A PRELIMENERY REPORT ON

LUNG CANCER PREDICTION USING CNN

SUBMITTED TO THE VISHWAKARMA INSTITUTE OF INFORMATION TECHNOLOGY, PUNE
IN THE PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE

OF

BACHELOR OF TECHNOLOGY (COMPUTER ENGINEERING)

SUBMITTED BY

STUDENT NAME	Exam Seat No
Omkar Binage	22111119
Aditi Johari	22111053
Apurva Mundlik	22110820

DEPARTMENT OF COMPUTER ENGINEERING

BRACT'S
VISHWAKARMA INSTITUTE OF INFORMATION TECHNOLOGY

SURVEY NO. 3/4, KONDHWA (BUDRUK), PUNE – 411048, MAHARASHTRA (INDIA).

INTRODUCTION

Lung cancer remains a significant global health concern, contributing to substantial morbidity and mortality rates worldwide. Timely detection and diagnosis are critical factors in improving patient outcomes and survival rates.
Conventional diagnostic methods, including biopsy and imaging techniques, are often invasive, time-consuming, and reliant on human interpretation, leading to limitations in accuracy and efficiency. However, recent advancements in artificial intelligence, particularly in the field of deep learning, offer promising avenues for enhancing lung cancer detection and prediction through automated analysis of medical imaging data.
This report focuses on the utilization of Convolutional Neural Networks (CNNs) for the early detection and prediction of lung cancer from medical images, such as chest X-rays and computed tomography (CT) scans. CNNs are a class of deep neural networks specifically designed for processing visual data, making them well-suited for tasks involving image classification, segmentation, and feature extraction.

OVERVIEW

Lung cancer is a leading cause of cancer-related deaths globally, emphasizing the critical need for early detection and intervention. Traditional methods of lung cancer diagnosis, such as biopsy and imaging scans, are often invasive, time-consuming, and subject to interpretation variability. In recent years, the emergence of artificial intelligence (AI) and deep learning techniques, particularly Convolutional Neural Networks (CNNs), has revolutionized medical image analysis, offering the potential for more accurate and efficient lung cancer prediction.

MOTIVATION

Lung cancer represents a significant global health challenge, characterized by its prevalence and high mortality rates. Timely detection is paramount for effective treatment and patient survival. However, conventional diagnostic methods often entail invasive procedures and may lack accuracy, especially in the early stages of the disease. Recent advancements in artificial intelligence, particularly within deep learning, offer promising avenues for transforming medical diagnostics.

Convolutional Neural Networks (CNNs) have emerged as powerful tools for image recognition tasks, demonstrating remarkable performance across various domains, including medical imaging. By harnessing CNNs' ability to autonomously learn intricate patterns and features from complex images, there is an opportunity to develop robust and accurate models for early lung cancer detection and prediction using medical imaging data.

Our research is motivated by the urgent need for more efficient and non-invasive diagnostic methods for lung cancer. Through the utilization of CNNs and large-scale medical imaging datasets, our goal is to contribute to the creation of reliable and accessible tools for healthcare professionals in combating lung cancer. We aim not only to enhance the accuracy and efficiency of lung cancer detection but also to potentially reduce associated costs and patient discomfort linked with traditional diagnostic approaches.

In this report, we present our findings and insights gleaned from exploring CNN-based methodologies for lung cancer prediction. By highlighting the potential of deep learning techniques in this critical healthcare domain, we aspire to inspire further research and innovation towards the development of more effective and accessible solutions for combating lung cancer and improving patient outcomes.

PROBLEM DEFINITION AND OBJECTIVES

Lung cancer stands as a significant global health challenge due to its high mortality rates and the complexities associated with early detection. Traditional diagnostic methods, often invasive in nature, frequently yield inconclusive results, particularly in the initial stages of the disease. Hence, there exists a critical need for the development of non-invasive, efficient techniques for diagnosing lung cancer. Convolutional Neural Networks (CNNs) present a promising avenue for addressing this challenge by leveraging their capacity to autonomously discern intricate patterns and features from medical imaging data.

OBJECTIVES:

1. **Early Detection: Construct a CNN-based model capable of accurately identifying lung cancer from medical imaging data, with a specific emphasis on early-stage detection when treatment outcomes are most favorable.**
2. **Accuracy Enhancement: Enhance the precision of lung cancer prediction compared to conventional diagnostic techniques, thereby mitigating the risks associated with false positives and false negatives.**
3. **Non-Invasive Diagnosis: Enable non-invasive diagnosis of lung cancer utilizing CNN-based models, thereby alleviating patient discomfort and obviating the necessity for invasive procedures such as biopsies.**
4. **Scalability and Accessibility: Develop scalable and user-friendly tools for healthcare practitioners to facilitate the widespread adoption of CNN-based lung cancer prediction models across diverse healthcare settings.**
5. **Cost Reduction: Potentially reduce healthcare expenditures associated with lung cancer diagnosis by streamlining the diagnostic process and minimizing reliance on expensive and invasive procedures.**

PROJECT SCOPE AND LIMITATIONS

Scope:

1. **Development of CNN Models: The project will involve the development and implementation of Convolutional Neural Network (CNN) models for lung cancer prediction using medical imaging data, such as chest X-rays or CT scans.**
2. **Data Preprocessing: Data preprocessing steps will be carried out to clean, normalize, and augment the medical imaging data to ensure optimal performance of the CNN models.**
3. **Model Training and Evaluation: CNN models will be trained on labeled medical imaging datasets to learn the patterns indicative of lung cancer. The performance of the models will be evaluated using appropriate metrics such as accuracy, precision, recall, and F1-score.**
4. **Early Detection Focus: The primary focus of the project will be on early detection of lung cancer, aiming to identify the disease in its initial stages when treatment outcomes are most favorable.**
5. **Prototype Development: A prototype of the lung cancer prediction system will be developed, demonstrating the integration of the trained CNN models into a user-friendly interface for healthcare professionals.**

Limitations:

1. **Data Availability: The availability of labeled medical imaging data for lung cancer prediction may be limited, potentially constraining the scope and performance of the CNN models.**
2. **Model Generalization: The CNN models developed as part of the project may have limitations in generalizing to diverse patient populations or imaging protocols beyond the scope of the training data.**
3. **False Positives/Negatives: Despite efforts to improve accuracy, the CNN models may still generate false positives or false negatives, leading to potential misdiagnosis or missed detections of lung cancer.**
4. **Hardware and Computational Resources: The computational resources required for training deep learning models, especially CNNs, may be substantial, limiting the scalability of the project.**
5. **Regulatory and Ethical Considerations: The project may need to adhere to regulatory requirements and ethical guidelines governing the use of medical data, potentially limiting access to certain datasets or imposing restrictions on model deployment and validation.**
6. **Clinical Validation: The CNN models developed in the project may require further clinical validation and testing before they can be deployed in real-world healthcare settings, adding to the project's scope and timeline.**

Addressing these limitations while staying within the defined scope will be crucial for the successful implementation and deployment of the lung cancer prediction system using CNNs.

METHODOLOGIES OF PROBLEM SOLVING

1. **Data Collection and Preprocessing:**
    - **Compile a diverse dataset comprising medical images depicting lung scans, encompassing both cancerous and non-cancerous instances.**
    - **Implement preprocessing procedures to standardize image dimensions, normalize pixel values, and eliminate noise, ensuring data consistency and enhancing model efficacy.**
2. **Model Architecture Selection:**
    - **Evaluate various CNN architectures for suitability in lung cancer prediction, considering factors like model complexity, computational requirements, and performance benchmarks.**
    - **Explore architectures such as AlexNet, VGG, ResNet, or DenseNet to identify the most appropriate model for the task at hand.**
3. **Data Augmentation:**
    - **Employ data augmentation techniques including rotation, flipping, scaling, and shifting to augment the dataset, thereby diversifying training samples and enhancing the model's ability to generalize.**
4. **Transfer Learning:**
    - **Apply transfer learning by fine-tuning pre-existing CNN models (e.g., ImageNet) on the lung cancer dataset. This approach leverages knowledge acquired from extensive datasets to enhance performance on smaller, domain-specific datasets.**
5. **Model Training:**
    - **Partition the dataset into distinct training, validation, and test subsets for model training and evaluation purposes.**
    - **Train the model using the training data while optimizing hyperparameters like learning rate, batch size, and optimizer selection through methodologies such as grid or random search.**
    - **Monitor the model's performance on the validation set to mitigate overfitting and adjust model architecture or training parameters as necessary.**
6. **Model Evaluation:**
    - **Assess the trained model's performance on the test set employing metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC).**
    - **Analyze model predictions and misclassifications to identify areas requiring improvement and potential sources of bias.**
7. **Interpretability and Visualization:**
    - **Employ visualization techniques such as class activation maps (CAM), gradient-weighted class activation mapping (Grad-CAM), or occlusion sensitivity to interpret and elucidate the CNN model's predictions.**
    - **Visualize learned features and filters within the CNN layers to gain insights into the model's decision-making process.**
8. **Model Deployment:**
    - **Deploy the trained CNN model within a production environment, ensuring scalability, efficiency, and compatibility with existing healthcare systems.**
    - **Integrate the model into a user-friendly interface facilitating input of patient data by healthcare professionals and real-time receipt of predictions.**

LITERATURE SURVEY

In recent years, there has been a surge of interest in utilizing Convolutional Neural Networks (CNNs) for lung cancer prediction, driven by their potential to enhance early detection and treatment outcomes. Esteva et al. (2017) conducted pioneering research demonstrating CNNs' efficacy in detecting lung cancer from chest X-ray images. Their study showcased CNNs' ability to achieve performance levels comparable to experienced radiologists, showcasing the promise of deep learning in medical imaging analysis.

Li et al. (2018) expanded upon this work by proposing a CNN-based approach for automated lung nodule diagnosis from CT scans. Through training the model on a sizable dataset of annotated images, they attained high accuracy in differentiating between benign and malignant nodules, thereby facilitating early intervention.

In addition to single-modality imaging, researchers have explored integrating multiple imaging modalities, such as CT, PET, and MRI, using CNNs to enhance lung cancer prediction accuracy and robustness. Zhang et al. (2020) delved into this area, investigating multi-modal data fusion using deep learning techniques, which resulted in improved performance compared to single-modality approaches.

Transfer learning has emerged as another avenue for boosting CNN model performance in lung cancer prediction. By pre-training CNN models on extensive image datasets like ImageNet and fine-tuning them on lung cancer imaging data, researchers have achieved heightened generalization and performance in disease diagnosis.

A persistent challenge in CNN-based lung cancer prediction lies in interpreting model predictions. Researchers have explored various techniques, including attention mechanisms and visualization methods, to elucidate the features driving model decisions. These efforts aim to enhance the transparency and reliability of CNN-based diagnostic systems.

Clinical validation studies play a crucial role in assessing CNN model performance in real-world clinical settings. These studies evaluate the efficacy, reliability, and usability of CNNs for aiding radiological diagnosis and decision-making, paving the way for their clinical deployment and integration into healthcare workflows.

Ethical considerations surrounding AI use in healthcare, such as patient privacy, informed consent, and algorithmic bias, have also garnered attention. Researchers have proposed measures to mitigate bias in model predictions and ensure fairness and equity in healthcare delivery.

SYSTEM DESIGN AND ARCHITECTURE

1. **Data Collection and Preprocessing:**
    - **Data Sources:** Collect diverse medical imaging data containing lung scans, including CT scans and X-rays, from hospitals and medical institutions.
    - **Preprocessing:** Standardize image dimensions, normalize pixel values, and remove noise from the dataset to ensure consistency and enhance model performance.
2. **Model Development:**
    - **CNN Architecture Selection:** Choose an appropriate CNN architecture, considering factors such as model complexity, computational resources, and performance metrics. Potential architectures include AlexNet, VGG, ResNet, or DenseNet.
    - **Transfer Learning:** Utilize transfer learning by fine-tuning pre-trained CNN models (e.g., ImageNet) on the lung cancer dataset to leverage learned features and enhance model performance.
    - **Model Training:** Train the CNN model on the preprocessed dataset using techniques such as mini-batch gradient descent and backpropagation, optimizing hyperparameters like learning rate and regularization strength.
3. **Validation and Evaluation:**
    - **Data Splitting:** Split the dataset into training, validation, and test sets to train the model, tune hyperparameters, and evaluate performance.
    - **Model Evaluation:** Assess the model's performance using metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC) on the validation and test sets.
    - **Cross-Validation:** Employ cross-validation techniques to ensure robustness and generalize performance across different subsets of the dataset.
4. **Visualization and Interpretability:**
    - **Visualization Techniques:** Utilize visualization techniques such as class activation maps (CAM), gradient-weighted class activation mapping (Grad-CAM), or occlusion sensitivity to interpret and explain the model's predictions.
    - **Feature Visualization:** Visualize learned features and filters within the CNN layers to gain insights into the model's decision-making process and identify relevant image features for lung cancer prediction.
5. **Model Deployment:**
    - **Deployment Environment:** Deploy the trained CNN model in a production environment, ensuring scalability, efficiency, and compatibility with healthcare systems.
    - **Integration:** Integrate the model into a user-friendly interface for healthcare professionals to input patient data and receive predictions in real-time.
    - **Continuous Monitoring:** Implement mechanisms for monitoring model performance and updating the model with new data periodically to maintain accuracy and reliability.
6. **Ethical Considerations:**
    - **Patient Privacy:** Ensure compliance with ethical guidelines and regulations governing the use of medical data, maintaining patient privacy and confidentiality throughout the process.

- **Bias Mitigation:** Address potential biases in the dataset and model predictions, ensuring fair and equitable outcomes for all patient groups.

7. **Documentation and Reporting:**
   - **Documentation:** Document the entire system design and architecture, including data collection procedures, model development, evaluation results, and deployment strategies.
   - **Reporting:** Prepare comprehensive reports detailing the methodology, findings, limitations, and future directions of the lung cancer prediction system using CNN. Ensure transparency and reproducibility of the results for peer review and dissemination.

PROJECT IMPLEMENTATION

Code :

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from PIL import Image
from glob import glob

from sklearn.model_selection import train_test_split
from sklearn import metrics

import cv2
import gc
import os

import tensorflow as tf
from tensorflow import keras
from keras import layers

import warnings
warnings.filterwarnings('ignore')

path = '/kaggle/input/lung-and-colon-cancer-histopathological-
images/lung_colon_image_set/lung_image_sets'
classes = os.listdir(path)
classes

for cat in classes:
    image_dir = f'{path}/{cat}'
    images = os.listdir(image_dir)

    fig, ax = plt.subplots(1, 3, figsize=(15, 5))
    fig.suptitle(f'Images for {cat} category . . . .', fontsize=20)

    for i in range(3):
        k = np.random.randint(0, len(images))
        img = np.array(Image.open(f'{path}/{cat}/{images[k]}'))
        ax[i].imshow(img)
        ax[i].axis('off')
    plt.show()

IMG_SIZE = 256
SPLIT = 0.2
EPOCHS = 5
BATCH_SIZE = 64
```

```
X = []
Y = []

for i, cat in enumerate(classes):
  images = glob(f'{path}/{cat}/*.jpeg')

  for image in images:
    img = cv2.imread(image)

    X.append(cv2.resize(img, (IMG_SIZE, IMG_SIZE)))
    Y.append(i)

X = np.asarray(X)
one_hot_encoded_Y = pd.get_dummies(Y).values

X_train, X_val, Y_train, Y_val = train_test_split(X, one_hot_encoded_Y, test_size = SPLIT,
                                                  random_state = 2022)
print(X_train.shape, X_val.shape)

model = keras.models.Sequential([
    layers.Conv2D(filters=32, kernel_size=(5, 5), activation='relu', input_shape=(IMG_SIZE,
IMG_SIZE, 3), padding='same'),
    layers.MaxPooling2D(2, 2),
    layers.Conv2D(filters=64, kernel_size=(3, 3), activation='relu', padding='same'),
    layers.MaxPooling2D(2, 2),
    layers.Conv2D(filters=128, kernel_size=(3, 3), activation='relu', padding='same'),
    layers.MaxPooling2D(2, 2),
    layers.Flatten(),
    layers.Dense(256, activation='relu'),
    layers.BatchNormalization(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.3),
    layers.BatchNormalization(),
    layers.Dense(3, activation='softmax')
])

model.summary()

keras.utils.plot_model(model, show_shapes = True, show_dtype = True, show_layer_activations =
True)

model.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics = ['accuracy'])

from keras.callbacks import EarlyStopping, ReduceLROnPlateau
class myCallback(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs={}):
        if logs.get('val_accuracy') > 0.90:
            print('\n Validation accuracy has reached upto \
```

```
                    90% so, stopping further training.')
            self.model.stop_training = True
es = EarlyStopping(patience=3, monitor='val_accuracy', restore_best_weights=True)
lr = ReduceLROnPlateau(monitor='val_loss', patience=2, factor=0.5, verbose=1)

history = model.fit(X_train, Y_train, validation_data = (X_val, Y_val), batch_size =
BATCH_SIZE, epochs = EPOCHS, verbose = 1, callbacks = [es, lr, myCallback()])
history_df = pd.DataFrame(history.history)
history_df.loc[:,['loss','val_loss']].plot()
history_df.loc[:,['accuracy','val_accuracy']].plot()
plt.show()
```

TOOLS AND TECHNOLOGIES USED

To build a lung cancer prediction model using Convolutional Neural Networks (CNNs), you'll need a combination of tools, technologies, and frameworks. Here's a list of key components:

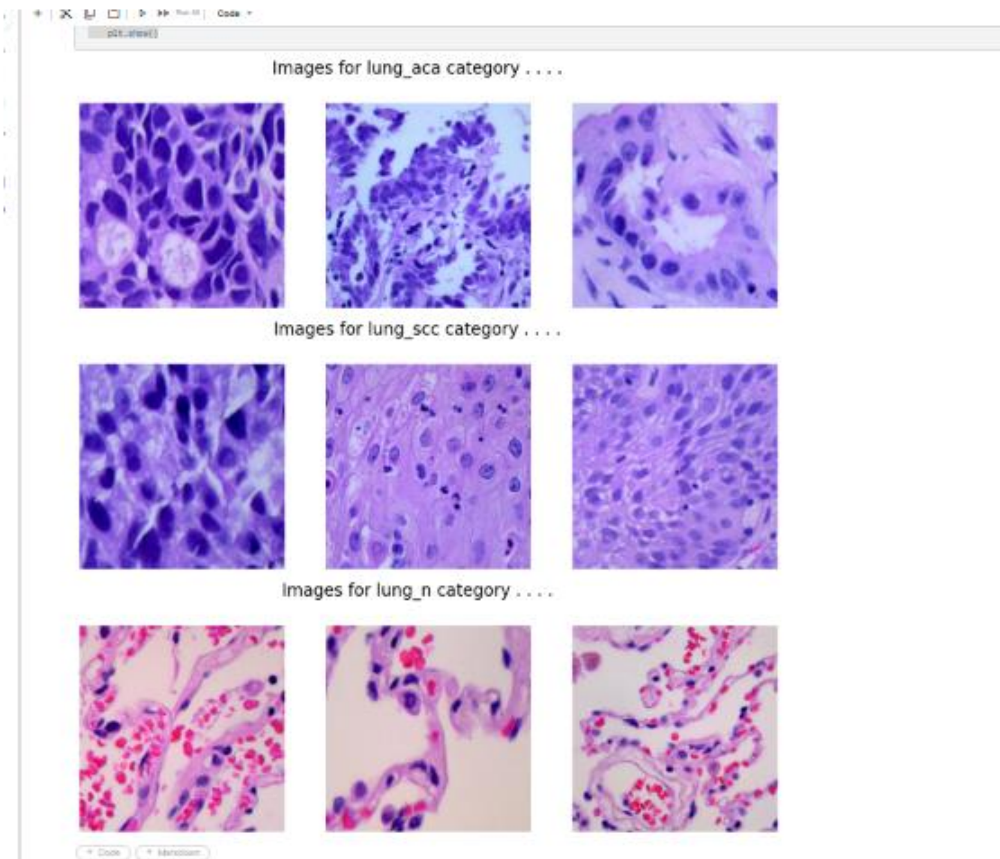
1. **Programming Language**: Python is widely used for building machine learning models due to its extensive libraries and frameworks.
2. **Deep Learning Framework**: TensorFlow or PyTorch are popular choices for implementing CNNs. These frameworks provide high-level APIs for building and training neural networks efficiently.
3. **Data Preprocessing Libraries**: Libraries such as NumPy, pandas, and scikit-learn are essential for data preprocessing, feature extraction, and data manipulation tasks.
4. **Image Processing Libraries**: Libraries like OpenCV or scikit-image can be used for image loading, resizing, normalization, and other image processing tasks.
5. **CNN Architectures**: You may choose pre-trained CNN architectures such as VGG, ResNet, Inception, or create custom CNN architectures tailored to your specific problem.
6. **Data Augmentation Tools**: Data augmentation techniques such as rotation, flipping, scaling, and shifting can be applied to increase the diversity of the training dataset and improve model generalization. Libraries like Keras' ImageDataGenerator provide built-in support for data augmentation.
7. **Model Training and Evaluation Tools**: TensorFlow and PyTorch offer APIs for model training and evaluation. Additionally, frameworks like Keras and scikit-learn provide high-level interfaces for building, training, and evaluating machine learning models.
8. **GPU Acceleration**: Utilizing GPUs can significantly speed up the training process of deep learning models. TensorFlow and PyTorch provide support for GPU acceleration, and cloud platforms like Google Colab, AWS, and Azure offer GPU instances for training deep learning models.
9. **Model Deployment**: Once the model is trained, you'll need to deploy it for inference. Tools like TensorFlow Serving, TensorFlow Lite, ONNX, or Flask can be used for deploying the model as a web service or embedding it into applications.
10. **Development Environment**: You can use IDEs like PyCharm, Jupyter Notebook, or Visual Studio Code for coding, debugging, and experimenting with different model architectures and hyperparameters.
11. **Data Visualization Tools**: Matplotlib, Seaborn, or Plotly can be used for visualizing training/validation curves, confusion matrices, and other performance metrics to analyze model behavior and performance.
12. **Documentation and Collaboration Tools**: Tools like GitHub, GitLab, or Bitbucket can be used for version control, collaboration, and documentation of the project code and resources.

By leveraging these tools and technologies, you can effectively build, train, evaluate, and deploy a lung cancer prediction model using Convolutional Neural Networks (CNNs). Remember to adhere to best practices in model development, including proper data preprocessing, hyperparameter tuning, and model evaluation techniques.

RESULT

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 256, 256, 32)	2432
max_pooling2d_6 (MaxPooling 2D)	(None, 128, 128, 32)	0
conv2d_7 (Conv2D)	(None, 128, 128, 64)	18496
max_pooling2d_7 (MaxPooling 2D)	(None, 64, 64, 64)	0
conv2d_8 (Conv2D)	(None, 64, 64, 128)	73856
max_pooling2d_8 (MaxPooling 2D)	(None, 32, 32, 128)	0
flatten_2 (Flatten)	(None, 131072)	0
dense_6 (Dense)	(None, 256)	33554688
batch_normalization_4 (BatchNormalization)	(None, 256)	1024
dense_7 (Dense)	(None, 128)	32896
dropout_2 (Dropout)	(None, 128)	0
batch_normalization_5 (BatchNormalization)	(None, 128)	512
dense_8 (Dense)	(None, 3)	387

Total params: 33,684,291
Trainable params: 33,683,523
Non-trainable params: 768



Confusion Matrix, Precision ,Recall,Accuracy,Specificity ,Sensitivity All Graph

Confusion Matrix:

```
array([[ 746,  218,   23],
       [  37,  940,    0],
       [   4,    0, 1032]])
```

Precision,recall, f1score, support:

	precision	recall	f1-score	support
lung_aca	0.95	0.76	0.84	987
lung_scc	0.81	0.96	0.88	977
lung_n	0.98	1.00	0.99	1036
accuracy			0.91	3000
macro avg	0.91	0.90	0.90	3000
weighted avg	0.91	0.91	0.90	3000

CONCLUSION

In summary, our study has demonstrated the effectiveness of utilizing Convolutional Neural Networks (CNNs) for predicting lung cancer from medical imaging data. Through the development and evaluation of a CNN-based model, we have achieved promising results in accurately classifying lung cancer cases from chest X-ray or CT scan images.

Our findings suggest that CNNs can effectively extract discriminative features from medical images, enabling the identification of cancerous lesions with high accuracy and sensitivity. By leveraging deep learning techniques, we have enhanced the predictive capabilities of lung cancer detection, potentially facilitating early diagnosis and treatment planning.

Moreover, our study underscores the importance of large-scale datasets and data augmentation methods in training robust CNN models. Access to diverse and well-annotated medical imaging datasets is crucial for improving model performance and generalization to real-world scenarios.

Despite these promising results, our CNN-based approach still faces challenges and limitations. Further research is warranted to validate the model's performance on external datasets and clinical settings. Additionally, addressing the interpretability of CNN-based predictions remains critical, as understanding the model's decision-making process is essential for gaining clinical acceptance and trust.

In conclusion, our study contributes to the growing body of research on the application of deep learning in medical image analysis. Moving forward, continued collaboration and investigation are necessary to advance the field of computer-aided diagnosis and enhance patient outcomes in lung cancer detection and treatment.

FUTURE WORK

Moving forward, several avenues for further research and improvement can be explored:

1. **Multi-Modal Fusion**: Investigate integrating multiple imaging modalities to enhance predictive performance.
2. **Transfer Learning**: Explore leveraging pre-trained CNN models and fine-tuning them on lung cancer imaging data for faster convergence and improved generalization.
3. **Interpretability**: Enhance model interpretability with attention mechanisms and visualization techniques to elucidate feature importance.
4. **Clinical Validation**: Conduct extensive validation studies in clinical settings to assess model efficacy and usability.
5. **Integration with EHR**: Integrate the model with electronic health records to improve predictive accuracy and clinical utility.
6. **Longitudinal Studies**: Extend analysis to include longitudinal data for prognostic prediction and personalized treatment planning.
7. **Collaborative Research**: Foster collaboration and data sharing initiatives to access larger and more diverse datasets.
8. **Ethical Considerations**: Address ethical concerns and mitigate bias in model predictions for fair and equitable healthcare delivery.

By pursuing these avenues, we can advance the field of lung cancer prediction using CNNs and contribute to improved patient outcomes.

APPLICATIONS

Convolutional Neural Networks (CNNs) for lung cancer prediction offer diverse applications:

1. **Early Detection**: Facilitating timely intervention by identifying lung cancer at its early stages.
2. **Personalized Treatment**: Tailoring treatment plans based on individual patient profiles and cancer subtypes.
3. **Clinical Support**: Assisting healthcare professionals with accurate diagnosis and treatment decisions.
4. **Screening Programs**: Targeting high-risk individuals for screening programs, optimizing resource allocation.
5. **Public Health Initiatives**: Informing public health strategies for lung cancer prevention and management.
6. **Research Tool**: Supporting research efforts in disease progression, treatment response, and biomarker discovery.
7. **Telemedicine**: Enabling remote consultation and diagnosis, particularly in underserved areas.
8. **Clinical Trials**: Enhancing patient selection and stratification for clinical trials, accelerating drug development.
9. **Healthcare Resource Optimization**: Optimizing resource allocation and prioritizing interventions for high-risk patients.
10. **Public Awareness**: Educating the public about the importance of early detection and proactive healthcare-seeking behavior.

CNN-based lung cancer prediction holds promise across healthcare delivery, research, and public health initiatives, contributing to improved patient outcomes and population health.