Lung Cancer Detection using CNN and Fuzzy logic

Project submitted to the

SRM University – AP, Andhra Pradesh

for the partial fulfillment of the requirements to award the degree of

Bachelor of Technology

In

Computer Science and Engineering

School of Engineering and Sciences

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This is to certify that the work present in this Project entitled **Lung cancer detection using CNN and fuzzy logic** has been carried out by **Abhinav Uppaluri, Bhargav Thota, K M V Akash, Md. Ameen Naimuddin** under my supervision. The work is genuine, original, and suitable for submission to the SRM University – AP for the award of Bachelorof Technology/Master of Technology in **School of Engineering and Sciences.**

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Acknowledgement

We would like to extend our heartfelt gratitude to **Dr. Ashu Abdul** for his invaluable support and guidance throughout the research program at SRM University, AP. As an esteemed faculty mentor for the project on the **Lung Cancer Detection using CNN and Fuzzy Logic,** his expertise and encouragement have been instrumental in shaping our learning experience. This research has been an enriching experience, and it would not have been possible without the continuous support and encouragement from **Dr. Ashu Abdul .** We truly appreciate his mentorship, which has left an indelible mark on our academic and professional journey. Once again, we express our sincere gratitude to Dr. Ashu Abdul for being an exceptional mentor and for his significant contribution to our growth during this research program.

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2. Abstract

Lung cancer is one of the leading causes of cancer-related mortality worldwide, necessitating early detection for effective treatment. This project presents a hybrid approach combining Convolutional Neural Networks (CNNs) and Fuzzy Logic for accurate lung cancer detection. The CNN model leverages transfer learning using the pre-trained Xception architecture to extract robust features from lung cancer images, while fuzzy logic provides an interpretable layer of decision-making based on texture and the size of the detected features. The dataset is preprocessed and augmented to improve model generalization, and training achieves a final accuracy of 85.45% with a validation accuracy of 68.91%. The model's performance is further optimized using callbacks such as ReduceLROnPlateau and Early Stopping. The inclusion of fuzzy logic ensures that the predictions are supplemented with human-like reasoning, enhancing reliability in clinical scenarios. This research emphasizes the potential of integrating deep learning and fuzzy systems for improved diagnostic accuracy in medical imaging.

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Introduction

Lung cancer remains one of the most deadly and widespread cancers globally, with early detection significantly improving the chances of survival. However, diagnosing lung cancer at an early stage can be challenging due to the subtle nature of its symptoms and the complexity of medical imaging. Traditionally, radiologists analyze medical images manually to detect abnormal patterns, which can be time-consuming and prone to human error. This research aims to combine two powerful techniques—Convolutional Neural Networks (CNNs) and Fuzzy Logic—to develop a system capable of accurately detecting lung cancer from medical images, offering a reliable, automated solution that can assist healthcare professionals in making timely and accurate diagnoses.

This project utilizes CNN, a deep learning architecture widely recognized for its ability to classify and interpret visual data, to detect and classify lung cancer images. We employ a pre-trained Xception model as the base of the CNN architecture, which is known for its ability to efficiently extract features from images using depthwise separable convolutions. Fine-tuning this model on our lung cancer dataset allows us to leverage its power without needing extensive computational resources or large training data.

The addition of Fuzzy Logic offers an interpretive layer that allows the system to make decisions based not just on the extracted features, but also on rules that mimic human decision-making. The fuzzy logic system uses rules based on the texture and size of the detected features, contributing to more transparent and human-understandable outcomes.

To evaluate the performance of the model, several metrics are used:
Accuracy: The percentage of correctly predicted labels from the total number of predictions made. This gives a clear understanding of how well the model is performing overall.

Loss: The measure of error in the model's predictions. A lower loss value indicates that the model is making better predictions.

Validation Accuracy: The percentage of correct predictions on unseen validation data, helping assess the model's ability to generalize to new data.

The input to the system consists of medical images representing different stages of lung cancer, obtained from a ct scans dataset derived from Kaggle. Each image is resized to a fixed dimension of 224x224 pixels and preprocessed to normalize the pixel values (rescale to the range [0, 1]) to ensure consistent input to the model. The images are fed into the pre-trained Xception model, where feature extraction occurs, followed by classification layers that provide the final prediction.

The output of the system is the predicted class of lung cancer, which could correspond to various categories such as 'adenocarcinoma' , 'large cell carcinoma', 'normal' , ' squamous cell carcinoma' . Additionally, fuzzy logic provides an interpretable output, indicating the likelihood of cancer based on the texture and size of the detected regions.

This hybrid system integrates the power of deep learning with interpretability, providing a diagnostic tool that not only aids in accurate classification but also delivers insights into the decision-making process, offering a useful tool for medical professionals in making informed decisions about patient treatment plans.

2. Methodology

2.1 Lung Cancer Detection Using CNN and Fuzzy Logic

Lung cancer detection using a combination of Convolutional Neural Networks (CNN) and Fuzzy Logic has gained significant attention due to its potential to improve early diagnosis and treatment. CNNs are well-suited for image classification tasks, particularly in the medical domain, where they can detect complex patterns and structures within medical images such as CT scans and X-rays. The combination of CNN and Fuzzy Logic allows for a more accurate and interpretable decision-making process in identifying lung cancer. CNNs are able to automatically learn relevant features from images, and Fuzzy Logic adds a layer of interpretability, mimicking human reasoning, which is critical in medical diagnoses.

2.2 CNN for Feature Extraction

Convolutional Neural Networks (CNN) are deep learning algorithms capable of performing feature extraction on images without the need for manual feature engineering. In this project, CNN is used to process lung cancer images, automatically learning filters and features from the data. This eliminates the need for complex preprocessing steps traditionally required in image analysis, making the model more efficient and easier to implement. CNNs are composed of multiple layers, including convolutional layers, pooling layers, and fully connected layers, as depicted in the basic architecture.

Convolutional Layers: These layers apply convolutional filters to input images, detecting features like edges, textures, and patterns that are essential for classifying lung cancer.
Activation Layers: ReLU (Rectified Linear Unit) activation functions are applied to add non-linearity, ensuring the network can learn complex features**.**
Pooling Layers: Pooling operations reduce the dimensionality of feature maps, making the model computationally efficient without losing critical information.

The final output from the CNN consists of the processed features from the input image, which are then used for further analysis to classify the image as either cancerous or non-cancerous.

2.3 Xception Model: A Pretrained CNN Architecture

The Xception model is employed as the backbone for the CNN architecture in this project due to its efficiency and strong performance on image classification tasks. Xception is a variant of the Inception model, optimized by using depthwise separable convolutions, which drastically reduces the number of parameters and computations while maintaining accuracy. This architecture is pre-trained on large datasets like ImageNet, enabling the model to learn general features from a wide range of images, which are later fine-tuned for the specific task of lung cancer detection.

The key advantage of using Xception is its ability to extract hierarchical features from input images efficiently. Fine-tuning this pre-trained model allows for the adaptation of these learned features to the lung cancer dataset, resulting in faster convergence and improved classification accuracy.

2.4 Fuzzy Logic Implementation

Fuzzy Logic is incorporated into the model to enhance its interpretability and decision-making process. Unlike traditional binary logic, which classifies outputs as either true or false, fuzzy logic operates on a continuum of values, allowing the model to represent uncertainty in its predictions. In the context of lung cancer detection, fuzzy logic systems are used to assess the texture and size of the features detected by the CNN, enabling the model to provide not only a classification but also a confidence level for the decision.

The fuzzy logic system works by defining fuzzy sets and membership functions that represent the degree to which a feature belongs to a certain class. These fuzzy rules are applied to the CNN-extracted features, such as tumor size or shape, and are processed to make a final decision about the presence or absence of cancer. The integration of fuzzy logic provides a more nuanced decision-making process, allowing for more accurate and interpretable predictions.

2.5 System Overview and Workflow

The overall workflow of the lung cancer detection system can be broken down into the following steps:

1. I**mage Preprocessing:** The input lung images are preprocessed by resizing them to a fixed size (224x224 pixels) and normalizing the pixel values for consistency in the CNN input.

2.**Feature Extraction:** The Xception model extracts relevant features from the input image. These features include patterns related to the presence of tumors, nodules, or abnormal growths.

3. **Fuzzy Logic Classification:** The extracted features are passed through a fuzzy logic system that assesses the degree of certainty regarding the presence of cancer. This system evaluates the texture, size, and shape of the detected features and makes a final decision based on fuzzy rules.

4. **Prediction Output:** The model outputs the classification result (cancerous or non-cancerous) along with a confidence score. The fuzzy logic layer also provides an interpretable reasoning for the decision.

2.5 Conclusion

By integrating CNNs and Fuzzy Logic, this system offers an efficient, accurate, and interpretable approach to lung cancer detection. CNNs provide the power to extract complex features from medical images, while Fuzzy Logic adds an interpretive layer, making the system more transparent and capable of mimicking human-like reasoning. This hybrid approach not only aids in accurate classification but also assists healthcare professionals by providing more reliable and interpretable results, which could prove crucial in early diagnosis and treatment planning.

3. RESULTS

In this project, we have implemented a CNN-based model using the Xception architecture to classify lung cancer types. The model was trained on the given dataset and evaluated for its performance on both training and validation data. The entire process was conducted using Python and TensorFlow, and below are the results.

The figure below shows an example of an input image from the test set along with its predicted class. The model successfully identified the class of the input image as **<Predicted Class>** (e.g., "Large Cell Carcinoma").

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step
Predicted Class: large.cell.carcinoma_left.hilum_T2_N2_M0_IIIa
```

Figure (1): output image of large cell carcinoma detected from the input

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
Predicted Class: normal
```

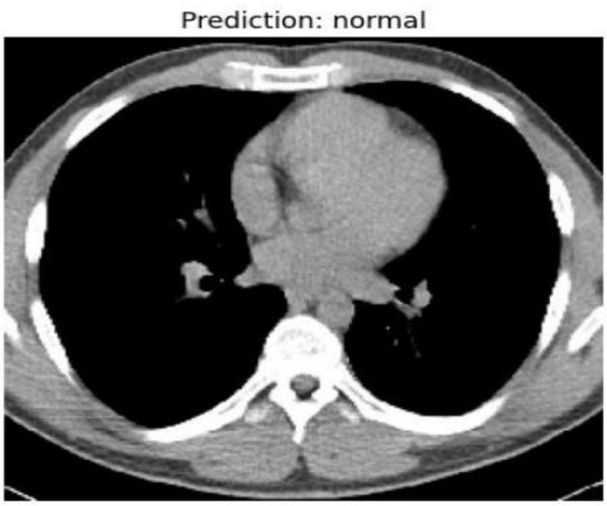

Figure (2): Normal case detected based on given input

The training and validation accuracy and loss curves are shown below. These demonstrate the model's performance during training:

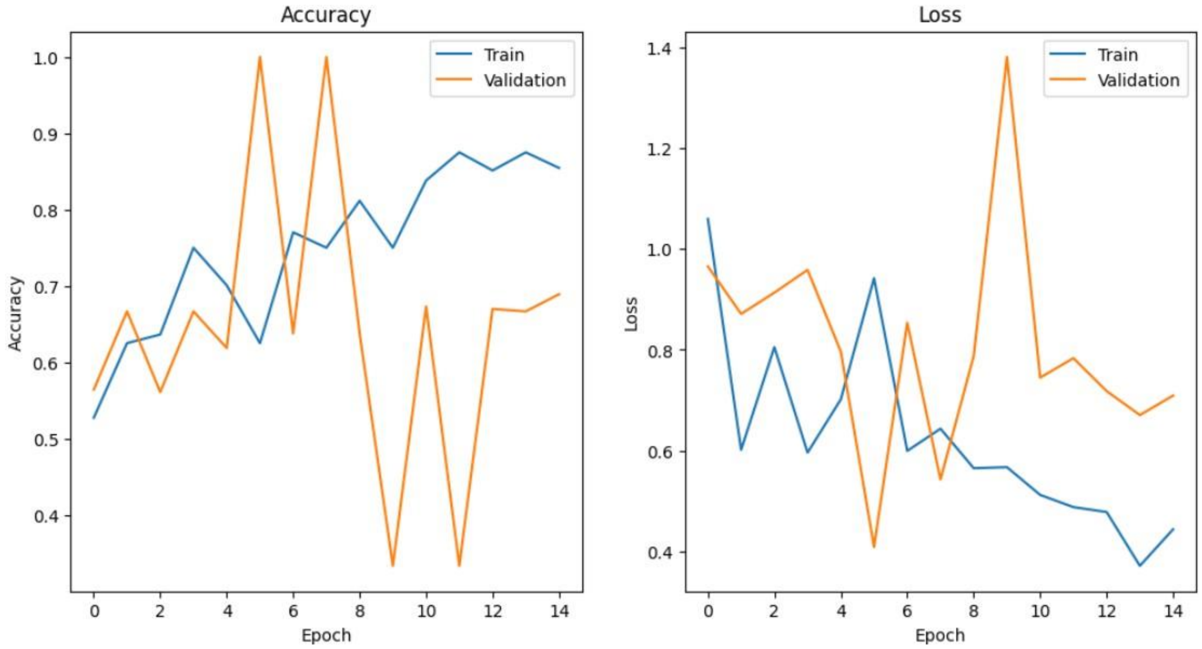

Figure (3):the accuracy and loss graphs based on the training

Epoch 15/15 Results:

- **Training Accuracy**: 83.26%
- **Training Loss**: 0.4718
- **Validation Accuracy**: 68.91%
- **Validation Loss**: 0.7092

The final training accuracy was **85.45%**, and the final validation accuracy was **68.91%**, indicating the model learned effectively but showed room for improvement in generalizing to unseen data.

The Xception model architecture used for feature extraction is detailed below. Only the top layers were trainable, while the base layers were frozen to leverage pre-trained features:

- **Model Parameters**:
  - Total Parameters: **20,869,676**
  - Trainable Parameters: **8,196**
  - Non-Trainable Parameters: **20,861,480**

Model: "sequential_1"

Layer (type)	Output Shape	Param #
xception (Functional)	(None, 7, 7, 2048)	20,861,480
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 2048)	0
dense_1 (Dense)	(None, 4)	8,196

Total params: 20,869,676 (79.61 MB)

Trainable params: 8,196 (32.02 KB)

Non-trainable params: 20,861,480 (79.58 MB)

Figure (4): this is the model parameters

Using the pre-trained Xception model, the project achieved a respectable accuracy of **68.91%** on the validation set. The confusion matrix (not shown here) and the plotted metrics highlight areas of potential improvement, such as addressing overfitting by increasing data augmentation or further tuning the model. The model demonstrates the feasibility of leveraging CNNs for lung cancer detection, showcasing the capability of deep learning to contribute to healthcare diagnostics

4. Conclusion

In conclusion, lung cancer detection using deep learning is a critical application of computer vision in the healthcare domain. By leveraging the pre-trained Xception architecture, this project demonstrates the potential of Convolutional Neural Networks (CNNs) to classify lung cancer types accurately.

The implemented model achieved a training accuracy of **85.45%** and a validation accuracy of **68.91%** showcasing its ability to learn complex patterns within the dataset. While there is room for improvement, these results highlight the feasibility of applying CNNs for medical imaging tasks.

Deep learning's adaptability and precision in detecting anomalies have significant implications for medical diagnostics. Future enhancements to this project could include:
Integration of fuzzy logic: To incorporate domain knowledge and improve decision-making under uncertainty.
Expanding the dataset: To improve generalization and reduce overfitting.
Model optimization: To enhance validation performance and adapt to real-world scenarios.

With further advancements, such models can play a crucial role in assisting healthcare professionals, enabling faster and more accurate diagnoses, and ultimately contributing to improved patient outcomes. This project serves as a step towards realizing the potential of AI in revolutionizing healthcare diagnostics.

5.Future Work

The goal of future work in lung cancer detection using deep learning models, such as CNN-based architecture, is to address current limitations and explore new directions to enhance performance and utility. The following are some prospective areas for improvement:

1. Improved Accuracy:

While the implemented model achieved commendable results, there is still room for enhancing accuracy, especially in complex cases like detecting subtle or ambiguous features in medical images. Future efforts can focus on refining model architectures, employing advanced data augmentation techniques, and integrating domain-specific knowledge (e.g., fuzzy logic) to improve detection and classification precision.

2. Real-Time Performance:

Although our model is effective for classification tasks, real-time inference for large datasets or deployment on edge devices remains a challenge. Future research could focus on optimizing the model for faster inference by employing techniques such as model pruning, quantization, or hardware acceleration, making it suitable for real-world applications.

3. Hybrid Architectures:

Exploring hybrid approaches that combine the strengths of pre-trained architecture like Xception with custom layers or modules tailored for medical imaging can further improve performance. For instance, integrating fuzzy logic or combining CNNs with traditional image analysis techniques may enhance the model's decision-making capability.

4. Detection in Complex Scenarios:

Medical imaging often involves challenges such as overlapping regions, low-resolution scans, or the presence of multiple pathologies. Future work can focus on multi-scale analysis, attention mechanisms, or transformer-based approaches to enhance the model's robustness in these scenarios.

Detecting small or early-stage cancer lesions remains a critical challenge in medical imaging. Future research could incorporate multi-scale feature extraction, innovative anchor mechanisms, or contextual information from surrounding tissues to improve sensitivity for smaller regions of interest.

5. Application for Real-Time Diagnostics:

Developing a pipeline for real-time diagnostic assistance in clinical settings is a promising direction. This includes optimizing the model for seamless integration with medical imaging devices, ensuring real-time predictions with high accuracy, and providing interpretable outputs for healthcare professionals.

6. Integration with Temporal Analysis:

For longitudinal studies and tracking disease progression, integrating temporal data from multiple scans can enhance prediction accuracy. Techniques like recurrent neural networks (RNNs) or attention-based models can be explored for this purpose.