DIAGNOSIS OF LUNG CANCER BASED ON CT SCANS USING DEEP LEARNING AND WEB APPLICATION

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Abstract. The early detection of lung cancer, which is the second most lethal type of cancer worldwide, plays a vital role in improving patient survival rates. The research introduces a lung cancer detection system that operates independently through deep learning techniques which evaluate Computed Tomography (CT) scan images. The development of a Convolutional Neural Network (CNN) model enables automatic subject identification through CT image processing which produces normal and malignant output results. The system uses image preprocessing and segmentation together with deep learning methods to classify images which results in better diagnostic results. The web-based application receives the trained model through Python Flask framework which allows users to upload CT scan images for instant diagnostic results. The proposed CNN model achieved 94.7% accuracy, 92.1% precision, 90.5% recall, and 91.3% F1-score during the evaluation of the labeled CT scan dataset which demonstrated its ability to detect lung cancer patterns. The proposed system functions as a dependable computer-aided diagnostic solution which helps healthcare professionals identify lung cancer at an early stage. The deep learning model, when combined with a web-based interface, enhances real-time medical analysis through its ability to provide easier access and support larger operational scales.

Keywords: Lung Cancer Detection, CT Scan Analysis, Deep Learning, Convolutional Neural Network, Medical Image Processing, Web-Based Diagnostic System

1 Introduction

Pulmonary carcinoma remains among the most prevalent and aggressive oncological conditions globally, representing a substantial proportion of cancer mortality statistics. The prognosis for affected individuals deteriorates markedly when identification occurs during advanced disease progression, underscoring the critical importance of timely discovery [1]. Current diagnostic protocols relying on visual interpretation of axial tomographic images by clinical radiologists present several limitations, including interpretive variability, substantial time investment, and dependence on specialist availability. These challenges become particularly pronounced given the exponential growth of medical imaging data volumes in contemporary healthcare systems [2]. The emergence of sophisticated computational intelligence methodologies has revolutionized medical image interpretation capabilities. Neural network architectures, particularly those employing convolutional operations, have demonstrated exceptional proficiency in extracting diagnostically relevant features from complex imaging data. These algorithmic systems progressively learn hierarchical representations of visual patterns, enabling identification of subtle pathological indicators that might escape human perception [3]. Such technological advancements create opportunities for developing decision-support systems that enhance diagnostic precision while optimizing clinical workflows. This research initiative focuses on creating an automated diagnostic framework for pulmonary malignancy identification using cross-sectional thoracic imaging.

Artificial Intelligence (AI) is the far most advanced technology pioneering in the functions of logical reasoning, handling decisions, brain like cognitive functions by training its model with huge data sets which are available over different domains. By having a better variance over large data sets the AI models have a better capability over analyzing complex patters, understanding languages, clearing larger problems with a better precision [4]. This way of AI work is now re-vamping all industries to reach a different dimension in today's competent world to solve real world problems in a very easier way. AI can also be categorized into general and specified category based on their nature of work and the problem it takes to solve. It often takes more complicated tasks and performs a predictive algorithm to approximate the results which in-turn give a better viability over the generated results [5]. These algorithms learn their predictive patterns based on the input data's give to the module. When the system is trained based on the large data models it has a better viability

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over the produced results. This technology is used to train the AI models which enhances the result prediction. Under normal way of training the data sets it uses revolutionary patterns of programming [6]. When an ML system is used for training the data set, it uses the meaning insights from the received information and also it processes the data set with increasing data progression [7].

This type of advanced training model makes the system More than half of all cancer deaths that occur throughout the world originate from lung cancer because early detection practices demonstrate a critical role in inducing patient survival outcomes. Lung cancer screening procedure employs Computed Tomography (CT) imaging because it enables the creation of precise lung nodule and lung tissue defect visual representations. Radiologists face difficulties with CT scan interpretation because screening procedures generate an excessive amount of imaging data which results in multiple diagnostic outcomes.

Deep learning progress together with medical image analysis progress has created CAD systems which enable finding of lung cancer. Convolutional Neural Networks (CNNs) perform automated learning from medical images by establishing essential features through image analysis without requiring anyone to create those features manually. Automated diagnostic systems depend on deep learning methods to assist radiologists in detecting malignant lung nodules with improved accuracy and speed which results in earlier clinical treatment and enhanced patient results.

2 Existing & Proposed Methods

2.1 Existing Methods for Lung Cancer Diagnosis Using Computer Tomography scans

Lung cancer analyses on manual detection methods using CT scans used by radiologist are subjected to human error. Conventional computer-aided diagnosis (CAD) systems use machine learning techniques like Support Vector Machines (SVM) and Random Forests to classify lung nodules [12]. These methods depend on handcrafted features such as shape, texture, and size, which may not capture complex patterns effectively [13]. The eminent Deep learning models like 2D CNNs have improved accuracy but often process CT scans slice-by-slice, ignoring 3D contextual information. Some approaches use U-Net architectures for lung nodule segmentation but struggle with false positives. Another limitation is the lack of real-time web inte-gration, making it difficult for doctors to access AI-assisted diagnostics efficiently. Existing systems also face challenges with small datasets, leading to overfit-ting and reduced generalization.

2.2 Proposed Method with Deep Learning-Based Lung Cancer Diagnosis with Web Integration

This introduces a 3D CNN-based deep learning model to analyze CT scans in volumetric form, improving nodule detection accuracy [14]. The model leverages transfer learning from pre-trained networks (e.g., ResNet3D) to enhance feature extraction. Additionally, a hybrid approach combining segmentation (U-Net) and classification (DenseNet) reduces false positives. We use here the CNN technique is the most widely used technique for designing AI systems. It produces an intrinsic approach for solving a problem. It uses object-based data classification method to process the algorithm design. It also holds good predictive model for image-based analysis. The layers in the CNN which includes, CN Layer, which forms the core building block of a CNN and this layer. Activation Function (ReLU) introduces non-linearity by replacing negative values with zero. This helps the model learn complex patterns efficiently. Pooling Layer (Max/Average Pooling), where Pooling minimizes spatial dimensions maintaining essential features. Max pooling selects the highest value in a window, making the network invariant to small shifts. Fully Connected Layer in which the layer connects every neuron from previous layers to classify the image based on extracted features.

Computation Procedures: First, the CNN receives an image (such as a 32x32 pixel RGB image) that is fed into the model [15]. Convolutional layers are then used to extract the image's features, and filters are applied to identify edges, textures, and forms. Next, is the non-linearity, herein the ReLU activation enhances feature learning. Followed by, Down sampling, where the pooling re-duces dimensions while preserving key features. Finally, the Classification is done where the fully connected layer predicts the output (e.g., "cat" or "dog").

3. Methodology & System Architecture Model

3.1 Pre-Processing of input image

The performance of DL (Deep learning) models suffers because medical CT scan images contain noise together with intensity changes and non-essential body parts. The research team conducted preprocessing operations to enhance image quality while maintaining image consistency before delivering data to the (CNN) system. This preprocessing pipeline includes four steps which involve noise reduction followed by intensity normalization and resizing before the system conducts lung region segmentation.

3.1.1. Noise Reduction

CT images may contain noise which originates from imaging devices and patient movement and the conditions during acquisition. The team applied Gaussian filtering to the CT images in order to reduce noise while maintaining essential structural elements of the images. Gaussian filtering creates a smoother image by decreasing high-frequency noise yet it preserves crucial information about edges. The Gaussian filter is mathematically defined as

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where:
x, y - represent pixel coordinates
σ- represents the standard deviation which controls how much the smoothing effect should operate
The process of filtering enhances image clarity while it improves lung nodule detection by making features easier to identify.

3.1.2. Intensity Normalization

CT scan images display different intensity values because various scanning devices and acquisition parameters produce different results. The researchers needed to establish dataset uniformity, so they conducted intensity normalization operations throughout the dataset. The team established a standard range for pixel values which resulted in decreased image variability across different images. The process of normalization uses this equation for its execution::

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}}$$

where:
I_{norm}- represents the original pixel intensity
I_{min} & I_{max}- represent the minimum and maximum pixel values
This step improves model convergence and ensures stable training of the deep learning model.

3.1.3. Image Resizing

Deep learning models require all input data to match a specific predetermined size. The research team made all CT scan images match a standard resolution of 224 × 224 pixels. The process of resizing maintains uniform input dimensions throughout the dataset while it decreases the model training process need for computational resources.

3.1.4. Lung Region Segmentation

The researchers used lung region segmentation to separate lung tissues from adjacent body structures which include bones muscles and background areas. The model uses segmentation to focus on the pulmonary area which contains lung nodules that usually appear.

The researchers employed threshold-based segmentation techniques together with morphological operations which included erosion and dilation to conduct their segmentation work. The operations refine lung boundaries while they remove tiny artifacts which can disrupt feature extraction processes.

3.1.5. Data Preparation for Deep Learning

The team converted segmented lung images into a standardized dataset which they used to create their training and testing subsets after finishing preprocessing work. The processed images became the input material which the CNN is used to extract features and perform the defined tasks.
The preprocessing pipeline significantly enhances image quality which enables the CNN model to receive pure and consistent input data for improved accuracy in lung cancer detection.

3.2 Segmentation and Classification Framework

The lung cancer detection system proposed for this study operates through two primary phases which include lung region segmentation and deep learning-based classification. The system uses these two components to accurately detect malignant lung nodules in CT scan images.

3.2. 1 Lung Region Segmentation

Segmentation represents an essential preprocessing step which enables the extraction of the lung region from all other anatomical structures visible in CT images. The process decreases background interference which enables the classification model to identify essential lung tissues.

The CT scan image gets processed by converting it into grayscale format before applying intensity thresholding to distinguish lung tissues from all other body parts. The thresholding operation can be expressed below:

$$S(x,y) = \begin{cases} 1, & \text{if } I(x,y) > T \\ 0, & \text{otherwise} \end{cases}$$

where :

I (x,y) - represents the pixel intensity
T - represents the threshold value
S (x,y) - represents the segmented output

Morphological operations which include erosion and dilation function to eliminate tiny artifacts while they enhance the lung area boundary definition. The process uses operations to remove noise which leads to better segmentation results. The system uses ROIs to extract segmented lung regions which will undergo further evaluation.

3.2.2 Feature Extraction Using CNN

The system sends the segmented lung images to the convolutional neural network so it can extract their features. The CNN learns to identify CT image features which include edges and textures and patterns that show lung nodules. Convolutional layers use their learnable filters to extract spatial features while pooling layers operate to decrease spatial dimensions yet preserve critical spatial details. The system uses extracted features to create advanced representations which the system will use for classification tasks.

3.2.3 Lung Cancer Classification

The system uses feature extraction to create feature maps which get transformed into fully connected layers for final classification. The network predicts whether the CT scan image corresponds to a normal lung condition or a malignant lung condition. The final prediction emerges from applying softmax activation. This function generates probability values for each possible classification.

$$P(y = i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

The system selects the class with maximum probability to make its final model prediction.

3.3 Proposed Architecture Model

The first phase in the architecture is the Data Collection, where in this phase all the image data sets are collected from the CT Scan machine which forms as the input for the system. It is then fed to Data Pre-Processing phase where it performs the data filtration process which cleans the data without any sort of spatial noises and also the Gaussian noise. Next phase is the Segmentation, here the image is then segmented and it is divided into small chunks of data pixels which are then processed further for computation. Next it is fed to Data Set Training phase where the small chunks of data are then used for designing the Deep Learning models which uses various ML techniques to re-wire the trained model to produce a robust predictive data set by using CNN's. These data set makes the model to be more viable in data predictions. Finally, it is then fed to a UI design - Python Flask Frame work is framed using a web application where the user can up-load the image for analysing the data classification. Once the image is uploaded, it then takes up the saved algorithm for image prediction and it classifies the up-loaded in "Normal" or "Abnormal" and intimate the user. The overall model is shown in Fig-1.

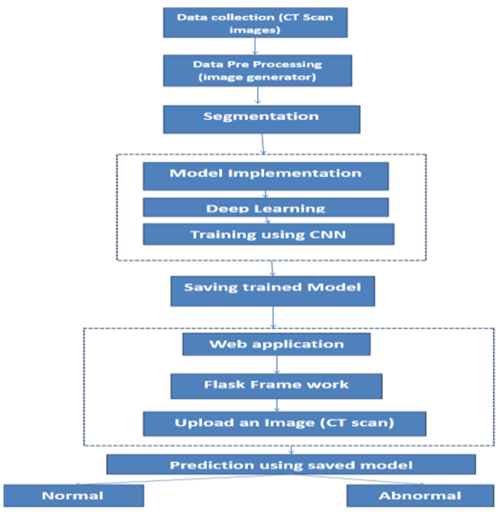

Fig 1 – Model of the Proposed Architecture

3.3.1 Convolutional Neural Network Architecture

This uses (CNN) structure which automatically obtains distinct features from CT scan images for classifying the images into normal and malignant categories. CNNs function as optimal tools for medical image analysis because they enable automatic development of hierarchical feature representations which do not require manual creation of features. Convolutional, activation, pooling, fully linked, and final classification layers are among the layers that make up the suggested CNN architecture.

3.3.2. Convolutional Layers

This operates as essential component which enables the CNN to unwind spatial features from the CT images by detecting edges and textures and patterns. In order to capture both low-level and high-level picture characteristics, the study makes use of several convolutional layers.

The convolution operation can be expressed as:

$$F(i,j) = \sum_{m} \sum_{n} I(i+m, j+n) K(m,n)$$

where,

i-represents the input image
k-represents the convolution kernel (filter)
F(i,j) - represents the output feature map

The proposed model operates through:
Conv Layer 1: 32 filters, kernel size 3×3
Conv Layer 2: 64 filters, kernel size 3×3
Conv Layer 3: 128 filters, kernel size 3×3

The layers in this system progressively obtain deeper image features which relate to lung nodules.

3.3.2. Activation Function

The network achieves nonlinearity through the application of the Rectified Linear Unit (ReLU) activation function which follows each convolutional layer. The ReLU is denoted as:

$$f(x) = max(0, x)$$

ReLU improves training efficiency which enables the network to acquire complex image patterns.

3.3.4. Pooling Layer

The pooling layers function to decrease the spatial dimensions of feature maps while they maintain essential information. The study uses max-pooling layers which operate with a pooling size of 2×2 as a standard procedure after every convolutional layer. Pooling operations enable systems to decrease their computational load while they maintain their ability to function under different input conditions.

3.3.5. Fully Connected Layers

The system requires that extracted features from convolutional layers be transformed into a flat representation which then moves to completly connected layers for the execution of classification through high-level reasoning. The proposed model includes:

Fully Connected Layer 1: 128 neurons
Fully Connected Layer 2: 64 neurons

Dropout regularization prevents overfitting through its application during the training process.

3.3.6. Output Layer

The softmax classification layer at the final layer predicts whether the CT image shows a normal lung or malignant lung condition. The softmax function computes output probabilities through this method:

$$P(y = i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

The output scores function transforms into probability values which serve as the basis for classification.

3.3.7 Parametric Function of CNN

Table 1 – CNN Function Parameter

Layer	Details
Input	CT scan image of size 224 × 224
Convolution Block 1	32 filters with 3×3 kernel, followed by ReLU activation
Pooling 1	Max pooling with a 2×2 window
Convolution Block 2	64 filters with 3×3 kernel, followed by ReLU activation
Pooling 2	Max pooling with a 2×2 window
Convolution Block 3	128 filters with 3×3 kernel, followed by ReLU activation
Pooling 3	Max pooling with a 2×2 window
Dense Layer 1	Fully connected layer containing 128 units
Dense Layer 2	Fully connected layer containing 64 units
Output	Softmax layer for multi-class prediction

3.4 Model Training Parameters

The convolutional neural network was developed through training with multiple optimized parameters which resulted in stable learning performance together with enhanced classification results. The training process was executed through the Python deep learning framework which used specific optimization techniques for its execution.

The network weight updates were synchronous Adam optimizer which used adaptive training methods together with momentum-based optimization methods. The begining learning rate was subjected to 0.001 which enabled efficient model convergence throughout the training process. The model was trained using a batch size of 32 photos each iteration after the dataset was split into training and testing sets. The selected batch size offers a training method which maintains both computational efficiency and training stability.

The network underwent 50 epochs of training which enabled the model to acquire essential CT image features through multiple learning cycles.

Binary cross-entropy loss function was employed during training to assess classification errors between expected and actual labels. It is defined as

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

where,

y_i - represents the true class label
p_i - represents the predicted probability
N- represents the total number of training samples

The training used dropout regularization in its completed connected layers with a 0.5 dropout rate to achieve better model generalization while avoiding overfitting problems. The training process used validation data to track model development toward stable convergence.

3.4.1 Training Configuration Summary

Table 2 – Training Configuration

Parameter	Value
Optimizer Algorithm	Adam Optimizer
Start Learning Rate	Setting to 0.001
Tag Batch Size	32 Samples
No. of. Epochs	50 trails in datasets
Loss Function	Binary Cross Entropy for binary
Regularization Tech	0.5 to reduce overfitting
Input Dimension	224 × 224 size before training

3.5 Performance Evaluation Metrics

The proposed deep learning model performance evaluation used standard evaluation metrics to assess its performance. The confusion matrix generates these metrics through its four essential elements:

The expression **"True Positive" (TP)** describes instances in which the algorithm accurately classifies lung pictures as cancerous. When normal lung pictures are accurately categorized as normal, they are referred to as **True Negative (TN).** When normal lung scans are mistakenly categorized as cancerous, the system raises a false warning, known as a **False Positive (FP).** When malignant lung pictures are mistakenly categorized as normal, the model is said to be **False Negative (FN),** indicating that cancer is not detected.

This performance metrics are calculated from the given values.

3.5.1 Accuracy

The accuracy of the model determines its ability to correctly identify both normal and malignant cases.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

3.5.2 Precision

The precision of the model shows the percentage of predicted malignant cases that were actually found to be malignant.

$$Precision = \frac{TP}{TP + FP}$$

3.5.3 Recall (Sensitivity)

The model's capability to find genuine malignant cases is assessed through its recall and sensitivity metrics.

$$Recall = \frac{TP}{TP + FN}$$

3.5.4 Specificity

The training capacity to accurately diffrentiate normal cases from other cases is evaluated through specificity.

$$Specificity = \frac{TN}{TN + FP}$$

3.5.5 F1-Score

The F1 score presents the harmonic mean, which delivers a comprehensive evaluation of classification effectiveness.

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

3.6 Data Set Selection

The study used CT scan images which researchers obtained from the public LIDC-IDRI dataset that scientists use to study lung nodule detection. The dataset contains annotated thoracic CT scans which multiple medical institutions collected from their patients. The study selected CT images that showed normal lung conditions and malignant lung nodules to use for model training and evaluation.

The dataset got divided into two parts which included 80 percent for training purposes and 20 percent for testing purposes. The convolutional neural network model used eighty percent of the photos for training and twenty percent of the photos for performance evaluation. The dataset enables the suggested model to learn key characteristics of lung nodules which help it to differentiate between normal CT images and pathological CT images..

3.7 Comparison with Existing Methods

The proposed CNN-based lung cancer detection model has undergone evaluation through comparison with existing techniques which researchers have published in scientific articles. The Support Vector Machine (SVM) in traditional machine learning systems depends on manual feature extraction which fails to identify the intricate patterns present in CT scan images. Deep learning models achieve superior lung cancer detection performance through their Convolutional Neural Networks (CNNs) which enable them to learn medical image features at multiple hierarchical levels. The researchers tested the proposed CNN model against existing methods by using the same dataset and they assessed both systems with standard performance metrics.

Table 3 – Comparison with Existing models

Method	Accuracy	Precision	Recall	F1-Score
SVM-Based CAD System	85.2%	83.4%	82.1%	82.7%
Conventional CNN Model	91.3%	89.8%	88.6%	89.2%
Transfer Learning Model	92.5%	90.7%	89.4%	90.0%
Proposed CNN Model	**94.7%**	**92.1%**	**90.5%**	**91.3%**

4. Web application implementation using "FLASK"

The web application needed to detect the cancer through its accessible interface which developers built using Python Flask. Flask provides developers with a compact web framework that simplifies the process of creating machine learning web services which enable fast model deployment.
The web application consists of three main components which include the user interface and backend processing module and prediction engine.

4.1 User Interface

The frontend interface allows users to upload CT scan images through a web browser. The user interface is designed with HTML, CSS, and JavaScript, making it simple for users to upload their photos..

4.2 Backend Processing

The application uses Python Flask framework to build its backend system. The user CT scan image upload process starts when the Flask server receives the image through HTTP request delivery. The system processes the uploaded image by sending it to the preprocessing module which conducts operations that include noise removal and normalization and resizing.

4.3 Model Prediction

The trained convolutional neural network model receives the image after preprocessing to extract features and classify the data. It analyse the condition as normal or malignant.

4.4 Result Display

The Flask server receives the prediction result which then appears on the web interface. The system provides a clear output which shows the predicted lung condition to users who need to understand the results easily.

5. Workflow between CNN Model and Web Interface

The system requires a web interface to display its results while processing CT images through the convolutional neural network model. The web application shares its workflow with the trained model to create a user interface that connects with the prediction module. The user begins by accessing the web application through their web browser to upload a CT scan image using the available graphical user interface. The uploaded image is transmitted to the server through an HTTP request handled by the Flask framework. The Flask server receives the uploaded image file which it stores before passing the file to the preprocessing module. The image undergoes preprocessing which includes noise reduction, normalization, resizing, and lung region segmentation to prepare the image for the upcoming analysis stage.

The trained convolutional neural network model, which is stored in the Flask environment, receives the processed image after that. The model processes CT scans to extract information which it uses to determine whether lungs are malignant or normal. The system produces a forecast which it transmits back to the Flask server for presentation on the user interface. The web application displays both the expected category and the classification result obtained from the provided CT scan image.

6. Results and Discussions

Here, we use Python framework called as Flask which is a web based framework written in Python script, designed to be simple, flexible, and lightweight. Unlike full-stack frameworks like Django, Flask provides only the essential components needed for web development, allowing developers to add extensions as required. It is ideal for small to medium-sized applications, REST APIs, and prototyping. The main objective of using the Flask Framework is Minimalistic & Easy to Learn, Built-in Develoment Server & Debugger, Jinja2 Templating Engine, RESTful Request Handling and extensible with Flask Extensions. While Flask is minimal, it can be extended using libraries like Flask-SQL Alchemy (for databases). In these cases, the python frame work is used for its analysis and they also used for the image prediction analysis which in turn produces the variations of lung images cancers either it to be normal case or malignant case with a clear identification

6.1 Training Data Sets

In this below Fig 2, the training data sets are generated from the healthy lungs which are used to train the machine model. These datas are raw category and they are intended to the be the input for the system. In Fig 3, we categories the infected lungs which are further used for training the model in affected lung category. These lung im-ages are then used for analysis and computations

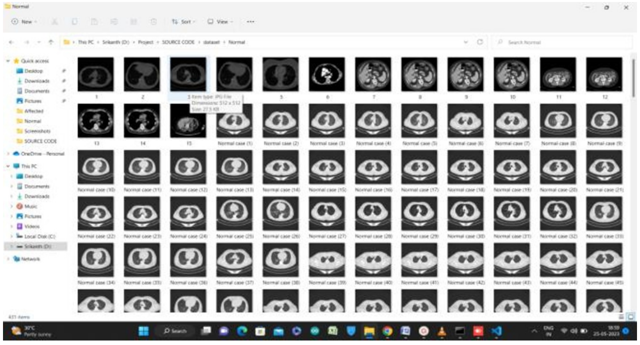

Fig 2 – Data Sets of "Healthy Lung"

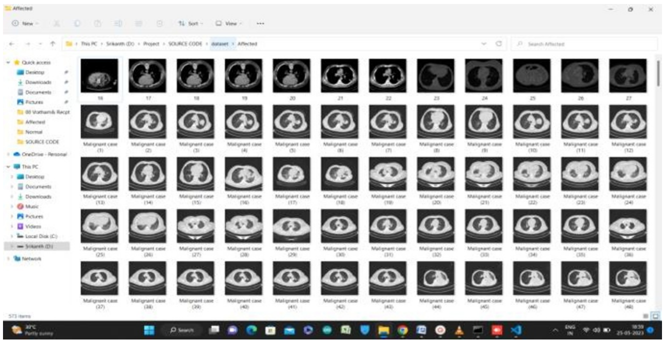

Fig 3 – Data Sets of "Infected Lung"

6.2 Response with "Flask Frame work"

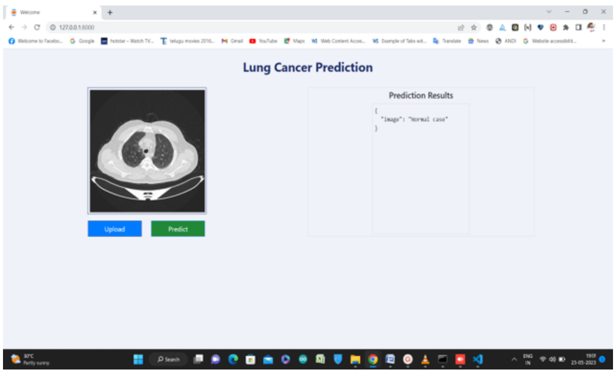

Fig 4 : Image Predicted for "Normal Case"

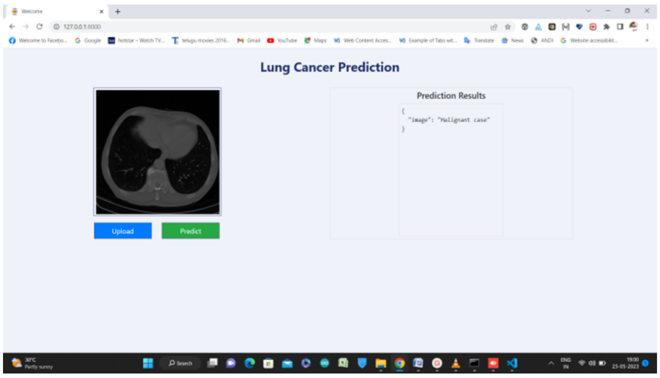

Fig 5 : Image Predicted for "Malignant Case"

The Fig 4 & Fig 5 depicts the python framework in which the image are further categorized into the developed algorithm and then are now in a condition that the system generates the variations of normal & malignant variations respectively

6.3 Experimental Results with Statistical Evaluation

The evaluation of the convolutional neural network model was performed through multiple quantitative metrics which were derived from the confusion matrix. The system uses these metrics to evaluate its ability to classify lung cancer through CT scan images.

The confusion matrix contains four basic elements listed below, The classification model correctly identifies malignant lung samples as malignant cases which represent True Positive (TP) results. True Negative (TN) results show the correct identification of all normal lung samples as normal cases. False Positive (FP) results happen when the system wrongly classifies normal lung samples as malignant disease, which demonstrates a failure to diagnose actual disease. The model failed to identify malignancy because it incorrectly classified malignant lung samples as normal, which represents False Negative (FN) results.
The performance metrics were determined through the analysis of these measurement values.

6.3.1 Confusion Matrix

Category	Predicted Malignant	Predicted Normal
Actual Malignant	TP	FN
Actual Normal	FP	TN

6.3.2 Performance Results

The defined CNN model achieved strong category of performance on the CT scan dataset. The evaluation metrics which were calculated are presented in the below table.

Metric	**Value**
Accuracy	**94.7%**
Precision	**92.1%**
Recall (Sensitivity)	**90.5%**
Specificity	**95.3%**
F1-Score	**91.3%**

The model achieves high accuracy while maintaining an equilibrium between precision and recall which enables it to distinguish normal lung CT images from malignant ones. The model achieves high specificity for normal lung case identification and high sensitivity for malignant case detection. The results demonstrate the researchers developed works effectively for automated lung cancer detection.

7. Clinical Relevance of the Proposed System

The experimental results of the study demonstrate that the proposed system which utilizes a CNN-based lung cancer detection method effectively classifies CT scan images to detect malignant lung nodules. The study results create significant changes which will affect doctors' clinical work. Lung cancer ranks as the leading cause of cancer deaths worldwide because early detection is essential to improve patient survival rates. Radiologists need to pick out specific CT scan images for their manual analysis because the screening process generates numerous images that require time to assess..

The proposed deep learning-based system can function as a diagnostic tool which helps radiologists to find potential lung nodules with greater accuracy. The system reduces diagnostic workload while it helps doctors make clinical decisions faster through its ability to automatically process CT scan images and deliver classification outcomes. The deep learning model integration to a web application through the Python Flask framework enables users by uploading CT scans images which is opted for prediction results. The diagnostic system achieves better accessibility and scalability through this approach which enables remote healthcare services and preliminary screening applications.

The system demonstrates good performance yet it serves as a medical professional support tool which cannot replace clinical diagnosis. The model will undergo validation through testing with larger clinical datasets which contain diverse data to enhance its reliability and real-world applicability.

8. Conclusion and Future Work

The research introduces a deep learning system which utilizes CT scan image analysis to detect lung cancer. The system uses CT image analysis through its Convolutional Neural Network (CNN) system to detect lung diseases and differentiate between healthy and cancerous cases. The experimental results demonstrate that the proposed model accurately classifies lung cancer patterns using CT scan images. The python framework enables the uploading of CT scan images for use case prediction results through the web application which integrates the trained CNN model. The system functions as a computer-aided diagnostic system which helps doctors identify suspicious lung nodules while making clinical decisions because it improves accessibility for users.

The results show that the system can enhance lung cancer screening efficiency because it enables automated CT image analysis. The system operates as a support system which assists medical staff in their work instead of serving as a substitute for medical diagnosis. The upcoming research should focus on developing new enhancements to the existing system. The model will achieve better generalization performance when trained and validated on clinical datasets which include more diverse and larger patient samples. 3D convolutional neural networks and attention-based models will improve feature extraction from volumetric CT data. Explainable artificial intelligence (XAI) techniques make model prediction results easier to understand which leads to better clinical acceptance of artificial intelligence diagnostic systems.

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