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A Web Application for Lung Cancer Analysis and Detection using Deep Learning Approach

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Abstract: ***Lung cancer is one of the most common and deadly cancers worldwide. One of the most effective ways to fight canceris todiscoveritearlyenoughtoimprovethepatient's chances ofsurvival.TheDiscovery oflung canceratanearly stage helpsin reducing its risk. Various technologies like MRI, isotopes, X-rays, and CT scans are used for diagnosis of lung cancer. The studying of lung nodules helps a doctor to determine if the patient is malignant. These nodules sometimes have a chance of growing undetectedbythenakedeye. In thisproject,Lungcancer stageis detectedwith the help of patientdetails, symptomsand CT scans by using Machine learning and Deep learning algorithms with open-source datasets. The proposed approach uses Machine learning algorithms to study past medical records and determine if the patient has lung cancer. Deep learning models are used to analyze the CT scans to determine the stage of lung cancer. Themajorgoal of thisproject isto find nodules as small as 3 mm to detect cancer stage accurately. Finally, the machine learning model calculates the patient's estimated medical insurance costs. This project is useful for the early detection of lung cancer in individuals and can help them in overcomingthese health conditions. The effectiveness of cancer prediction systems helps the people to know their cancer risk with low cost and it also helps the people to take the appropriate decision based on their cancer risk status.***

Keywords: Cancer,U-Net,DeepLearning,MachineLearning(ML),ConvolutionalNeuralNetwork(CNN)

I. INTRODUCTION

Lung cancer is repeatedly identified as one of the deadliest diseases in the history of humankind. It has been one of the most common cancers and one of the top causes of death. Lung cancer kills over 7.6 million people globally each year, as per the World Health Organization (WHO). The number of cancer patientsis predicted to climb further, reaching roughly17 million by 2030.

AccordingtotheCenters for DiseaseControl and Prevention (CDC),individuals whosmoketobaccoare 15ton30 timesmorelikely than non - smokers to develop or succumb from lung cancer. Lung cancer in non - smokers can be triggered by radon, passive smoking,airpollution,or otherreasons. Worksiteexposuretoasbestos, diesel fumes, or otherpollutantscanalsoleadtolungcancer in nonsmokers. Typical symptoms include coughing (often with blood), chest discomfort, wheezing, and loss of weight. However, these symptoms do not generally appear until the malignancy has advanced.

Cancer is caused by a variety of factors, ranging from behavioral factors such as a high BMI, tobacco and alcohol use, to physical carcinogens through exposure to UV rays and radiation, as well as some biological and hereditary carcinogens. However, the aetiology may differ from one victim to the next. Soreness, exhaustion, nausea, chronic cough, breathing difficulty, weight loss, muscularpain, bleeding,bruises, andother symptomsarefrequentincancerpatients. However,noneofthesesymptomsisuniqueto cancer,nor aretheyall presentin everypatient. CT scans that look for nodules in thelung are frequentlyused to detect lung cancer. Lungnodules (or masses) arelittleabnormalareasthat can befoundduringa chest CTscan.Byexaminingthenodules,adoctor can determine whether or not this scan is malignant.

Doctors can evaluate nodules larger than 7 millimeters in diameter, and physicians frequently instruct patients to wait to see if the nodule develops. If it does not develop, the nodule is harmless. There is a greaterlikelihood thatthe nodule may go undiscovered. As aresult, determining cancer without a comprehensive diagnosticmethod, such asa Computed Tomography(CT) scan, Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) scan, ultrasound, or biopsy, is difficult. In most cases, victims exhibit little to no indications in the early stages, and by the time symptoms emerge, it is typically too late.

The goal of this studyis to look at alternative ways for detecting and recognizing lung cancer in its earlystages. As a consequence, lung cancer can be treated before it progresses to the point where therapyis no longer viable.

Thefocus ofthisworkissolelyonthedetectionandpredictionoflungcanceranditsstages.

II. LITERATURE SURVEY

Everyyear,cancer killsaround onein everysix people[1-2],with lungcancer toppingthelistwith 1.76million fatalitiesin 2016.[1]

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Earlycancer identification can give a proper therapytonot onlyprolong but even save a person's life, hence increasing the survival rate. [1]-[4].

Deep residual learning has been used by SiddharthBhatia et al. (2019) [6] to detect lung cancer. They provide a set of preprocessing algorithms for obtaining cancer-vulnerable lung characteristics from images using UNet and ResNet models. They compare the efficiency of classifiers such as Random forest and XGBoost in predicting carcinogenic CT images. The authors achieve the highest accuracy of 84\% when they mix the two classifiers.

In this study(2019) [9], IbrahimM.Nasser etal. created anArtificialNeuralNetwork (ANN)toidentifythepresenceor absenceof lung cancer in thehuman body. Symptoms such asyellowfingers,anxiety, chronicdisease, and others were utilizedto identifylung cancer. Theywere employed asinput variablesto their ANN, along with additionalinformation of thepatient.The ANNmodel was shown to be 96.67\% accurate in detecting the absence or presence of lung cancer.

Wookjin Choi et al. (2018) [10] attempted to address various shortcomings identified in the existing literature in their article. They used hierarchical clustering to identify dis- crete radiomic characteristics before building a support vector machine (SVM) model with just two key features chosen using a least absolute shrinkage and selection operator (LASSO). They created this model using two CT radiomic characteristics to indicate the malignancy of pulmonary nodules. It provided an 84.6\% accuracy rate.

GayathriDevi Nagalapuram et al.(2022) [OUR]offereda review of several approaches employed in numerous prac- tical experiments in their research. They determined that all techniques might go beyond simply determining if a patient's status isnormal or not. They also indicate that the majority of accuracies for a healthcare endeavor arerelatively mediocre.

III. PROPOSED DESIGN

The fundamental purpose of this study was to review past medical information in order to discoverlung cancer, forecast if the patient has lung cancer using CT scans, and then determine the location of the cancer nodule in the scan. Estimating medical insurance costs provides further assistance.

Theproposeddesignwasbroadlydividedinto6stages:

1) *LungCancerDetectionbasedon Symptoms:*TheRandom Forest Classifier wastrainedona dataset includingpreviouspatients' symptom records and was used to determine whether or not the patient has lung cancer.
2) *Lung Cancer Classification using CT Scans:* The IQ-OTHNCCD lung cancer dataset is used to train the Convolutional Neural Network. This CNN model categorizes CT scans as normal, benign, or malignant.
3) *Lung Cancer Nodule detection using Deep Learning:* UNET model trained using the LUNA 16 dataset for nodule detection. The mhd files in the dataset are converted to png files for training the UNet. Also, mask extraction is performed to train the CNN to identify nodules and variety of preprocessing steps are performed to segment out the ROI (the lungs) from the surrounding regions of bones and fatty tissues.
4) *Medical Insurance Cost Prediction:* Aninsurance dataset was used to train the Random Forest Regressor to estimatea patient's insurance costs if the individual has lung cancer.
5) *DataAnalysisusingPlotly:* Plotlyinteractivegraphswereusedon analytical webpages. Thevisualsimprovecomprehension of the datasets.
6) *Develop a Web Application:* All of the above procedures are combined to produce a web application for improved user engagement. The program aids in the detection of lung cancer in real time and the assessment of medical insurance costs.

The proposed project is a web application with the main web page comprising four buttons. The first button directs the user to the lung cancer detection based on symptoms, thesecond button to the lung cancer classification based on CT scanspage, and thethird button takes the user to the lung cancer nodule detection using deep learning. Finally, the fourth button directs the user to themedical insurance cost prediction. A flowchart of the proposed design is shown in Fig. 1.

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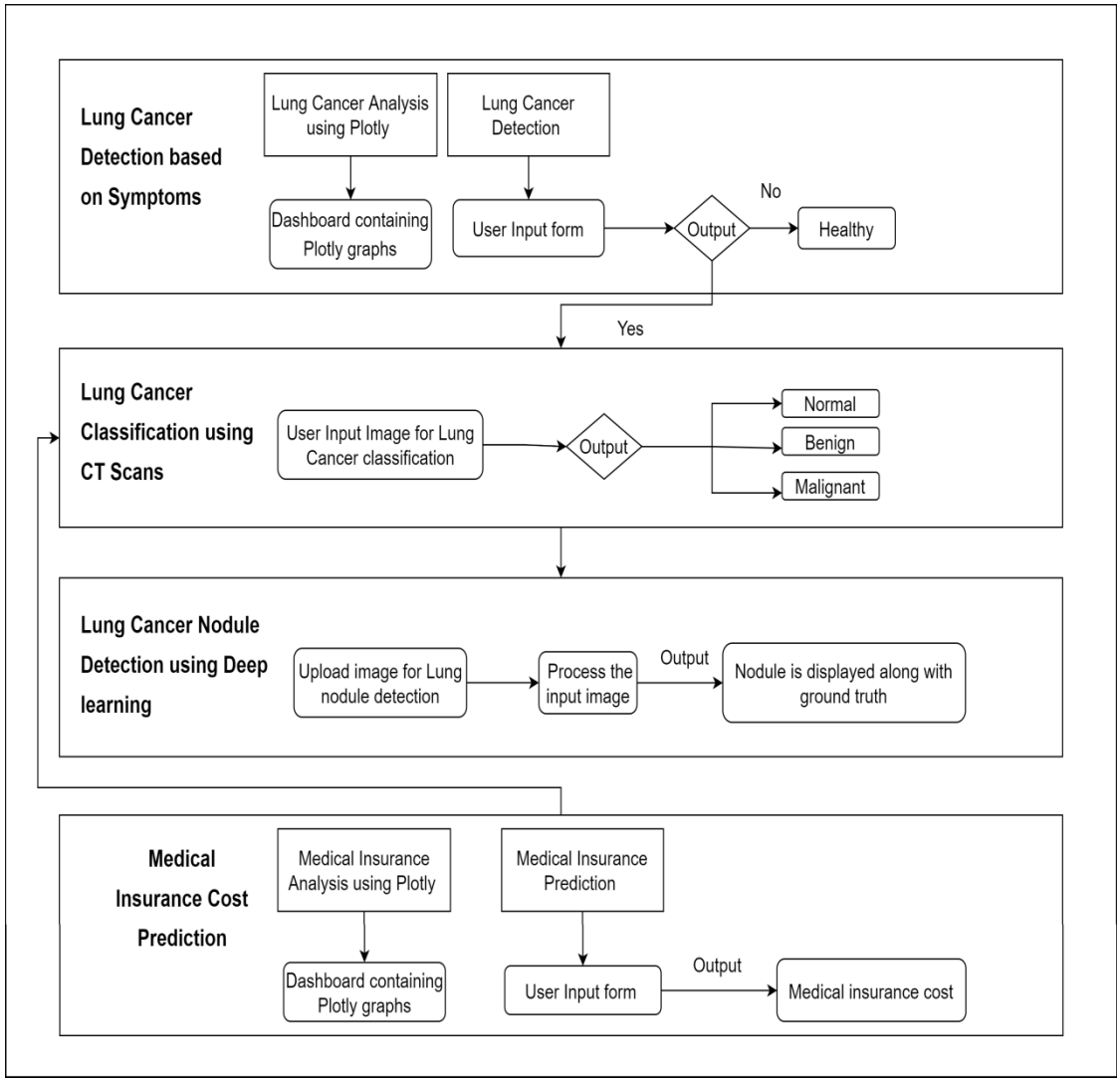


Fig.1ProposedWorkflow

The lung cancerdetectionbased onsymptoms page contains two buttons. Onclicking the first button, the interactive graphs made by Plotly are displayed. The visualizations provide a better understanding of the datasets. The lung cancer detection button comprises a form thattakes user symptoms as inputand classifies whether ornot thepatienthas lung cancer. Ifoutput isnothealthy then the user is directed to lung cancer type classification page. If it is healthy, then the user is directed to a page containing the message and a button to go to the type detection page.

Thelung cancer type detection pagecontainsa messagethatpatient maybe atriskandan image upload button wherethepatient can upload the image and then click submit button.

The trained CNN model predicts whether the output is malignant, benign or normal case. The output page will display the CT scan image, the type of cancer case and a button to direct the user to nodule detection page.

The lung cancer nodule detection page contains a button to upload the CT scan images. On clicking the upload button, the trained UNET model will predict themalignant noduleand directs the user to the output page which displays thenodule in the CT scan.

The Medical insurance page contains two buttons. The first button directs the user to the plotly dashboard which provide insights about the dataset andthe second button takes userto theestimation form which takes user details. Thetrained RFR model estimates lung cancer treatment costs and displays it on the output page when user clicks the submit button. This output page also contains a button to navigate user to type detection page.

Thisproposedflaskwebapplicationprovidesaccurateresultstoalltheusersinlesstimeeffortlessly.

IV. IMPEMENTATION/METHODOLOGY

Theprojecthasdifferentmodulesimplementedwithdifferentmethodologiesasshowninfig.2Eachmoduleandits implementation will be explained in depth in the sections that follow.

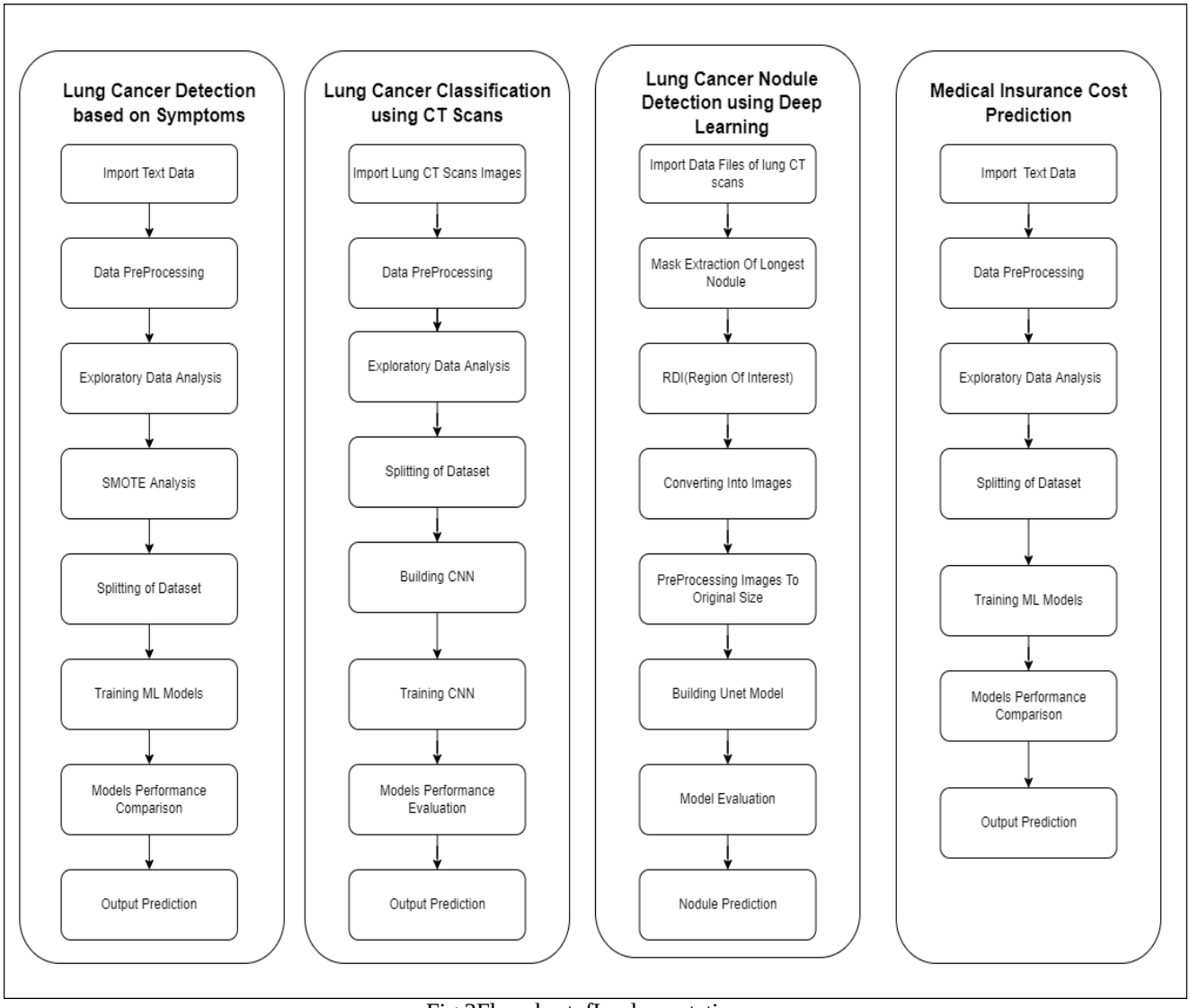


Fig.2FlowchartofImplementation

A. Lung Cancer Detection Basedon Symptoms

Lung cancer can be caused by a variety of symptoms and habits. We construct models to predict whether or not a patient has lung cancer using user data.

1) *Data Analysis:* A comprehensivedataanalysis is requiredtodeterminethetypeofdata with which weareworking.TheSurvey Lung Cancer dataset was obtained from the *data.world*website. The data is gathered through the website's online lung cancer prediction system by collecting user inputs. The users who visited this site implemented this throughout the month of August 2013. The data set contains 309 entries with 16 variable columns.
2) *Data Processing:* This step is wherecertain alterations tothe data aremade. Someadjustments included renaming columns and encoding categorical data. Resampling was employed to balance the dataset since it was uneven, with 87.4% of people having lung cancer and the remaining 12.6% people not having lung cancer. To expand the number of instances in the dataset in a balanced manner, the Synthetic Minority Oversampling Approach (SMOTE) was employed as an oversampling technique.
3) *Data Exploration:* Determining the relationship between distinct variables. Among all features, Anxiety and Yellow Fingers show the highest correlation whereas Peer pressure and Gender show the least.

Certaininferencesarereachedtoaidour understanding,suchas:

- Malesoutnumberfemalesinnumber
- Maleshavea0.4oldermeanagethan females
- Malesmokersoutweighfemalesmokers
- Femalesaremorelikelytohaveyellow fingertips
- Femalesfrequentlyexhibitanxietysymptoms
- Femalesfacehigherpeerpressure
- Chronicillnessisalsomoreprevalentamong women

Furtherinvestigationwasconductedwithregard to all factors.Thegatheredfindingswereutilizedto developadashboardpage, which is depicted in the succeeding sections.

4) *Model Building:* The generation of different training and testing samples allows us to evaluate model performance. As aresult, we divide our modelling dataset into training and testing samples using the scikit-learn library's train test split() method. Following data splitting, the train data is sent to several models for training. The models utilized are KNN: K-Nearest Neighbors, RFC: Random Forest Classifier, SVC: Support Vector Classifier, DTC: Decision Tree Classifier. The models are built to forecast once they have beentrained. The predicted values are compared to the validation data to determine the accuracyof each model. The RFC model had thehighest accuracyand was chosen as the best model to predict the existence of cancer based on the user's symptoms.

B. Medical Insurance Cost Prediction

The insurance dataset is used to train a model that can forecast the approximate cost of insurance that a cancer patient will require. The forecast will be based on the information provided by the user.

1) *Data Analysis:* A comprehensive data analysis is required to determine the type of data we are working with. The Medical Insurance Dataset was obtained from Kaggle and had 1338 records with 7 variable columns.
2) *DataProcessing:*Thisstepiswheresomeadjustmentstothedataaremade.Categoricaldatawas encoded.
3) *Data Exploration:* Studying the features reveals that Smokers and Charges have the highest correlation whereas Smoking and Age, and Smoking and Number of Children have the least.
4) *Model Building:*Thegeneration ofdifferenttraining and testing samples allows us toevaluatemodel performances. As aresult, we divide our modelling dataset into training and testing samples, to which models were implemented using about 1070samples for training and 268 samples for testing.

Followingdatasplitting,thetraindataissenttoseveralmodelsfortraining.Themodelsutilizedareasfollows:

- Linear Regression
- RandomForestRegressor
- DecisionTreeRegression
- LassoRegression

Toassessthecorrectnessofeach model,thepredicted valuesarecomparedtothevalidation data.TheRFRmodel waschosen asthe best model to anticipate insurance premiums based on user input since it had the highest accuracy.

C. Lung Cancer Classification Using CTscans

Lung cancer can be caused by a variety of symptoms and habits. We construct models to predict whether or not a patient has lung cancer using user data.

1) *Data Analysis:* The lung cancer dataset from Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) was gathered in the aforementioned specialty hospitals over a three-month period in autumn 2019. It comprises CT imagesofpatientswith lung cancer at variousstagesaswell ashealthyparticipants. Oncologistsandradiologistsfrom these two hospitals marked the IQ-OTH/NCCD slides. The collection comprises 1190 pictures depicting CT scan slices from 110 different cases. These instances are classified aseither normal, benign, or malignant. 40 of these instances have been classed as malignant, 15 as benign, and 55 as normal. Gender, age, educational achievement, location of residence, and living situation differ across the 110 cases. An example of benign, malignant andnormal case is given in Fig. 3.

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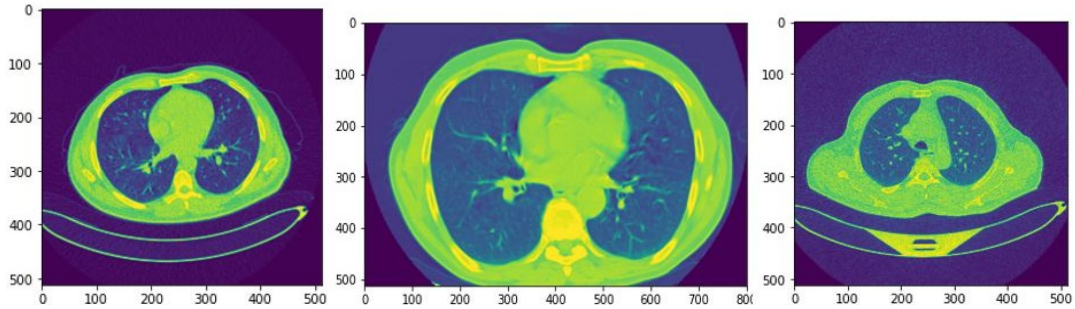


Fig.3Benign,MalignantandNormalCases

2) *Data Processing and Exploration:* Thevisual data isjumbled and then displayed using colormaps. Using onehot encoding, the data is normalized, transformed, and encoded.
3) *Model Building:* The data is subsequently divided into two sets: training and testing. The data split includes photos from all three classes in both sets. A Convolutional Neural Network was built to predict the right cell classifications from photos. For feature extraction from photos, we employed three Conv2D layers with MaxPool2D layers in between. ReLU is the activation function employed. The output layer has just three neurons with SoftMax activation functions, which correspond to the three types of tumors (Benign, Malignant, and Normal). The model is then built using RMSprop as the optimizer and Categorical Crossentropyas theloss function. We will train the model with the class weights for three epochs. The training was terminated in the third epoch when a decent accuracy of roughly 92% was established.

D. LungCancerNoduleDetectionUsingDeepLearning

1) *Data Analysis:* Scans with a slice thickness of more than 2.5 mm were eliminated from the dataset. There are 888 CT scans in all. Annotations were collected throughout a two-phase annotation procedure by four experienced radiologists and are also available in the LIDC/IDRI database. Each radiologist labelled lesionsasnon-nodule, noduleless than 3 mm, or nodulegreater than 3 mm. The specifics of the annotation procedure may be found in their publication. All nodules greater than or equal to 3 mm that are acknowledged by at least three out of four radiologists constitute the challenge reference standard. Irrelevant findings are annotations that are not included in the reference standard (non-nodules, nodules less than 3 mm, and nodules annotated by just one or two radiologists). All CT scans and annotations are contained in subset0, which is a zip file. The annotations used as a reference standard for the 'nodule detection' track are stored in a csv file. CT images are saved in MetaImage (mhd/raw) format in subset0. The pixel data is kept in a separate raw binary file for each mhd file. One discovery per line is contained in the annotation file, which is a csv file. The scan's SeriesInstanceUID, the x, y, and z positions of each discovery in world coordinates, and the matching dimension in mm are all listed on each line. There are 1186 nodules in the annotation file.
2) *Data Processing and Exploration:* It is necessary to minimise the domain size before entering the CT images into the U-net architecture in order to obtain more accurate findings. To segment out the ROI (the lungs) from the surrounding areas of bones and fatty tissues, a number of preprocessing processes are used. These include the following:

- BinaryThresholding
- Selectingthetwolargestconnectedregions
- Erosiontoseparatenodulesattachedtobloodvessels
- Dilationtokeepnodulesattachedtothelungwalls
- Fillingholesbydilation
- Convertingthemhdfilestopng

Theimagefile's index is collected, andtheindex image's directoryis saved. Theimageis then opened, enlarged, and transformed to grayscale, after which its index is saved. Along with the grayscale picture, themask of the image corresponding to the index is also saved. After that, masks may be read simply specifying the mask's directory. Finally, the mask image is preprocessed by shrinking and normalising the pixel value before being stored at the same index position in the output arrayas the pre-processed mask image. The picture is stored in X[n], while the mask is stored in y[n].

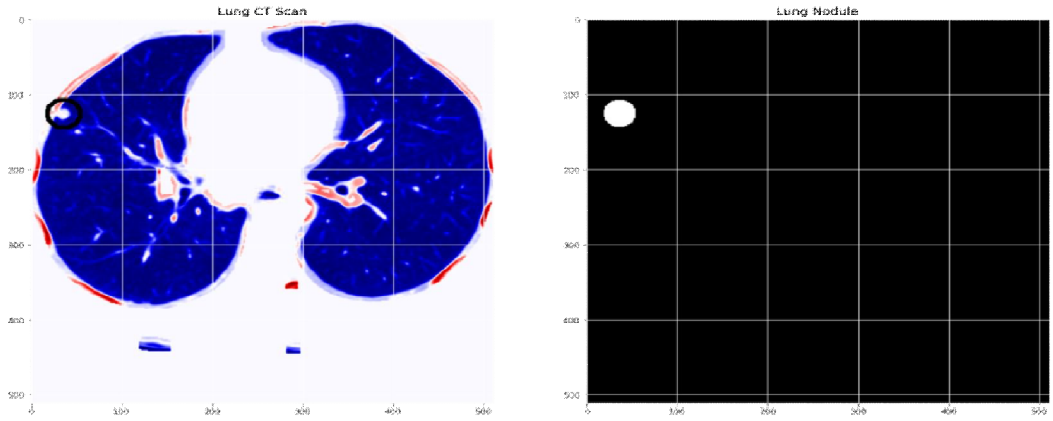


Fig. 4 CT Scan and its corresponding Lung Nodule mask Visualization and shows theplot ofthepre-processed sampleimageandthemask ofthepictureexhibitingthenodule.

3) *Model Building:* The base model and the custom layer that accepts that base mode input whose output is subsequently transferred to the UNet model anticipate an input shape of 512x512x1. The output of the UNet model is then sent to further ConvNet layers with ReLU activation followed by a flatten layer and two dense layers. After that, the output is reshaped to 512X512. Finally, we've used the base model to construct a model that receives input (inp) and outputs (x out). The model is then built using Adam asan optimizer and BinaryCrossentropyas a loss function. With the class weights, we'll train themodel for three epochs. The training was halted at the tenth epoch since a decent accuracyof around 98\% had been achieved.

V. EXPERIMENTATION AND RESULTS

A. *LungCancerDetectionBasedonSymptoms*

As previously indicated, many models were used, and the finest of them were picked to be employed.Table I shows the train andtest accuracies for the various models utilized for lung cancer detection based on symptoms.

TABLE IACCURACYOFMODELSFORSYMPTOMSBASEDDETECTION

Model	Train_Accuracy	Test_Accuracy
RFC	98.020312	0.969136
SVC	96.296296	0.969136
DTC	98.876574	0.919753
KNN	94.444444	0.907407

TheRandomForestClassifierperformedthebest.

B. *MedicalInsuranceCostPrediction*

TableIIshowsscorefor thevariousmodelsutilizedformedicalinsuranceprediction.

TABLEIIACCURACYOFMODELSFORINSURANCEPREDICTION

Model	Train_Accuracy	Test_Accuracy
RandomForest Regression	88.91	86.29
DecisionTreeRegression	88.02	86.18
LassoRegression	74.61	76.18
Linear Regression	74.61	76.18

RandomForestRegressorhasyieldedthebestperformance.

C. *LungCancerClassificationUsingCTScans*

The following experimental results were obtained after utilizing the developed CNN model to predict a random picture. The first valueis theclass oftheobject with thehighest valuein thearray. Theclass's categorylabel is thefollowing value.As seen in Fig.5, the picture was correctly anticipated.

```
[[0.04567198 0.5397512  0.41457677]
 [0.09867036 0.6228367  0.27849287]
 [0.01539725 0.90645313 0.07814966]]
1
Malignant cases
```

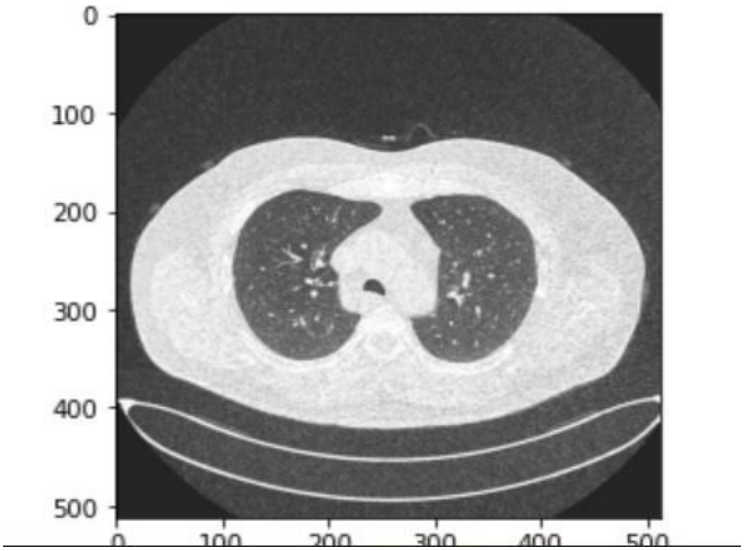


Fig.5Prediction ofrandomlychosenimage

Adataframewithanticipatedvalueandequalitytoitsactualvalueisdevelopedwithfurther experimentation.

The model makes modest errors on just portion of the data if the accuracy is high and the loss is low, which is the optimum condition. The CNN model's loss and accuracy (Fig. 6) are shown in the charts below. The CNN Model yields an accuracy of 92.42% and a miss class of 7.58%

The performance of the CNN model is also evaluated using different performance metrics such as precision, recall, and f1-score, each of which provide an accuracy of 92%

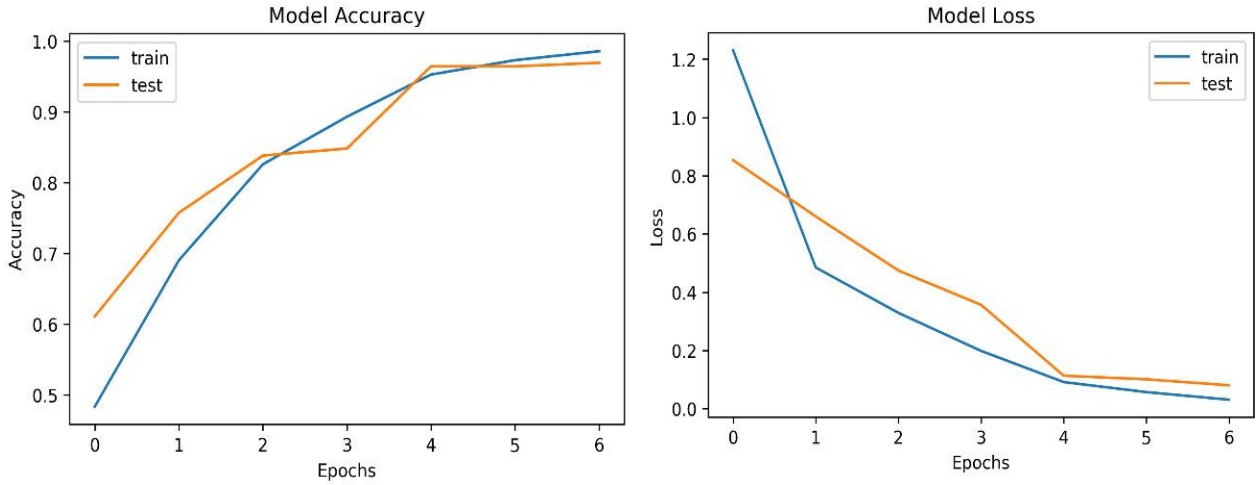


Fig.6CNNmodelAccuracyand Loss

D. LungCancerNoduleDetectionusingDeepLearning.

A learning curve is a graph representing model learning performance as a function of time or experience. In machine learning, learning curves are a common diagnostic tool for algorithms that learn progressively from a training dataset.

After each update during training, the model may be tested on the training dataset and a holdout validation dataset, and graphs of the measured performance can be constructed to demonstrate learning curves.

Examining model learning curves during training may help detect learning issues, such as an underfit or overfit model, as well as whether the training and validation datasets are sufficiently representative. The learning curve for lung cancer nodule identification is seen in Fig. 7. The curve is an example of a good fit

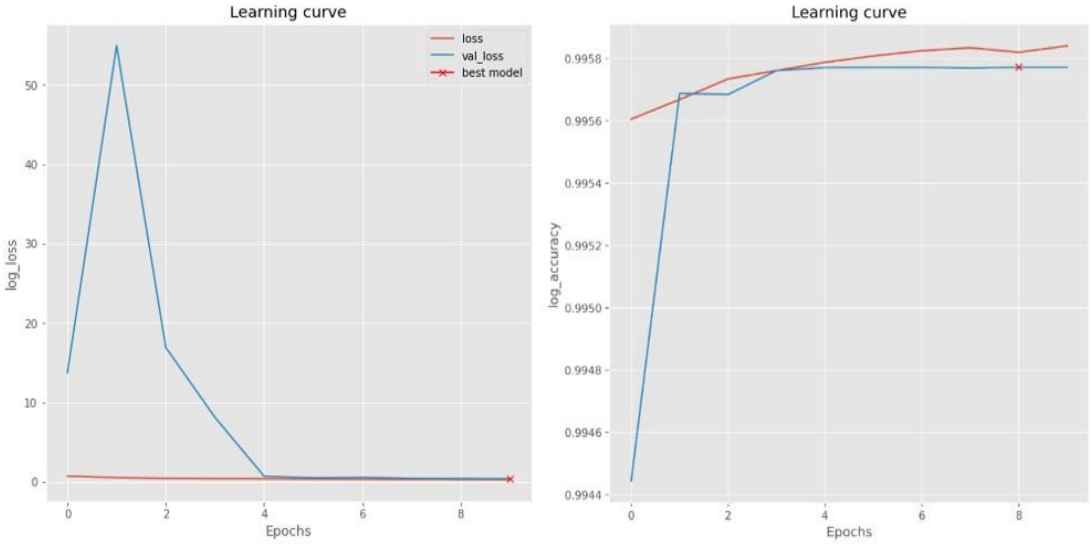


Fig.7TheLearningCurveforlungcancernoduledetection

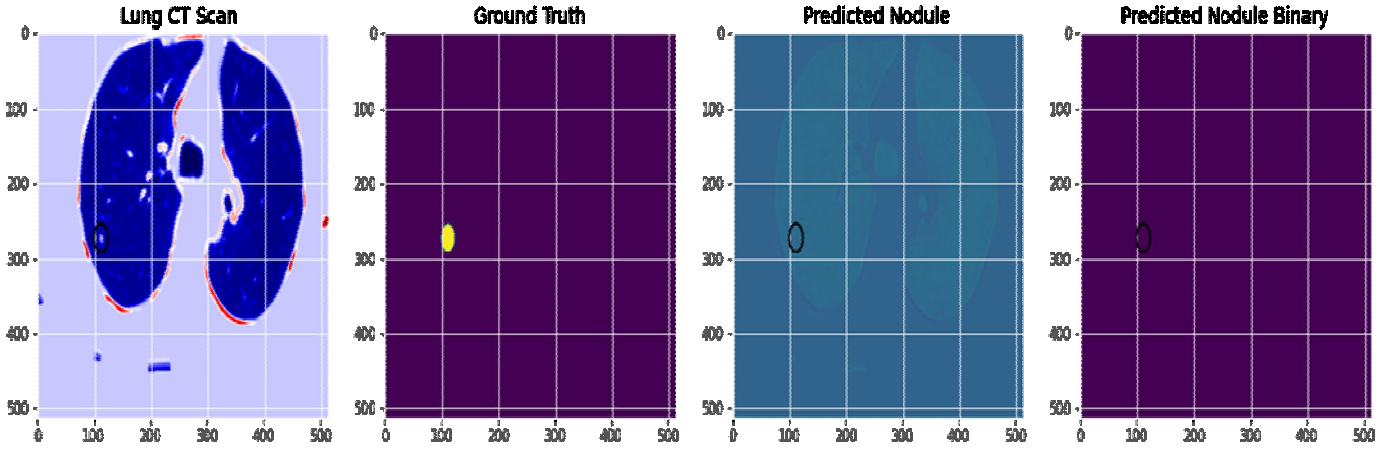


Fig.8OutputImageofdetected nodule

Fig.8showstheoutputimagethatincludestheLungCTScan, GroundTruth, PredictedNoduleandPredictedNoduleBinary.

E. WebAppIntegrationUsing Flask

A web application is created with thehelp of flask web framework to simplifythe usage of theproposed project to all userstheapp. To test the proposedweb application in a real-world, test data and images of CT scans are selected based onthe convenient use of theapplicationsandseveralexperimentswereconductedtotestthemodel'srobustness.Onperforming real-timetestingonthe proposed system using different sets of people, good results were achieved.

F. ComparisonofProposedModels

Theaccuracyoftheproposed model iscompared with differentmodelsfrompreviouslydoneexperimentsasshown in TableIII. The proposed models outperformed the others in terms of performance.

TABLEIII COMPARISONOFPROPOSEDMODELS

Modules	Ref	ModelUsed	Accuracy
LungCancerNodule Detection	[19]	ResNet50+SVMRBF	93.19
	[18]	CNN	92.63
	[20]	DFCNet	89.52
	[8]	CNN	64.40
	[10]	SVM-LASSO	84.60
		ProposedUNet	98.00
Lungcancerclassification usingCTscans	[21]	3DMixNet	88.83
	[21]	3DMixNet+GBM	90.57
	[6]	EnsembleofUNet+RandomForestand ResNet+XGBoost	84.00
	[7]	SVM	86.67
	[22]	Fine-tuningConv4ofAlexNet	85.21
		ProposedCNN	92.42
Lungcancerpredictionon the basisofsymptoms	[9]	ANN	96.67
		ProposedRFC	96.91
MedicalInsuranceCost Prediction	[23]	StochasticGradientBoosting	85.82
	[23]	XGBoost	85.36
	[24]	RFR	85.00
		ProposedRFR	86.29

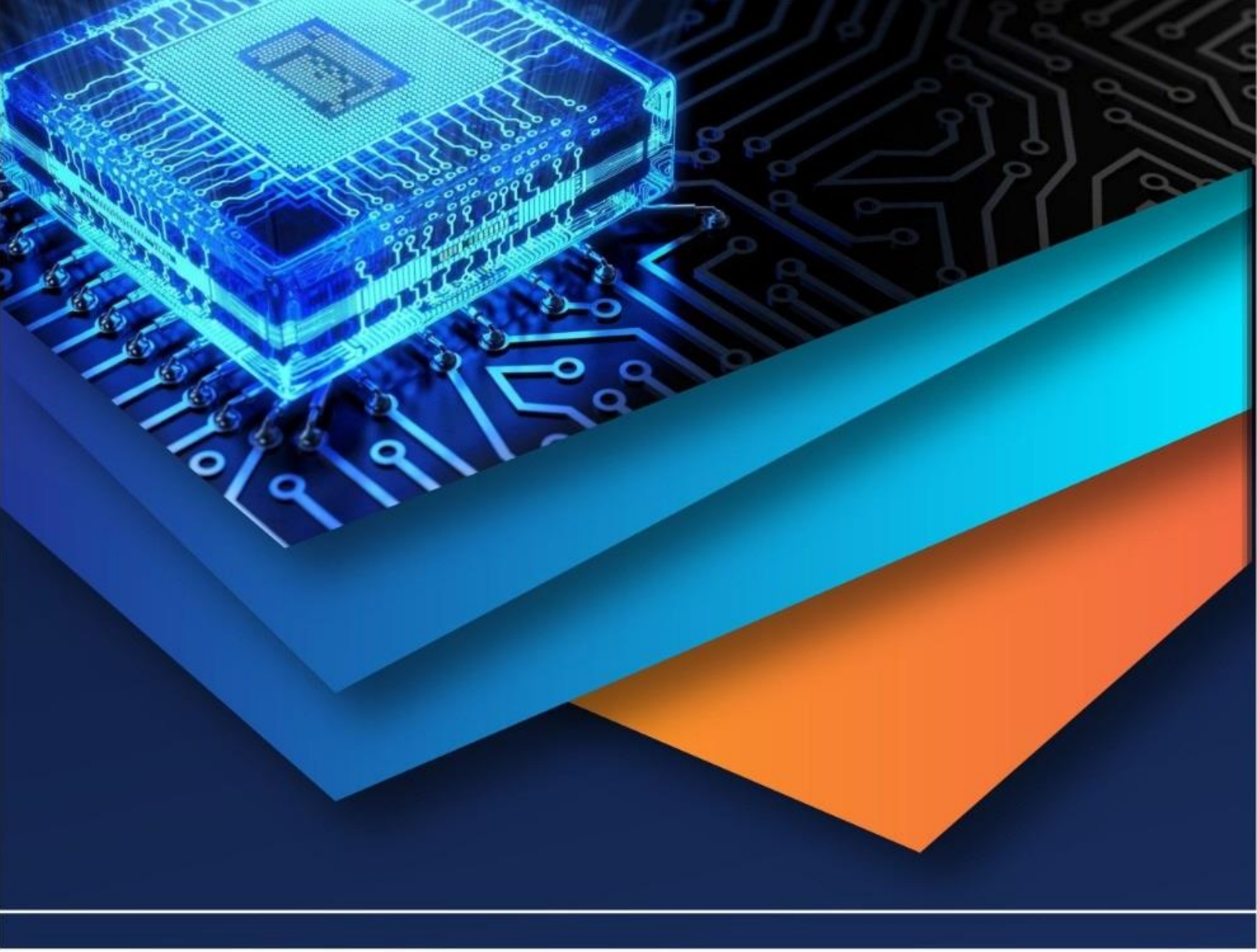
VI. CONCLUSION

The goal of this project was to create a method for overcoming the challenges of lung cancer by utilizing Machine Learning and Deep Learning techniques to predict the presence of cancer in the lungs using medical records, as well as interpret CT images to accurately identify nodules with diameters as small as 3mm at a low cost and in less time. Along with that, to be able to make this technology available to everyone in the form of a web application. All of the objectives were met, as evidenced by the following outcomes.RandomForestClassifierwith96.9\%accuracyforsymptom-basedrecognitionandRandomForestRegressorwith 86.3\%accuracyfor predictingmedicalinsurancecosts. TheCNN model, which was created toanalyzeCTimages,Theaccuracyof the CNN model used to analyze CT images was 92.42%. Finally, the UNet model designed to detect nodules on CT scansperformed excellently, with a 98% accuracyrate. The developed strategyis, in general, highlydependable for users.

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