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Analysis of Different Classification Algorithms for Lung Cancer Detection

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ABSTRACT

Early diagnosis of lung cancer is crucial to ensure curative treatment and increase survival rates. Lung CT Scan imaging is the most frequently used method for diagnosing Cancer. However, the examination of Lung CT Scans is a challenging task and is prone to subjective variability. In this study, we developed a computer-aided diagnosis system for automatic Lung Cancer detection using Lung CT Scan images. We employed deep transfer learning to handle the scarcity of available data and designed a Convolutional Neural Network (CNN) model along with the Machine learning methods: Random Forest (RF), Support Vector Machines (SVM), and Decision Tree (DT). The proposed approach was evaluated on publicly available Covid-19 CT scan dataset.

Keywords : C Lung CT Scan images. Deep Learning, CNN, Transfer Learning, RF, SVM, and DT.

I. INTRODUCTION

In 2018 it was estimated that approximately 9.6 million deaths were claimed by lung cancer. Lung cancer tops the list if a person talks about the types and their shares. Estimated cases of lung cancer are around 2.09 million with 1.76 million deaths which account for around 84% deaths. Due to this reason lung cancer has been entitled as one of the most fatal diseases. Tumor is made by multiplication of abnormal cells in lung cancer. Cancer cells tend to spread really fast due to blood streams ans lymph fluid that is present in lung tissue. In general, due to normal lymph flow, cancer cells frequently migrate to the middle of the chest. As cancer cells migrate to other tissues, metastasis occurs. It is important that cancer be detected as early as possible as it tends to spread and is beyond curable in case of a larger spread. It is difficult to diagnose lung cancer since it shows symptoms in the final stage and it is nearly impossible to save a person's life in the final stage. Images of lungs for examination are captured by imaging techniques such as Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic resonance imaging (MRI) and X-ray. CT image technique is the most common out of the mentioned methods due to its ability to give a view excluding overlapping structures. Interpreting and recognizing cancer is complicated for doctors. CT photographs are accurate for the diagnosis of lung cancer. To identify lung cancer, image processing, and deep learning methods will be used. Accuracy can be improved using these approaches. Tumor detection and determination of its form, size, and location is a tough task. Timely detection helps in saving a lot of time. And this time can be used in providing early treatment to the patient. In this project, pre-processing (removing noise if any), post processing (segmentation) and classification techniques will be used to classify tumors into one of the two groups i.e. Malignant and Benign. Benign refers to a non-cancerous tumor and it doesn't spread to other parts. Abnormal cells divide without control in malignant and may invade surrounding tissues. Exploring different methods to diagnose lung cancer will be a prime aim in this paper. Computed tomography can be used to capture images of lungs across various dimensions so that a 3D image of the chest can be formed. This 3D image can be used to detect tumors present. Normally a doctor or any field expert uses a CT image to detect cancer. Due to the large number of CT images, it is difficult for a doctor or radiologist to detect cancer quickly and accurately. But with the advancement in technology, Computer-Aided Diagnosis (CAD) can be utilized to complete this duty efficiently and in considerably less time. This process has two separate processes i.e. first to identify all the nodules present in the CT image and second to classify the detected lung nodules.

II. RELATED WORKS

Correlation of chest CT and RT-PCR testing for coronavirus disease 2019 (COVID-19) in China: A report of 1014 cases: Background Coronavirus disease 2019 (COVID-19) is diagnosed using chest computed tomography (CT), which is a crucial addition to reverse transcription polymerase chain reaction (RT-PCR) assays. Purpose to assess the diagnostic efficacy and reliability of a chest CT against an RT-PCR test for COVID-19. Resources and Procedures Between January 6 and February 6, 2020, 1014 patients in Wuhan, China, who had chest CT and RT-PCR testing were a part of this study. In order to evaluate the effectiveness of chest CT in the diagnosis of COVID-19, RT-PCR was used as the reference standard. Additionally, the dynamic conversion of RT-PCR findings (negative to positive, positive to negative) for patients who had several RT-PCR assays was examined in comparison with serial chest CT scans for those patients who had a gap of at least 4 days between RT-PCR testing. Results RT-PCR findings from 601 of the 1014 patients (or 59%) and chest CT scan results from 888 of the 1014 patients (or 88%) were both positive. Based on positive RT-PCR data, the sensitivity of the chest CT in detecting COVID-19 was 97% (95% confidence interval: 95%, 98%; 580 of 601 patients). 308 of the 413 individuals (or 75%) who had negative RT-PCR results also had positive chest CT findings. Of the 308 patients, 33% (103 of 308) and 48% (103 of 308) were deemed probable cases, respectively. The mean time between the initial negative and positive RT-PCR findings at the analysis of serial RT-PCR assays and CT scans was 5.1 days and 1.5 seconds; the mean time between the initial positive and subsequent negative RT-PCR results was 6.9 days and 2.3 seconds. 60% (34 of 57) to 93% (14 of 15) of the 1014 patients had first CT scans that were positive and consistent with COVID-19 before (or concurrently with) the initial positive RT-PCR findings. Before the RT-PCR findings became negative, 24 of 57 patients (42%) exhibited improvement on follow-up chest CT scans. Conclusion Coronavirus illness can be accurately diagnosed with chest CT in 2019 (COVID-19). The key method for the current COVID-19 detection in epidemic regions may be a chest CT scan.

Identifying medical diagnoses and treatable diseases by image-based deep learning: The reliability and interpretability of clinical-decision support systems for medical imaging are problematic. Here, we develop a diagnostic tool based on a deep-learning architecture to screen patients for common, curable retinal illnesses that might cause blindness. With the use of transfer learning, our system can train neural networks with a small fraction of the data required by traditional methods. We exhibit performance equivalent to that of human experts in diagnosing age-related macular degeneration and diabetic macular edoema using our method on a dataset of optical coherence tomography pictures. We also offer a more clear and understandable diagnostic by emphasizing the places that the neural network picked up on. Using chest X-ray pictures, we further show how our AI system may be used to diagnose juvenile pneumonia in general. In the long run, this tool could help hasten the diagnosis and referral of these curable illnesses, enabling earlier treatment and better clinical results. Video summary.

A study of cross-validation and bootstrap for accuracy estimation and model selection: We examine strategies for estimating accuracy and contrast the two most popular approaches, cross validation and bootstrap. Ten-fold cross-validation may be preferable to the more expensive leave-one-out cross-validation for picking a suitable classifier from a group of classifiers (model selection), according to recent experimental results on simulated data and theoretical re cults under constrained scenarios. In this paper, we provide a large-scale experiment to assess the impact of various parameters on the Naive-Bayes and C4.5 algorithms on real-world datasets. For bootstrap, we alter the number of bootstrap samples, whereas for cross validation, we modify the number of folds and whether the folds are stratified or not. Our findings show that tenfold stratified cross validation is the most effective model selection technique for real-world datasets similar to our own, even though utilizing more folds is computationally feasible.

Deep feature extraction and classification of hyper spectral images based on convolutional neural networks: Due to the benefits of deep learning, a regularised deep feature extraction (FE) approach is proposed in this study for the classification of hyperspectral images (HSI) using a convolutional neural network (CNN). The suggested method uses a number of convolutional and pooling layers to extract nonlinear, discriminant, and invariant deep features from HSIs. Target detection and picture categorization can both benefit from these attributes. Furthermore, a few methods, like as L2 regularisation and dropout, are examined to prevent overfitting in class data modelling in order to overcome the typical issue of imbalance between high dimensionality and limited supply of training samples for the classification of HSI. Our proposal for a 3-D CNN-based FE model with coupled regularization to extract useful spectral-spatial characteristics from hyper spectral data is more significant. Finally, a virtual sample improved technique is suggested to further boost performance. Three popular hyper spectral data sets—Indian Pines, University of Pavia, and Kennedy Space Center—are utilised to test the suggested methods. The collected findings show that the suggested models with sparse restrictions produce results that are competitive with those of cutting-edge techniques. Additionally, the suggested deep FE provides a new avenue for investigation.

Rectifier nonlinearities improve neural network acoustic models: Systems for continuous voice recognition with a wide vocabulary benefit significantly from the use of deep neural network acoustic models. Recent research using rectified linear (ReL) hidden units shows substantial improvements in final system performance compared to sigmoidal nonlinearities, which are more frequently employed. For the 300-hour Switchboard conversational speech recognition challenge, we investigate the usage of deep rectifier networks as acoustic models in this study. Networks with rectifier nonlinearities outperform their sigmoidal counterparts by 2% using straightforward training approaches without pretraining. To measure the differences between the ways ReL units and sigmoidal units encode inputs, we examine hidden layer representations. Finally, in an effort to further enhance deep rectifier networks, we assess a ReL unit version with a gradient that is more accessible to modification.

III. METHODOLOGY

Proposed system:

Convolution Neural Network (CNN) and transfer learning (MobileNet) of deep learning are used in our suggested technique to classify if a person has lung cancer or not. In order to guarantee curative therapy and boost survival rates, early cancer detection is essential. Therefore, accurate categorization is crucial for the correct therapy, which will be made feasible by applying the technique we have suggested. Below is a block schematic of the suggested technique.

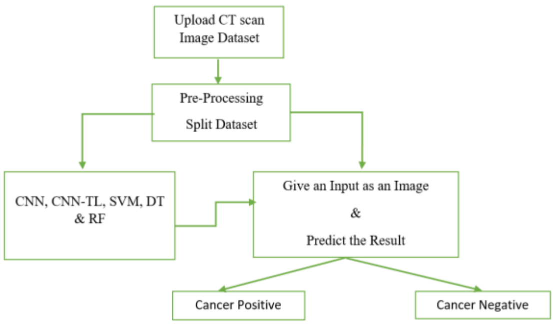


Figure 1: Block diagram

IV. Implementation

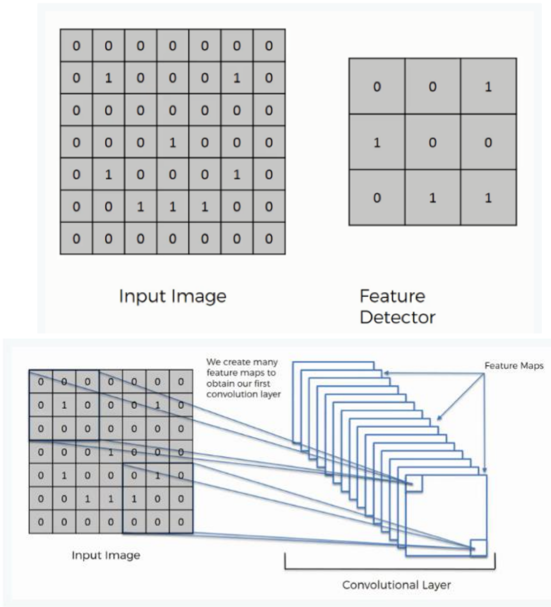
The project has implemented by using below listed algorithm.

1. Convolutional Neural Network

Step1: convolutional operation

The convolution operation is the first component of our strategy. We will discuss feature detectors in this phase since they essentially act as filters for neural networks. Additionally, we'll talk about feature maps, their parameters, how patterns are found, the detection layers, and how the results are laid out.

The Convolution Operation

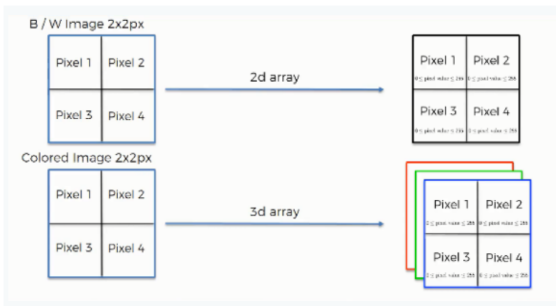


Step (1b): ReLU Layer

The Rectified Linear Unit or Relook will be used in the second portion of this process. We will discuss Relook layers and examine the role of linearity in Convolutional Neural Networks.

Although it's not required to comprehend CNN's, it wouldn't hurt to take a brief course to advance your knowledge.

Convolutional Neural Networks Scan Images



Step 2: Pooling Layer

We'll discuss pooling in this section and learn exactly how it typically operates. But max pooling will be the central concept in this situation. However, we'll discuss a variety of strategies, including mean (or total) pooling. This section will conclude with a demonstration created with a visual interactive tool that will undoubtedly clarify the entire idea for you.

Step 3: Flattening

Here's a quick explanation of the flattening procedure and how to switch between pooled and flattened layers when using convolutional neural networks.

Step 4: Full Connection

Everything we discussed in the previous section will be combined in this section. By understanding this, you'll be able to visualize Convolutional Neural Networks more clearly and understand how the "neurons" they create ultimately learn to classify pictures.

Summary

Finally, we'll put everything in perspective and provide a brief summary of the idea addressed in the section. If you think it will help you in any way (and it probably will), you should look at the additional tutorial that covers Cross-Entropy and Soft axe. Although it is not required for the course, it will benefit you greatly to be familiar with these principles since you will probably encounter them when working with convolutional neural networks.

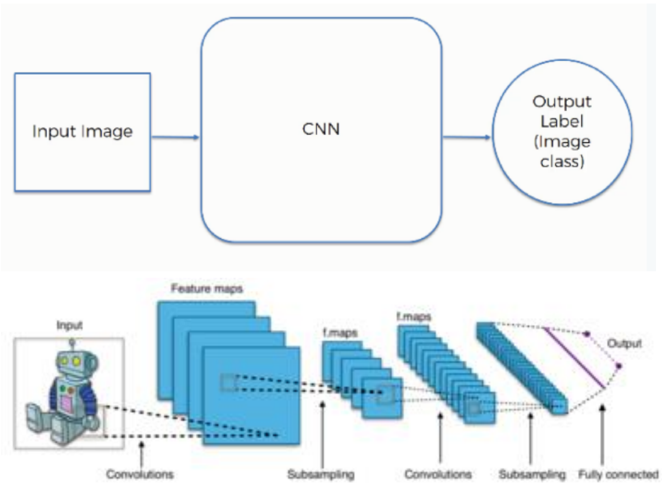


Fig. CNN Architecture

2. RNN:

A recurrent neural network operates on the idea that by preserving a layer's output and sending it back into the input, it can anticipate that layer's output.

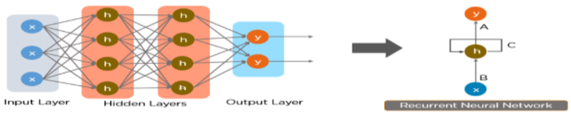


Fig: Simple Recurrent Neural Network

Feed-Forward Neural Networks:

- A feed-forward neural network only permits information to pass from the input nodes through the hidden layers and to the output nodes in a forward manner. The network doesn't contain any loops or cycles.
- A simplified representation of a feed-forward neural network may be shown here:

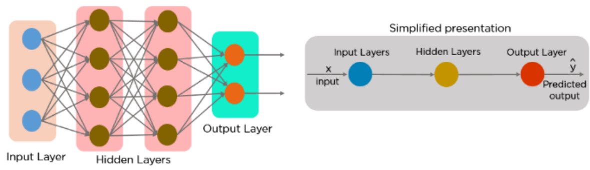


Fig: Feed-forward Neural Network

Why Recurrent Neural Networks are better?

- The feed-forward neural network had the following problems, which led to the development of recurrent neural networks:
- Cannot process sequential data; Only takes into account current input; Unable to recall prior inputs
- The Recurrent Neural Network is the answer to these problems (RNN). An RNN can handle sequential data, accepting both the input data being used at the moment and inputs from the past. RNNs' internal memory allows them to remember prior inputs.

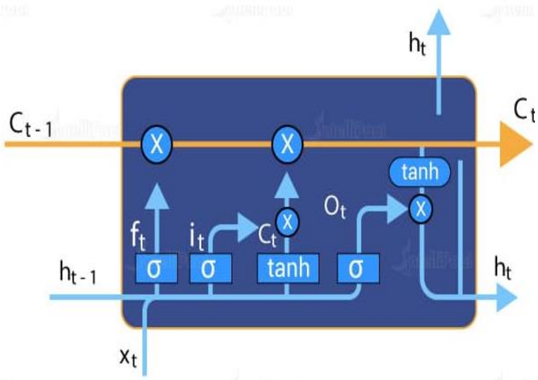
Applications of RNN:

- NLP
- Time series

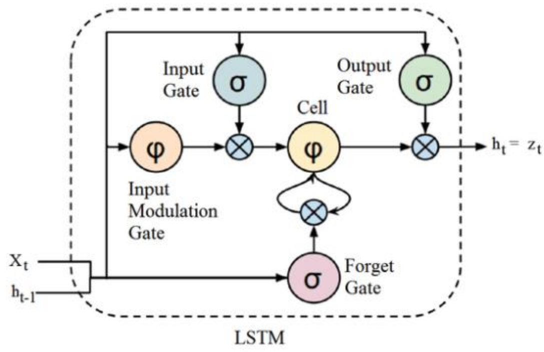
- Language Translation.

3. LSTM:

- A few problems in the feed-forward neural network led to the development of recurrent neural networks, including:
- It simply takes into account the current input and cannot memories earlier inputs. It cannot handle sequential data.
- Recurrent Neural Network provides an answer to these problems (RNN). The present input data as well as inputs from the past are both acceptable to an RNN when handling sequential data. Because of their internal memory, RNNs are able to remember past inputs.
- A variety of recurrent neural networks (RNNs) are able to learn long-term dependencies, particularly in issues involving sequence prediction. Aside from singular data points like photos, LSTM contains feedback connections, making it capable of processing the complete sequence of data.
- A memory cell known as a "cell state" that preserves its state over time plays a key function in an LSTM model. The horizontal line that passes across the top of the figure below represents the cell state. It may be compared to a conveyor belt through which unmodified information just travels.



- In an LSTM, information may be added to or subtracted from the cell state, and gates control this. These gates may allow information to enter and exit the cell. It has a sigmoid neural network layer and a pointwise multiplication operation that help the mechanism.
- The forget gate is another name for the remember vector. By multiplying 0 to a point in the matrix, the forget gate's output instructs the cell state which pieces of information to forget. Information is stored in the cell state if the forget gate's output is 1. The weighted input/observation and prior hidden state are applied using the sigmoid function obtained from the equation.



LSTM Cell

- The input gate is the common name for the save vector. Which data should be added to the cell state or long-term memory is decided by these gates. The activation functions for each gate are crucial components.
- The input gate has a range of [0,1] and is a sigmoid function. The sigmoid function alone cannot eliminate or forget memories since the equation of the cell state is a summation of the past cell states.
- If a float number may only be added between [0,1], the result will never be zero, off, or forgotten. For this reason, the input modulation gate contains a function for tanh activation. Tanh has a range of [-1, 1], and it permits memory loss in the cell state.
- The output gate is the common name for the focus vector. Which of the matrix's potential

values ought to advance to the next hidden state?

- The forget gate is the first sigmoid activation function. Which details from the prior cell state should be forgotten? (Ct-1). Our input gate is the first tanh activation function and the second sigmoid. Which information ought to be discarded or kept to the cell state? The output gate's last sigmoid indicates which data should be sent to the following concealed state.

LSTM Applications:

LSTM networks find useful applications in the following areas:

- Language modeling
- Machine translation
- Handwriting recognition
- Image captioning
- Image generation using attention models.

4. Random Forest:

A random forest is a machine learning method for tackling classification and regression issues. It makes use of ensemble learning, a method for solving complicated issues by combining a number of classifiers.

In a random forest algorithm, there are many different decision trees. The random forest algorithm creates a "forest" that is trained via bagging or bootstrap aggregation. The accuracy of machine learning algorithms is improved by the ensemble meta-algorithm known as bagging.

Based on the predictions of the decision trees, the (random forest) algorithm determines the result. It makes predictions by averaging or averaging out the results from different trees. The accuracy of the result grows as the number of trees increases.

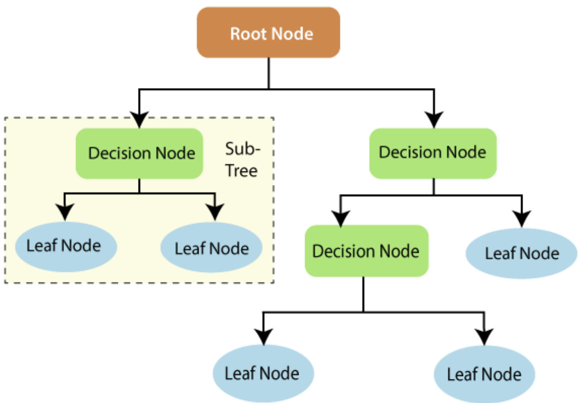
The decision tree algorithm's shortcomings are eliminated with a random forest. It improves precision and decreases dataset overfitting. Without requiring several settings in packages, it makes forecasts (like Scikit-learn).

Features of a Random Forest Algorithm:

- It offers a useful method of addressing missing data; • It is more accurate than the decision tree algorithm.
- Without hyper-parameter adjustment, it can generate a fair prediction.
- It addresses the issue of decision trees' overfitting.
- At the node's splitting point in every random forest tree, a subset of characteristics is chosen at random.

A random forest algorithm's building components are decision trees. A decision support method that has a tree-like structure is called a decision tree. We will learn about decision trees and how random forest methods function.

- Decision nodes, leaf nodes, and a root node are the three parts of a decision tree. A training dataset is divided into branches by a decision tree algorithm, which then separates those branches further. This process keeps on until a leaf node is reached.
- The nodes in the decision tree indicate characteristics that are used to forecast the outcome. The leaf node cannot be further subdivided. Links to the leaves are provided by decision nodes. The three categories of nodes in a decision tree are depicted in the diagram below.



Information theory can provide further light on decision trees' operation. The foundation of a decision tree is information gain and entropy. An review of these key ideas will help us better comprehend the construction of decision trees.

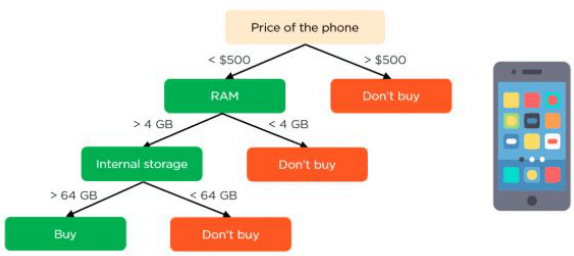
Uncertainty may be measured using entropy. Given a collection of independent variables, information gain measures the degree to which uncertainty in the target variable is minimized.

Using independent variables (features) to learn more about a target variable is the idea behind information gain (class). The information gain is calculated using the entropy of the target variable (Y) and the conditional entropy of Y (given X). In this instance, the entropy of Y is reduced by the conditional entropy.

Decision trees are trained using information acquisition. It helps to make these plants' uneasiness lessened. A significant information gain denotes the removal of a large amount of uncertainty (information entropy). Splitting branches, a crucial step in the creation of decision trees, depends on entropy and information gain.

Take a look at a straightforward decision tree example. Let's say we want to forecast whether or not a consumer would buy a mobile phone. His selection is based on the phone's characteristics. Using a decision tree diagram, this analysis may be displayed.

The above-mentioned phone features are represented by the decision's root node and decision nodes. The leaf node reflects the outcome, whether a purchase is made or not. The pricing, internal storage, and Random Access Memory are the primary criteria for selection (RAM). The following is how the decision tree will look.



decision-tree application in random forest

The fundamental distinction between the random forest method and the decision tree algorithm is that the latter randomly selects the root nodes and groups the nodes. To get the necessary forecast, the random forest uses the bagging approach.

Bagging entails using many samples of data (training data) as opposed to a single sample. Predictions are made using characteristics and observations from a training dataset. Depending on the training data that the random forest algorithm receives, the decision trees provide a variety of results. The highest ranking of these outputs will be chosen as the final output.

The operation of random forests may still be explained using our initial example. The random forest will contain several decision trees rather than just one. Assume that there are only four decision trees in all. In this instance, four root nodes will be created using the training data, which consists of the phone's observations and characteristics.

The four features that potentially affect the customer's choice are represented by the root nodes (price, internal storage, camera, and RAM). By randomly choosing characteristics, the random forest will divide the nodes. The results of the four trees will be used to choose the final forecast.

The majority of decision trees will select the ultimate result. The ultimate forecast will be purchasing if three trees predict buying and one tree predicts not buying. It is anticipated that the client will purchase the phone in this instance.

5. Support Vector Machine (SVM):

One of the most well-liked supervised learning algorithms, Support Vector Machine, or SVM, is used to solve Classification and Regression issues. However, it is largely employed in Machine Learning Classification issues. One of the most well-liked supervised learning algorithms, Support Vector

Machine, or SVM, is used to solve Classification and Regression issues.

The SVM algorithm's objective is to establish the optimal line or decision boundary that can divide n-dimensional space into classes, allowing us to quickly classify fresh data points in the future. A hyperplane is the name given to this optimal choice boundary.

Formally speaking, a support-vector machine creates a hyperplane or group of hyperplanes in a high- or infinite-dimensional space that may be applied to tasks like outliers identification, regression, and classification. Generally speaking, the higher the margin, the smaller the classifier's generalization error, therefore a decent separation is obtained by the hyperplane that has the longest distance to the nearest training-data point of any class (so-called functional margin).

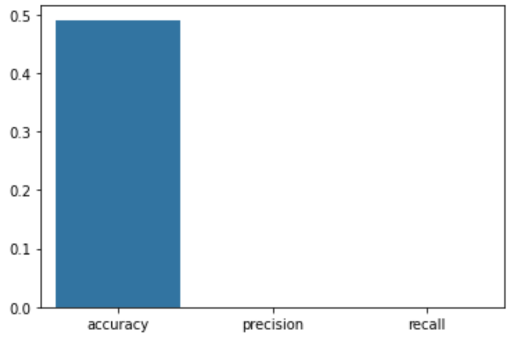
Support Vector Machine (SVM) is a Supervised Machine Learning algorithm that is used for regression and/or classification. Although it is occasionally quite helpful for regression, classification is where it is most often used. In essence, SVM identifies a hyper-plane that establishes a distinction between the various types of data. This hyper-plane is only a line in two-dimensional space.

Each dataset item is plotted in an N-dimensional space using SVM, where N is the total number of features and attributes in the dataset. Find the best hyper plane after that to divide the data. As a result, you must now realize that SVM can only conduct binary classification by nature (i.e., choose between two classes). But there are several methods for solving multi-class issues.

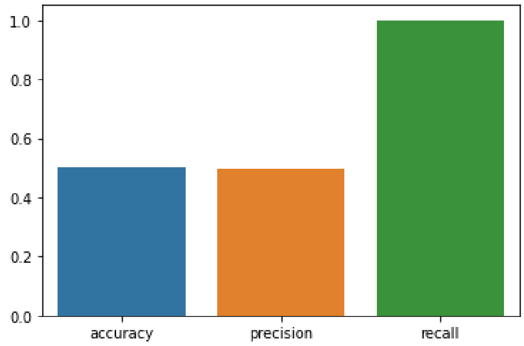
V. RESULTS AND DISCUSSION

The following screenshots are depicted the flow and working process of project.

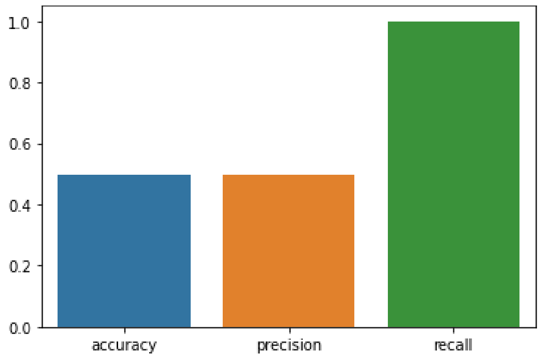
SVM Algorithm:



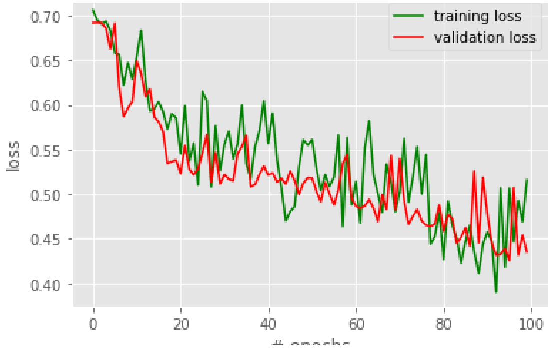
Random forest algorithm:



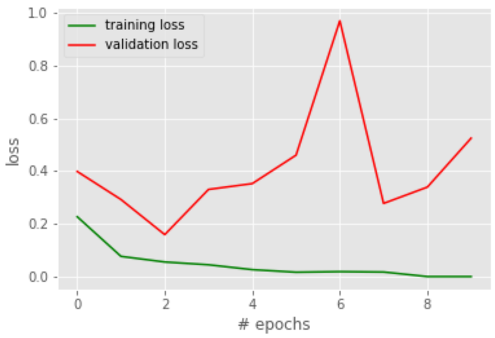
Decision tree algorithm:



CNN algorithm:



CNN with Transfer Learning (MobileNet)



VI.CONCLUSION

Lung cancer is among the most lethal illnesses that have ever occurred. Unfortunately, once the disease has spread or progressed significantly, it is very difficult to cure. One of the rapidly developing technologies, computer-aided detection (CAD), aids in the early detection of cancer by taking into account a variety of patient-related inputs, including scans like CT, X-ray, and MRI scans, patients' unique symptoms, biomarkers, etc. SVM, CNN, RF, DT, CNN-TL, and other techniques are utilised to increase accuracy and facilitate the procedure. We want to list all the significant studies that have been conducted in recent years that can be improved upon to provide better findings via the use of this review article.

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