LUNG CANCER DETECTION USING CNN ALGORITHM THROUGH DIGITAL IMAGE PROCESSING

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ABSTRACT

It is well knowledge that cancer is one of the leading causes of death worldwide, and that lung cancer is the worst form of the disease. Lung cancer has a far larger population at risk than many other major killers, such as cardiovascular disease. Therefore, the key to survival when dealing with lung cancer is early diagnosis. In recent years, Convolutional Neural Networks have been the subject of much study in the healthcare sector. One option for early cancer detection is image classification. Kaggle is first visited to get CT scan datasets. The pre-processing technique improves images. Two models, Manual CNN and Alex Net, will be trained on the picture dataset. The processed pictures will then be utilized to determine whether a CT scan image is malignant (cancerous), benign (noncancerous), or normal, based on the model with the best accuracy.

INTRODUCTION

Many people's health, happiness, and well-being are all negatively impacted by man-made dangers such pollution from cars and factories. The effects of this on the body, and the lungs in particular, are negative. Lung damage seems to be the second most common cause of death in men and the third most common cause of death in women. Eighty-five percent of all instances may be traced back to tobacco use and smoking, and this accounts for twenty percent of all deaths. Traditional methods, such as relying on professionals to review CT-scans, have been extensively used despite how time consuming they may be. As a result, state-of-the-art methods for autonomous illness detection were developed, including those based on Machine Learning, Big Data, or even simple image recognition. In this study, we use a variety of Machine Learning calculations and deep learning to focus on better recognizing cellular breakdown in the lungs using convolution neural organizations, as opposed to the conventional and antiquated methods that have been used in this area for the progression of cancer for decades. The method as a whole winds up being really helpful and well-liked in many various contexts. It benefits in several ways. The model learns to automatically hide highlights, which improves the likelihood of a positive result. It uses image and channel convolution to assign invariant highlights to the resultant layer. The cycle will continue until the desired harvest is achieved. To prevent the model from being wrong, hyper-boundary tuning may be applied to the layers in a similar fashion. Convolution refers to the process of doing mathematical operations between two processes in order to develop a third ability. The yield exercise may provide a figurative understanding of how well the two data charts correspond to one another. In general, the knowledge and bits used in an AI computation come from obscure sources.

Deep Learning

As a subset of artificial intelligence (AI) based on neural networks, deep learning may be thought of as a form of model of the human brain. It's getting a lot of attention now since there are signs that in the past, humans lacked the ability to effectively prepare for and make use of complex information. Neurons are often used as a metaphor for deep learning. Deep learning is a specific form of artificial intelligence that has achieved remarkable efficiency and adaptability by learning how to approach the world as a settled progression of theories, with each concept describing corresponding to more straightforward concepts and more conceptual portrayals processed as far as less theoretical ones. The human brain has somewhere about a hundred billion neurons, each of which is connected to many of its neighbors. How it does this replication of neurons in a computer is the question at hand. By doing so, it creates a bogus network of nodes and connections (a "fake neural net"). There are some input value neurons, some output value neurons, and maybe a dense network of hidden neurons in between.

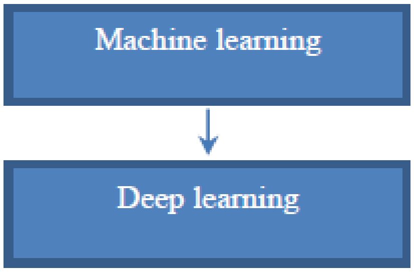

Figure 1: Introduction

In order to find the right response, it must first assess a certain complexity; this is important in itself, but it also serves to validate Deep Learning's value. The relevant information must be uncovered, and it must be structured such that it corresponds with the identified difficulty. Do it right and implement the Deep Learning Algorithm. Using this approach to train the dataset is recommended. A last round of testing on the dataset is required.

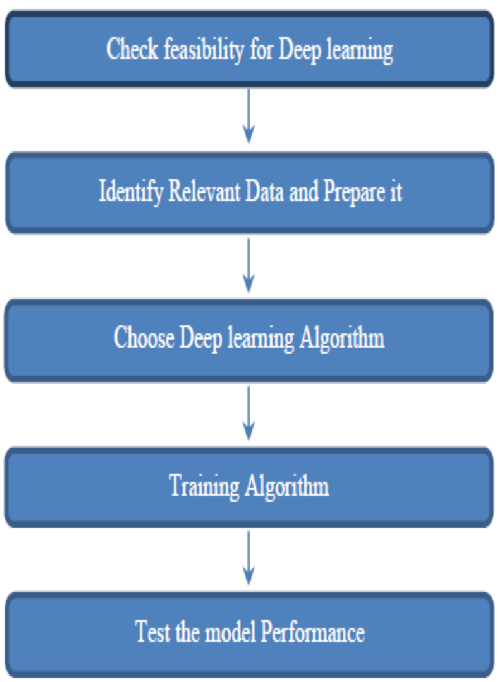

Figure 2: The process flow

1.2 Purpose

Existing system	Proposed system-
In the existing system, lung cancer dataset is trained on several models in the absence of a user interface.	The proposed model will be trained using the best accurate model which will be deployed on a web server as a user interface.

Table 1: Existing versus Proposed system

1.3 Problem Statement

The goal of this research is to apply deep learning methods to identify and categorize lung cancer CT pictures as normal, malignant, or benign, and to provide a user interface where an image may be uploaded as input and a diagnosis returned.

1.4 Requirement Analysis

Software Requirements

Operating System: Windows / Linux
Simulation Tool: Anaconda with Jupyter Notebook

Hardware Requirements

Processor: Pentium IV/III
Hard disk: minimum 80 GB
RAM: minimum 2 GB

2. LITERATURE REVIEW

The constructed Convolutional neural network can identify and detect nodules in the medical pictures; P. Monkam et al. presented a complete examination of several approaches based on this network. Models of CNNs include 3DCNN, 3D U-Net, 2DCNN, 2DCNNs, SVM, and Naive Bayes. The study begins with a quick overview of convolutional neural networks (CNNs) before diving into the specifics of several medical picture sources, such as LIDC/IDRI, LUNA16, and the Kaggle Data Science Bowl. It also details some of the current obstacles that hinder identification, such as amassing a big, properly labeled medical datasets. The research demonstrates that using CNN to identify nodules and classify them as cancerous or benign yielded outstanding results, lending credence to the strategy's potential for early diagnosis.
Second, H. Guo et al. suggested using a technique called KAMP-Net to make forecasts. For better prediction, KAMP-Net employs a collective architecture made up of characteristics collected using clinical information and features revealed by the Dual-Stream network (DSN). It does not depend only on AI-

generated features. It is shown that KAMP-Net outperforms competing approaches. This research presents Low-Dose Computed Tomography (CT), an alternative to X-ray that improves cancer detection and diagnostic accuracy and reduces cancer-related mortality. This paper presents a unique method that combines the CNN and SVM model to produce the final result.

About 1% of all erythrocytes are leukocytes found in bone marrow. Hematologic malignancies are possible if the white erythrocyte count is allowed to rise unchecked. D.Kumaret., in a separate study, developed a model that uses the deep learning method, convolutional neural network, to completely remove the possibility of error during the hand-operated phase. Images of cells are used to "train" the structure. The photos are first pre-processed, then features of interest are extracted. The augmented Convolutional neural network (CNN) template is then trained to identify the specific malignancy present in the cells. The total "97.2%" accuracy is far higher than what you'd get with an SVM or other machine learning method.

In 4.4, a system using a Convolution Neural Network was suggested by R. Y. Bhaleraoet al. The proposed study demonstrates the whole cycle of image processing, from gathering raw image data from repositories like LIDC, Kaggle, and LUNA16 to presenting the final processed picture. MATLAB was used for the preliminary image processing. The photos were pre processed, and the CNN model was trained to make predictions based on those images. The research suggests using CNN instead of other machine learning designs like Naive Bayes and Support Vector Machines since it yields better results. The suggested archetype attained an overall accuracy of 94.34%.

Fifth, a novel technique for identifying lung cancer was presented by M. B. Khumancha et al. The strategy relies on comparing and contrasting two data sets, data1 and data2. The LIDC/IDRI data set was utilized for nodule detection, whereas the Kaggle data set was used for cancer detection. The article created two Convolutional modules, the first of which is a CNN module used to identify nodules in datasets, and the second of which is a model used to identify malignant signs within those datasets. Accuracy was determined to be 90.78% based on the actual count, while precision was determined to be 89.24%.

In their article, Zheng,S. et al., employ MIP pictures and a Convolutional Neural Network to automatically identify lung nodules. The method presented in this study improves the chances of finding the nodule. It pioneered the use of MIP-Maximum intensity projection pictures, which aid in the detection of pulmonary nodules during CT-based magnetic resonance imaging evaluation. It is proposed to feed the CNN model MIP pictures instead of the standard CT scan datasets. The MIP images that were used to make the diagnosis of a lung nodule were of good quality because of their thickness. The precision of the system is proportional to its thickness. .Lung cancer has a high fatality rate, thus early identification is essential. In another article, Rajeswari worked on developing a method for determining the malignancy degree using a network of nodes called U-Net. This paper's primary objective is to provide a CAD system for nodule detection. Since there is already so much CT data available, CAD is being used to make the most of the powerful clinical support it offers. Extraction of the raw CT datasets is followed by pre-processing. An ROI mask is used for segmentation. The CAD system then receives all the pre processed data and detects individual nodules. Classifying nodules is completed, and false positives are reduced. The categorization will determine if the condition is malignant or not.

3.SYSTEM DESIGN AND ARCHITECTURE

3.1 General

The word "design" suggests a comprehensive visual representation of a future creation. Detailed below is the system design that constitutes the model's entire architecture.

3.2 Design architecture

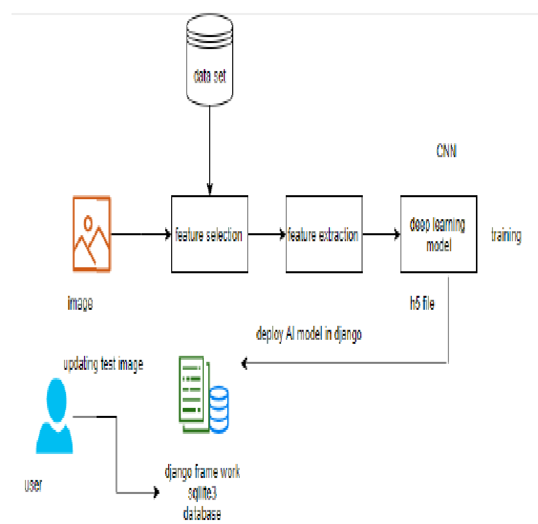

Figure 3: Design architecture of detection process

Specifically, data from "The Iraq-Oncology Teaching Hospital (IQ-OTH/NCCD)" are being gathered. The pulmonary dataset was collected and analyzed by radiologists at the aforementioned institution over the course of three months. The data set was located on the Kaggle platform. This dataset consists of annotated images and features separate "train" and "test" directories. In all, there are 1190.png pictures in the collection. There are three lessons in each of the folders. Normal, malignant, and benign instances are the three categories used to categorize these conditions. Models,2D CNN and AlexNet, are trained using the data set.The most precise model is then sent to Django, a user interface framework.

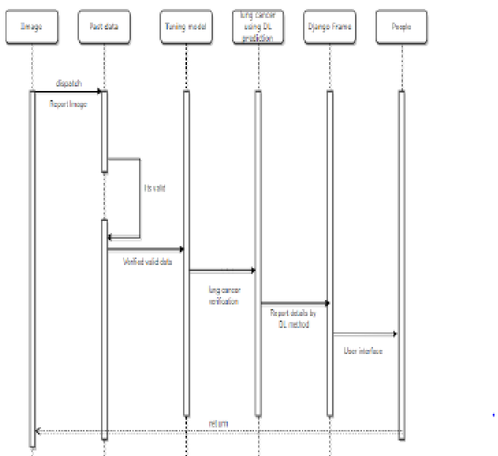

Figure 4: Sequence Diagram of lung cancer detection

3.3 CNN Model steps

The model (CNN) is trained using the learned dataset in order to identify the test picture. Several distinct CNN layers exist, including Convolution2D, Dropout, Dense, Flatten, MaxPooling2D, and Flatten. Once the model has been trained, it can be used to classify the lung cancer images in the dataset. After properly training and analyzing the dataset, the model is next compared to a test picture in order to provide a diagnosis.

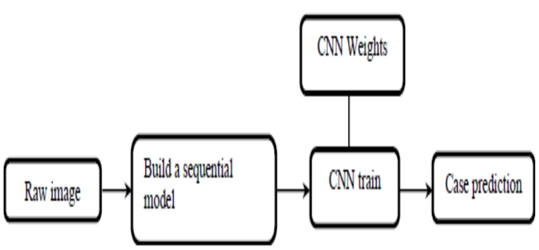

Figure 5: Model Architecture

Conv2D is an activation-function-driven layer that takes a single image and transforms it into a series of distorted images. For each layer beyond the first two in MaxPooling2D, we take the maximum of the matrix's calculated values. The picture is flattened to remove the waviness that resulted from the involving process. This dense layer is the key to the model's entire association. Dropout is used to prevent data-fitting, and the yield layer's single neuron determines which characterization image is utilized. The picture Data Generator is the process by which a picture is transformed by applying transformations such as scaling, shearing, zooming, and inverting the levels. This picture data generator combines every conceivable path in the image. Methods of Instruction: Designing information from the train_datasets stock is constrained by the train_data-gen.flow_from_directory threshold. The image's intended dimensions are shown in Target_size. Model test data is created using Test_data-gen.flow_from_directory, and the above is equivalent to it. The steps_per_epochs variable tells us what the model will do with the planned data and is utilized by fit_generator to fit the data into the model.

Time periods: It shows us how the forward and inverted passes of the model's setup procedure will go.

When incorporating endorsement/test data into the model, the validation_data variable is used. The number of endorsement/tests is indicated by the validation_steps variable.

3.4 Architecture

A convolutional neural network typically consists of an output layer, an input layer, a fully connected layer, and one or more convolutional layers. Input Layer: The picture must first undergo pre processing before it can be sent into the layer. This is why we use a hand-tunable input layer with its fixed dimensions. The datasets used for training, testing, and validating the model consists of 48x48 grayscale photos. Layers of Convolution and Pooling: Convolution and pooling are performed in bulk during the processing. CNN filter weights are changed in batches that comprise N images. For every convolution layer, we take an N-by-width-by-color-channel-by-height batch of input images.

Four-dimensional convolutions are established between image cluster and highlight maps at each convolution layer. After convolution, the only variables that shift are the image's width and height.

Calculating Image Width: (Initial Picture Width minus Channel Width plus 1)

Image height = original image height - channel height + 1 After down testing and sub sampling each convolutionlayer, also known as pooling, dimensional reduction is complete. Average pooling and maximum pooling are two well-known approaches to this problem. In this endeavor, we apply max pooling after every single convolution. Pools of size 22 are used to divide a picture into squares with a maximum of four pixels in each corner. After pooling, the only modified measurements are width and height. This structure makes use of two pooling layers in addition to convolution layers. The input picture has N1x48x48 dimensions at the first convolution layer. The image's dimensions are 48 pixels across and 48 pixels high. Each picture batch is N pixels in size, and there is just one color channel. A convolution with map 1 x 20 x 5 x 5 yields an image batch size of N x 20 x 44 × 44. After convolutional pooling is performed with a pool size of 2 x 2, the resulting image size is N x 20 x 22 x 22. After applying a second convolution layer, the final picture size is N x 20 x 18 x 18. The pooling layer that comes after the second convolution layer produces a picture with dimensions of N x 20 x 9 x 9.

Fully Connected Layer:

This layer is inspired by the nervous system, namely the brain's neuronal signal transmission. A huge number of input characteristics are collected. The characteristics are transformed by the trainable weights that are linked to the layers. Two concealed layers, of 300 and 500 units each, are used in fully linked layers. The layer weights are trained using forward data propagation, and any inaccuracies are corrected via backward data propagation.

The initial stage of backward propagation is to determine the discrepancy between the actual and forecaster values. Each weight adjustment is analyzed at each stratum. Many hyper-parameters, such as network density and learning rate, can be adjusted to modify the architecture's complexity and training time. This layer includes the hyper-parameters of momentum, regularization, learning rate, and decay. Second pooling layer yields Nx20x9x9, whereas the first secret layer's contribution to the entirely related layer is Nx500. The final result of the pooling layer is a resampled picture with dimensions of N by 1620. A subsequent hidden layer receives the input. It is the output of the first hidden layer that feeds the second. The second concealed layer is N times 300 in size. The output layer, into which the picture is input for classification, is given a number corresponding to the number of classes.

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Output Layer

The third kind of category exists in the output layer, which is linked to the output of the second hidden layer. The output probability of the three groups is utilized. The most probable category is used to make the prediction.

3.5 Modules

Module 1: Import the given picture from datasets

The ImageDataGenerator function in keras's preparation phase is required for the import of our data index, where we also do operations such as scaling, rotating, cropping, and magnification. At that point, we used the data generator to bring in our photo datasets from the organizer. Here we specify the abilities to train for and when to do so (train, test, approve), as well as the target size, training group size, and training style.

Module 2: To prepare the module by given picture datasets

Using a classifier and a fit generator that works similarly, we take preparation steps based on age, and then use the total number of ages, approval information, and preparation steps to finalize our datasets.

Module 3: Working interaction of Layers in CNN model

Deep Learning's Convolutional Neural Networks are algorithms that can take images as input, bias and weight various aspects of those images, and then use that information to distinguish one image from another. ConvNet, in contrast to other classification techniques, requires little processing time before it can be used. Unlike previous approaches, ConvNets don't need filters that are hand-engineered; instead, the algorithm can learn on its own with enough training. The human brain's visual cortex provided a rich source of inspiration for the design and operation of ConvNet. Neurons only react to stimuli within a certain region, and this area is called the receptive field. Their partnership requires 1,024 data units over four layers: 256 data units in the top secret layer, eight data units in the second secret layer, and two data units in the output layer.

Input Layer

This convolutional neural network layer stores specialized image information. Three-dimensional structures deal with visual data. The role of the input layer is to transform the image's dimensions into a single column. Let's pretend there's a picture with the dimensions "28x28=784"; before feeding it into the input, it has to be transformed into a single column.

Convolution Layer:

The convolution layer is sometimes referred to as the "feature extractor layer" since it is responsible for removing the image's features of interest. First and foremost, an image segment is linked to the Convo layer in order to carry out a complicated action, as shown before. Between the open fields and the channel, it calculates the speck item. The result is a single whole number representing the output. Then, repeat the procedure using a Stride to channel through the subsequent responsive field of a similar information picture. It will cycle over the whole picture again rehashing the same interaction.

Pooling Layer:

After convolution, the pooling layer reduces the image's spatial volume. In between the first and second convolution layers is a pooling layer. When a fully connected layer follows convolution, but not a pooling layer, Depending on the complexity of the layer, extensive processing power may be needed. Therefore, max pooling is the only method for reducing an input image's spatial volume. In a single depth slice, max pooling has been implemented with a stride of two. A 4 × 4 input is reduced to a 2 x 2 output, as can be seen.

Fully Connected Layer (FC):

Layer loads and angles are fully related. Each neuron in a fully connected layer is linked to those in the layers belowit. It may be used to sort photographs into several categories after being trained on how to do so.
Layer of Output: The name is encoded in the last layer using a one-hot encoding scheme.
Module 4: Model Deployment in Django Framework and ROI Expectations
This section takes the completed deep learning model and converts it into an information design document (.h5 record) that can be used in our Django system to improve the user interface (UI) and predict the outcome for benign, malignant, and normal cases, respectively.

4. IMPLEMENTATION

4.1 Algorithm

The model will use CNN (convolution neural networks), which has been shown to outperform other machine learning methods such as Naive Bayes, Support Vector Machine (SVM), and Random Forest. The CT-Scan image dataset and the output tag are the inputs to the CNN algorithm, which then automatically performs feature extraction. The convolutional layers provide the features and parameters to be used during training.

4.2 Image Data Augmentation

Data augmentation may be used to supplement a dataset with additional images to help with class imbalance. In order to prevent the model from being under trained, this technique is used to increase the number of samples of each image in the dataset. The training set's diversity might be enhanced by applying image alteration techniques like flipping, rotating, and stretching.

4.3 Convolution Neural Network (Manual CNN)

The training parameters are denoted by the Convolution Neural Network (CNN) bands. Improving the quality of input data and making Convolution Neural Network (CNN)-based operations dependent on exceptional training may both increase their reliability. The shown Convolution Neural Network is also a critical factor in improving performance. Extra bands indicate very high levels of training. The following are some of the most crucial components of a Convolutional Neural Network:
The first layer, a box-shaped array of pixels known as the "input layer," contains the information that is sent into the networks. Input data is fed into the next layer, which is called the convolutional layer, whose primary job is to pull out the image's highlights. Truly, this segment of CNN is unparalleled. The convolutional layer is made up of a sequence of kernels that must perform convolution. Lower-level features are taken from the input by the first few layers, while more complex features are extracted by the deeper layers. Third, a "activation layer" that introduces intermittent behavior and facilitates sophisticated data learning. This model's foundational function, ReLu, bestows a constant gradient supervision rate onto the CNNs throughout training. Degradation of dimensions takes place at the fourth layer, called the max-pooling layer. Assumptions might be made about the domain in which maximum pooling must be performed. The first step in MPL is to apply a max filter on the area that does not cross the original sector. Cascades of layers, including Convolutional, Activation, and Max-pooling, are used to achieve attribute extraction. A malignant (cancerous), benign (non-cancerous), or normal outcome may be predicted from an input picture using the suggested CNN model.

4.4 AlexNet Deep Learning Model

AlexNet is a sophisticated and very effective pre-trained model that was developed using the 15 million annotated photos and 21,000 distinct classes that make up the ImageNet dataset. The overall number of layers of AlexNet is 8, consisting of 5 convolutional layers and 3 fully linked layers. Two GPUs are required for initial performance. Modern AlexNet implementations, however, often rely on a single GPU.
AlexNet employs ReLu-Nonlinearity rather than tanh-Nonlinearity.

The model is more time-efficient because to the ReLu function. Due to the size of the dataset, AlexNet may split the neurons in two and train them on separate graphics processing units (GPUs). As a result, more complex models may be trained in less time. Manual CNN and AlexNet will undergo a thorough evaluation against one another. In order to further categorize the input picture into malignant, benign, or normal Equations, the model with the best accuracy and minimal loss will be selected.Depending on the complexity of the layer, extensive processing power may be needed. Therefore, max pooling is the only method for reducing an input image's spatial volume. In a single depth slice, max pooling has been implemented with a stride of two. A 4 × 4 input is reduced to a 2 x 2 output, as can be seen. Fully Associated Layer (FC): The FC layer contains loads and angles. Each neuron in a fully connected layer is linked to those in the layers below it. It may be used to sort photographs into several categories after being trained on how to do so. The name is encoded in the output layer using the one-hot encoding method.

Module 4: Model Deployment in Django Framework and ROI Expectations

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4.5 Steps

4.5.1 Preparing from Scratch:

You need to compile a massive marked informative index and create an organization layout to become acquainted with the highlights and model before you can produce a profound organization from scratch. This is helpful for novel applications or those with a high expected yield class diversity. Organizations often need days or weeks to prepare for this approach because of the vast amount of knowledge and the rapid rate of learning.

4.5.2 Transfer Learning:

Numerous deep learning implementations make use of exchange learning. A loop in which a pre-trained model is tweaked. New data with previously unlabeled classifications is fed into an existing network structure, such as AlexNet or Google Net. If you rearranged the filing system, for instance, you could switch to categorizing just dogs or cats instead of a thousand different objects. The processing time is reduced to a matter of hours or minutes, and it needs much less expertise (in the form of preparing numerous photographs rather than millions).

4.5.3 Feature Extraction:

Deep learning, however less prevalent, may be addressed more narrowly by treating the company as a component extractor. At the time of the cycle of preparation, we are able to retrieve the features that were extracted from each layer. This means that the attributes may be utilized to improve artificial intelligence models like support vector machines.

4.6 Libraries

numpy: For Managing Image Arrays

Os.In order to see the image from the train and test catalog on our computers, we must first enter the record framework.

random: To reorganize data in order to counteract biasing Our foresight outcome may be visualized using matplotlib. Simply use the Tensor Board in tensor flow to reflect on the calamity and Adam Bend our result data or acquired log.

4.6.1 Numpy:

The term "Numerical Python" has been shortened to "NumPy." It's a Python development module that's freely available to the public and provides rapid precompiled capabilities for numerical and mathematical schedules. In addition, NumPy enhances the Python programming language with fantastic data structures enabling practical calculation of multi-dimensional clusters and structures. The implementation is unfazed, concentrating on enormous screens and cross sections. To further chip away at these lattices and displays, the module provides a vast library of high-level mathematical skills. It's the main package for Python's smart enrollment system. Among its many advantages are an excellent N-dimensional display object, advanced (broadcasting) limitations, practical direct polynomial mathematics, the Fourier Transform, and ad hoc number capacity tools like Numpy Array. A tuple of non negative integers may request a numpy bunch, which is a subset of characteristics and the sum of a comparative type. The group's position is represented by the number of estimates. A group's condition is a tuple of whole integers that specifies the size of the representation along each estimate.

5. RESULT AND ANALYSIS

5.1 Output

Both the 2D CNN and the Alex Net CNN models are trained using the same data. Cases are classified as benign, malignant, or normal using the trained model, which is then deployed in the Django framework. The final product of the model's implementation is utilized to identify and classify lung cancer.

Table 2: Validation accuracy of each model

MODEL	ACCURACY
Manual CNN	96.88%
AlexNet Architecture	51.56

- The validation accuracy after CNN model training is 96.88 percent.
- The final measured accuracy after training the Alex Net model is 50.79.

MANUAL CNN METRICS

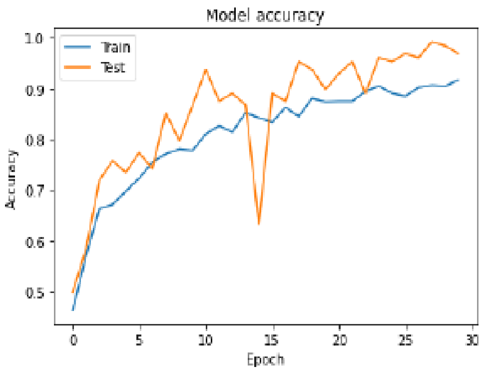

Figure 6: Manual CNN: Epoch versus accuracy graph

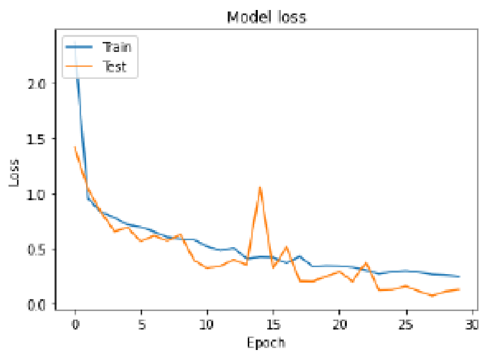

Figure 6: Manual CNN: Epoch versus accuracy graph

The following two graphs demonstrate the training and testing losses and accuracy of a Manual CNN. With each passing epoch of training and testing, the model's accuracy improves as the loss decreases.

ALEXNET CNN METRICS

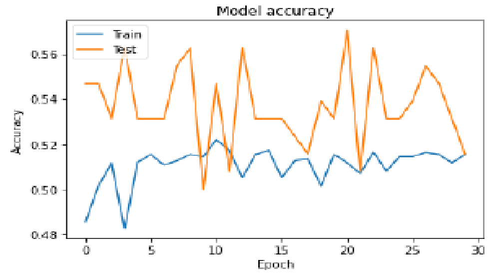

Figure 8: AlexNet CNN: Epoch versus accuracy graph

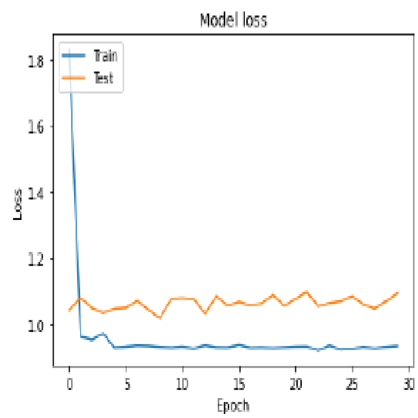

Figure 9: AlexNet CNN: Epoch versus loss graph

The accuracy of the AlexNet CNN model varies significantly between training and testing. The model's accuracy rises and falls, but its value stays in the range of 0.54 to 0.56. Model loss during training and testing, on the other hand, was shown to be consistent between 1.0 and 1.2.

DJANGO FRAMEWORK

After determining that Manual CNN is the most accurate trained deep learning model, we will install it in the Django framework, where it will be used to power the user interface and make predictions. Here's how the structure works:

1: Input CT Image
2: Upload test image
3: Click upload
4: Image data visualization will be done
5: Click on Result

Figure 10: Django-based user interface result template

6.CONCLUSION AND FUTURE WORK

6.1 Conclusion

The greatest strategy to reduce the fatality rate from lung cancer is by accurate categorization and early diagnosis. For the purpose of evaluating nodules in CT scans (Medical imaging), two CNN-based algorithms have been presented. This paper's goal is to utilize a user interface framework to implement the best model available for detecting lung cancer. Kaggle is mined for CT scans, and then image augmentation is used to improve the quality of the data sent into our model. The cancer-predictive CNN model is trained both manually and using AlexNet. Deep Learning is a cutting-edge sub field of AI research that is paving the way for more efficient Convolution Neural Network-based software. The approach that is being planned will also take into account the capability of transformation and the temporal law of the mechanism for identification of cancer. The suggested system is based on a convolutional neural network (CNN) model, with the goals of improving accuracy, minimizing processing time, and maximizing efficiency in the process of cancer diagnosis. Manual convolutional neural networks (CNNs) were used to identify the nodule, and the results showed exceptional accuracy, making this a potentially useful technique for early diagnosis. Therefore, we calculate accuracy and loss and find that Manual CNN provides the highest accuracy (around 96.88 val accuracy) compared to AlexNet (around 51.56 val accuracy).The model with the best combination of accuracy and loss is then selected for prediction. Django was used to deploy the Manual CNN, and the output was shown.

6.2 Future Scope

More progress can be made on CNN models to improve early detection and management of lung cancer, which could theoretically lower its censorious death rate. With efficient hyper parameter tuning, many knowledge-based models may be trained on a bigger datasets, and then the model with the highest accuracy can be utilized for prediction. The accuracy of the AlexNet CNN model may be improved by training it on a big datasets. AlexNet CNN model development for analysis alone, including tuning of hyper parameters and a novel data structure. Additional cutting-edge methods may be integrated later on. Enhanced image processing allows for better data collection. Prediction results may be shown in a web application or a desktop program for real-time deployment of the model. To further optimize the effort, the implementation may be done in an AI environment. Additionally, the CNN model can be broadly contrasted with other transfer-learning models.

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