rapidly, and the number of samples analysed on a daily basis was exceptionally large, causing a delay in the analysis and report generation process. To lessen this delay, a CAD strategy based on the use of Resnet-50 to diagnose COVID-19 using chest X-ray images. This research investigation made use of the COVID-19 Image Data Collection, which included 359 X-rays. After the photos were pre-processed, data augmentation was performed, which aids in the creation of the most recent models by randomly applying numerous transformations to open training sets. Data Rescaling sub-process resized the images to a uniform size. The study has the advantage of capturing significant image features and descriptions that can be utilised with similar and smaller datasets. This reusability feature of the pre-trained model saves time and is useful when the training dataset is restricted. The accuracy of the system was 96.23% [13].

ResNet-50 was used for the Poultry Disease Prediction Algorithm. The investigation produced a new set of data with the right illness characteristics expressed in chickens. The system's model accuracy is 93.56%. ResNet Residual Blocks in deep-learning improve training performance up to 93.56% by combining SURF and K-means, which helps to increase the data with multilayer CNN. It aids in avoiding undesirable risks such as overfitting and disappearing gradients. The disease data sets extract characteristics by varying the parameters and feature count [14].

Resnet and VGGNet are contrasted based on their employment as Image Captioning encoders. The MS COCO Dataset, which included 82,783 training images and 40,504 validation images, was used for this comparison. A basic LSTM with one cell was used as a decoder. To compare the performance of these models, the "Karpathy" data split was used. All captions were converted to lower case and terms with occurrence less than 5 times was removed, yielding a captioning vocabulary of 10,010 words. BLEU-4 was used as a statistic to evaluate various captioning models. The accuracy of the trained model with VGGNet and Resnet is 76.2% and 76.5%, respectively. According to the study, ResNet has a key advantage that it is easy to optimise and hence enhances accuracy by adding more layers [24].

Food Recognition was done using ETHZ-Food Dataset, UECFOOD100 Dataset & UECFOOD256 Dataset. Images were pre-processed to improve overall performance by applying image improvements and resizing to increase classifier accuracy and reduce training time. During the feature extraction procedure, distinct features are filtered using a 2-D Convolutional Filter, which result into a feature map. The presented system employs a Deep Convolutional Neural Network (DCNN) based on the ResNet-50 architecture, which achieved a top-1 accuracy of 41.08% on the ETHZ-Food 101 dataset, 39.75% on the UECFOOD100 dataset, and 35.32% on the UECFOOD256 dataset [25].

Literature Survey

Table 1: Comparison between different Lung Cancer Detection System

Author	**Method of Detection**	**Year**	**Problem Statement**	**Dataset**	**Number of Images Compared**	**Pre-processing Technique**	**Segmentation Technique**	**Feature Extraction Technique**	**Accuracy**
[15]	SVM	201	Lung	Lung	Not	Median	Watershed	Features	92%

	Classifier	8	Cancer Detection using CT Scan Images	Image Database Consortium (LIDC)	Available	Filter, then Gaussian Filter	Segmentation	such as Area, Perimeter, and others	
[19]	Deep 3D CNN	2018	Classification of lung nodules in CT scans using three-dimensional deep convolutional neural networks with a checkpoint ensemble method	LUNA16 Challenge Kaggle dataset	888 CT Scan Images	Sampling and Augmentation methods to address the data skewness problem	Not Available	Not Available	Not Available but max sensitivity is 91%.
[1]	Binarization technique With SVM Classifier	2018	Multi-Stage Lung Cancer Detection and Prediction Using Multi-class SVM Classifier	UCI machine learning database	500 infected lung CT JPEG	Selective Median Filter	Threshold and marker-controlled watershed	GLCM (Gray Level Co-Occurrence Method) technique	97% for cancer detection and 87% for cancer prediction.
[20]	SVM Classifier	2018	Lung Cancer Detection Using Image Processing and Machine Learning HealthCare	ELCAP Public Lung Image Dataset	200 Lung Images of both cancerous and non-cancerous	Grayscale conversion then Binarization	Original image is converted to Edge only image, then to dilated image and finally segmentation is done	Area, Perimeter and Eccentricity and these all are scalar quality	Not available
[17]	Classification using kNN	2020	Classification of Lung Cancer Stages from CT Scan Images Using Image Processing and k-Nearest Neighbour	Advanced Medical and Dental Institute (AMDI) Dataset	100 samples of CT Scan Images	Median Filter	Fuzzy Possibilities C Mean (FPCM) algorithm	Geometric features such as Area, perimeter and centroid were extracted	98.15%

[16]	SVM	2020	Automated Detection of Lung Cancer Using CT Scan Images	The dataset contains 000 T1-weighted contrast-enhanced images from 3 patients. Used in reference	This study tested 3 batches of images containing 26 images	Image Enhancement, then Median Filter	Thresholding based Otsu's technique is used	Not Available	95%
[18]	U-Net Convolutional Network	2021	Lung Cancer Detection and Classification using Machine Learning Algorithm	TCIA Dataset, Kaggle data science bowl 2017 provides Lung CT scans and LIDC Image Collection	Kaggle – 1595 Patients LIDC – 1018 Patients	Not Available	The U-Net Convolutional Network is used for biomedical image segmentation	Gaussian Naïve Bayes	62.31%
[21]	VGG-19, ResNet-101 and ResNet-50	2021	Deep Feature Selection and Decision Level Fusion for Lungs Nodule Classification	The American Association of Physicists in Medicine (AAPM) Dataset	22,489 CT images	Basic Image Pre-Processing Techniques	Not Available	The optimal layers for Deep Feature Extraction	80.90%, 86.28% and 81.42% using SVM Classifier

Various research has been done on prediction of Lung Cancer using different algorithms & classifiers. The Table 1 above indicates that lung cancer is diagnosed using Lung CT Scan images because they have less noise and are more resilient. The Fig. 1 & Fig. 2 compares the accuracy & specificity of different research done for prediction of Lung Cancer. In [15], Lung Cancer was predicted using an SVM classifier and the accuracy of the system was 92%. In [19], Classification of lung nodules in CT scans using three-dimensional deep convolutional neural networks with checkpoint ensemble method is described with a max average sensitivity of 91%. In [1], the lung cancer detection along with prediction was done with accuracy of 97% and 87%, respectively. In [17], kNN was used for the prediction of Lung Cancer using Lung CT Scan images & the accuracy of the system was 98.15%. In [16], Lung Cancer was diagnosed using SVM classifier and the accuracy of the system was 95%. In [18], U-Net Convolutional Network was used for Lung Cancer Detection and Classification using Machine Learning Algorithm with an accuracy of 62.31%. In [21], Deep Feature Selection and Decision Level Fusion for Lungs Nodule Classification was done using VGG-19, ResNet-101 & ResNet-50 with an accuracy of 80.90%, 86.28% and 81.42%, respectively using SVM Classifier.

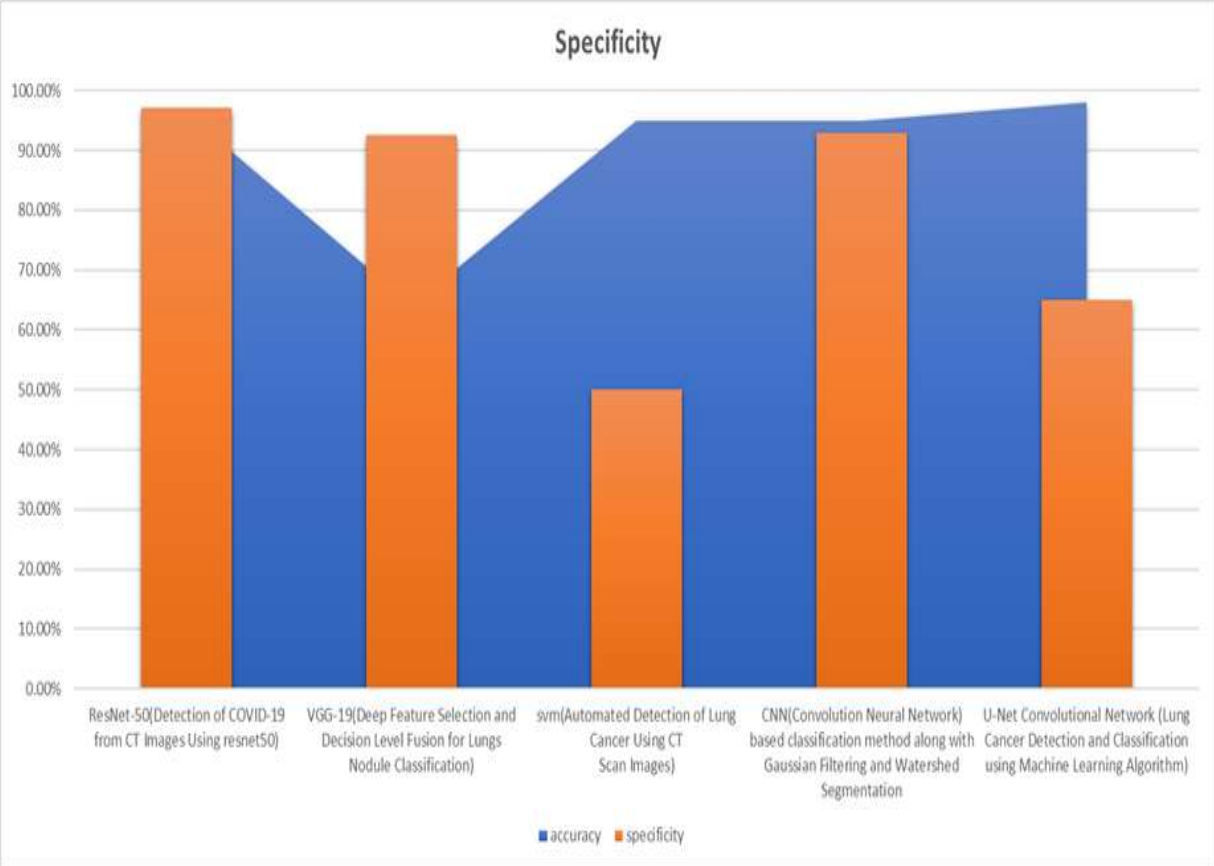

Figure 1: Comparison of Accuracy & Specificity for different Lung Cancer Prediction Systems

Figure 2: Comparison of Accuracy for different Lung Cancer Prediction Systems

Table 2: Comparison between different systems using ResNet-50 transfer learning

Author	Method of Detection	Year	Problem Statement	Dataset	Number of Images compared	Accuracy
[22]	ResNet-50	2018	A transfer convolutional neural network for fault diagnosis based on ResNet-50	Cohn–Kanade Dataset	Dataset consists of 593 sequences across 123 subjects and 2502 images	98.97%
[23]	ResNet-50	2019	Transfer Learning with ResNet-50 for Malaria Cell-Image Classification	National Library of Medicine (NLM) Dataset.	27,558 images	95.91%
[12]	ResNet-50	2020	Breast Cancer Diagnosis in Histopathological Images Using ResNet-50 Convolutional Neural Network	ImageNet Dataset	7909 Biopsy Histopathology images	99.10 %
[13]	ResNet-50	2020	Detection of COVID-19 from CT Images Using resnet50	Joseph Paul Cohen and Paul Morrison and Lan Dao COVID-19 Image Data Collection	359 X-ray images	96.23%
[14]	ResNet-50	2020	Using SURF to Improve ResNet-50 Model for Poultry Disease Recognition Algorithm	Self-Collected	disease images of chickens of 4 different diseases: Avian pox, bird-flu, Marek and Infectious laryngotracheitis.	93.56%
[24]	VGG and ResNet	2020	Comparison of VGG and ResNet used as Encoders for Image Captioning	MS COCO Dataset	82,783 Training Images and 40,504 Validation Images	76.2% and 76.5%
[25]	ResNet-50	2020	Food Recognition with ResNet-50	The Datasets used in the study are ETHZ-FOOD101, UECFOOD100 and UECFOOD256.	Each dataset contains 101 food classes and 1000 samples in each class	41.08% for ETHZ-Food 101 Dataset, 39.75% for UECFOOD100 Dataset and 35.32% for UECFOOD256 Dataset.

[21]	VGG, ResNet-101 and ResNet-50	2021	Deep Feature Selection and Decision Level Fusion for Lungs Nodule Classification	The American Association of Physicists in Medicine (AAPM) Dataset	22,489 CT images	64.05%, 76% and 66.92%

The Table 2 compares & contrasts use of ResNet-50 in different systems for prediction and diagnosis. The Fig. 3 compares the accuracy of different systems using ResNet-50. In [22], A transfer convolutional neural network was proposed for fault diagnosis based on ResNet-50 and the accuracy of the system was 98.97%. In [23], Transfer Learning with ResNet-50 was used for Malaria Cell-Image Classification and the accuracy of the system was 95.91%. In [12], Breast Cancer Diagnosis in Histopathological Images was done using ResNet-50 Convolutional Neural Network and the accuracy of the system was 99.10%. In [13], Detection of COVID-19 from CT Images Using ResNet-50 was proposed and the accuracy of the system was 96.23%. In [14], Poultry Disease was recognised utilising the ResNet-50 Model with an enhancement of SURF which made the accuracy of the system was 93.56%. The comparative analysis indicates, Resnet-50 has high accuracy in prediction for various systems as discussed in Table 2. This indicates that ResNet-50 can be useful for Pre-processing, Image Segmentation, Feature Extraction & Prediction of Lung Cancer, which might increase the accuracy of the Lung Cancer prediction system. So, our research system is mainly focussed on ResNet-50 transfer learning model for the prediction of Lung Cancer.

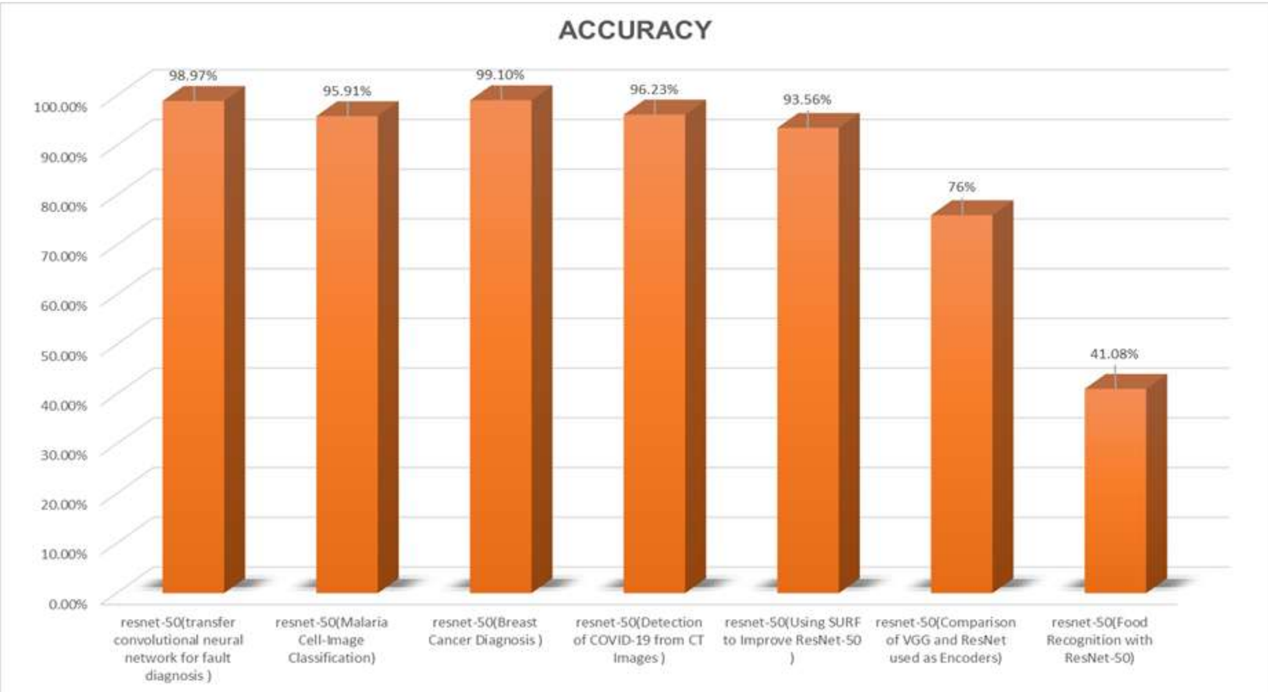

Figure 3: Comparison of Accuracy for different systems using ResNet-50

2. Conclusion

CNN has a major advantage that it can learn different features of the CT scan images for lung cancer. Within CNN, Resnet-50 transfer learning model could be used as a perfect replacement for the currently available algorithms that are used for the Lung Cancer Detection System as it has a key advantage that it is easy to optimise and hence enhances accuracy by adding more layers. ResNet-50 when used for the detection of lung cancer provided an accuracy of 66.92%. ResNet-50 comes with a variety of different medical systems such as Breast Cancer Detection with 99.10% accuracy, COVID-19 detection with 96.23% accuracy, Poultry Disease Recognition with 93.56% accuracy. This high accuracy of the ResNet-50 in various systems encouraged us to use it for the prediction of Lung Cancer which might increase the accuracy of prediction to approximately 95%. Hence, for this research we will be focussing on ResNet-50 for the diagnosis and prediction of Lung Cancer using Lung

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