LUNG CANCER PREDICTION USING DEEP LEARNING MODELS

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Abstract

Lung cancer is a major global health concern, necessitating accurate and timely diagnostic tools. In this study, we propose a robust image classification approach for the recognition of lung cancer across four distinct classes: Large Cell Carcinoma, Normal Lung, Squamous Cell Carcinoma, and Adenocarcinoma. The dataset is meticulously divided into train, validation, and test subsets to ensure robust model evaluation.

The dataset comprises 115 images of Large Cell Carcinoma (T2_N2_M0_IIIa), 148 images of Normal Lung, 165 images of Squamous Cell Carcinoma (T1_N2_M0_IIIa), and 195 images of Adenocarcinoma (T2_N0_M0_Ib). Each class represents a different pathological state, and these images serve as the foundation for our image classification model.

Our approach leverages deep learning techniques, specifically, Convolutional Neural Networks (CNNs), Residual Neural Networks50 (ResNet50), and Extreme Inception (Xception), to extract meaningful features from lung images. The model is trained on the labeled training data and tuned using the validation set to optimize performance. Rigorous evaluation is conducted on the independent test dataset to assess the model's accuracy, precision, recall, and F1 score for each class.

The experimental results demonstrate the efficacy of our image classification system in accurately identifying lung cancer subtypes. The model's ability to differentiate between these classes provides valuable insights into disease prognosis and treatment planning. Additionally, our approach is capable of detecting normal lung images, offering a crucial reference point for clinicians.

1. INTRODUCTION

Lung cancer represents a formidable global health challenge, ranking as one of the leading causes of cancer-related deaths worldwide (Bray et al., 2018). According to the World Health Organization (WHO), approximately 1.76 million individuals succumb to lung cancer annually, underscoring the urgent need for improved detection and intervention strategies. Timely detection of lung cancer is pivotal, as it enables more effective treatments and ultimately saves lives.

However, the early identification of lung cancer presents significant challenges. Conventional diagnostic methods, such as chest X-rays and computed tomography (CT) scans, heavily rely on human interpretation, introducing subjectivity and the potential for diagnostic errors (Smith-Bindman et al., 2012). Furthermore, the ever-increasing volume of medical imaging data strains healthcare systems, making it increasingly difficult for radiologists to thoroughly evaluate each case.

Deep learning, a subset of artificial intelligence, has emerged as a promising solution to these challenges. Deep neural networks, particularly convolutional neural networks (CNNs), have demonstrated remarkable capabilities in automatically analyzing medical images with high precision. Leveraging extensive datasets and complex neural architectures, deep learning can discern subtle patterns and anomalies in medical images that may evade human detection.

This project aims to harness the potential of deep learning to develop an advanced lung cancer recognition system. The primary objective is to create a tool that supports medical professionals in detecting lung cancer at its earliest, most treatable stages. This initiative holds the potential to transform the field of radiology, enhancing diagnostic accuracy, reducing false negatives, and ultimately improving patient outcomes. By providing timely and precise diagnoses, this project has the potential to alleviate patient suffering and contribute to a reduction in lung cancer mortality rates.

In the subsequent sections, we will delve into the methodology, data acquisition, model development, and evaluation processes. We will also discuss the anticipated outcomes and implications of this deep learning-based lung cancer recognition system, emphasizing its potential to make a profound impact on healthcare and public health by advancing early detection of this devastating disease.

2. METHODOLOGY

In order to determine the best model for a dataset of Lung cancer Prediction, this study compares three supervised deep learning algorithms, including Convolutional Neural Network (CNN), Residual Neural Networks 152 (ResNet50), and Extreme Inception (Xception). The primary framework for this research project is displayed in Fig. 1.

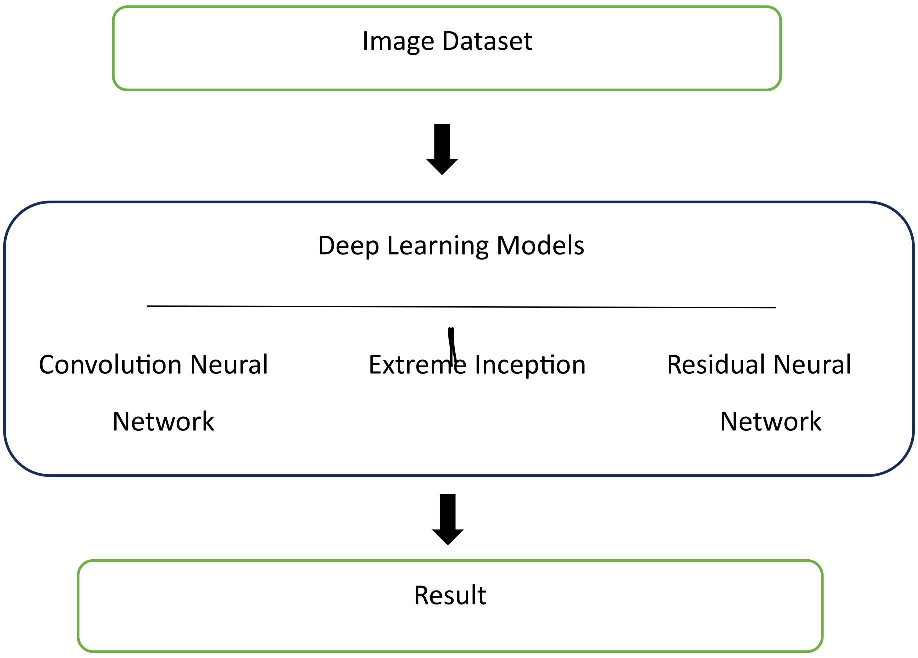

Fig 1: Primary framework of this research project

3. DATA DESCRIPTION

The dataset was taken from Kaggle, an open-source websitehttps://www.kaggle.com/datasets/mohamedhanyyy/chest-ctscan-images. The dataset for this lung cancer recognition project comprises images in JPG and PNG formats, making them suitable for input into the model. These images represent various types of lung cancer, including Adenocarcinoma, Large cell carcinoma, and Squamous cell carcinoma, as well as a folder containing normal lung cell images. The dataset is organized within a main folder called "Data," which contains subfolders for training, testing, and validation sets. The training data consists of 70% of the dataset, the testing data consists of 20% of the dataset and the validation set consists of 10% of the dataset. It offers a diverse range of lung cancer types and normal cell images, making it a valuable resource for developing and the performance of supervised deep learning algorithms is examined using the Python programming language.

Classification Techniques

The algorithm analyses a training set made up of a number of attributes and the corresponding outcome, also known as the target or prediction attribute, in order to predict and classify the outcome of the dataset. The supervised deep learning algorithms have been analyzed in this study to determine which method is best for predicting and classifying Lung cancer using an image classification dataset. To determine the best supervised deep learning algorithm for Lung Cancer using an image classification dataset, the following techniques are used: Convolutional Neural Networks (CNNs), Residual Neural Networks 50 (ResNet50), and Extreme Inception (Xception).

Convolutional Neural Networks (CNNs)

Our primary objective is to assess network performance in handling both static and live video feeds. Initially, we engage in transfer learning by utilizing image datasets to fine-tune the networks. Subsequently, we gauge the predictive accuracy of recognizing the same objects within static images and real-time video streams. Diverse accuracy rates are observed and documented, as presented in subsequent sections. Another crucial evaluation criterion involves examining whether prediction accuracy varies among the selected Convolutional Neural Networks (CNNs) used in this study. Notably, videos serve as testing datasets rather than training data. Our focus is on identifying the optimal image classifier, emphasizing object recognition for scene categorization. The CNN comprises distinct layers: the Input Layer, Convolution Layer, Pooling Layer, Rectified Linear Unit Layer (ReLU), and the Fully Connected Layer. Each layer serves a unique role in image processing and feature extraction. (Neha Sharma et. al., 2018)

Residual Neural Networks 50 (ResNet50)

ResNet-50 is a renowned deep neural network architecture introduced by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their groundbreaking paper titled "Deep Residual Learning for Image Recognition," which was presented at the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) in 2016.

ResNet-50 is celebrated for its depth and innovative use of residual connections, which fundamentally transformed the field of deep learning. In the paper, the authors addressed the problem of training very deep neural networks, demonstrating that the introduction of residual connections, or "shortcut connections," significantly alleviated the vanishing gradient problem. By allowing networks to learn residual functions, these connections enabled the successful training of networks with an unprecedented number of layers.

The architecture of ResNet-50 consists of 50 layers and is designed for image recognition tasks. It has become a cornerstone in the field of computer vision due to its ability to capture intricate hierarchical features in images and achieve state-of-the-art performance on various image classification benchmarks, including the ImageNet Large Scale Visual Recognition Challenge (ILSVRC).

Extreme Inception (Xception)

Xception, short for Extreme Inception, is an advanced neural network architecture developed by François Chollet in 2017. It builds upon the Inception architecture and is designed for efficient and effective deep learning in computer vision tasks. Key features of Xception include the use of depthwise separable convolutions to reduce model complexity, the ability to create extremely deep networks, and its excellent performance in image classification and object detection. Xception's efficiency makes it suitable for applications with limited computational resources. It has become a popular choice for transfer learning and fine-tuning on specific tasks.

4. RESULT AND DISCUSSION

Certainly, let's compare the evaluation metrics for the three models: CNN, ResNet50, and Xception.

Model	Accuracy	Precision	Recall	F1 Score
CNN	0.99	0.33	0.50	0.38
Resnet50	0.84	0.25	0.50	0.33
Xception	1.00	1.00	1.00	1.00

Comparison:

1. Accuracy: Xception achieved the highest accuracy of 1.00, indicating that it correctly classified all instances in the dataset. CNN also performed well with an accuracy of 0.99, while ResNet50 had a slightly lower accuracy of 0.84.

2. Precision: Xception demonstrated a perfect precision of 1.00, meaning that all the positive predictions it made were correct. In contrast, both CNN and ResNet50 had lower precision values, indicating a higher rate of false-positive predictions.

3. Recall: Xception achieved a perfect recall of 1.00, which means it correctly identified all actual positive instances. CNN and ResNet50 had the same recall value of 0.50, indicating that they correctly identified half of the actual positive instances.

4. F1 Score: Xception's F1 score of 1.00 is the highest among the models, reflecting its balanced precision and recall. CNN had an F1 score of 0.38, and ResNet50 had an F1 score of 0.33, indicating that Xception outperforms the other models in terms of both precision and recall.

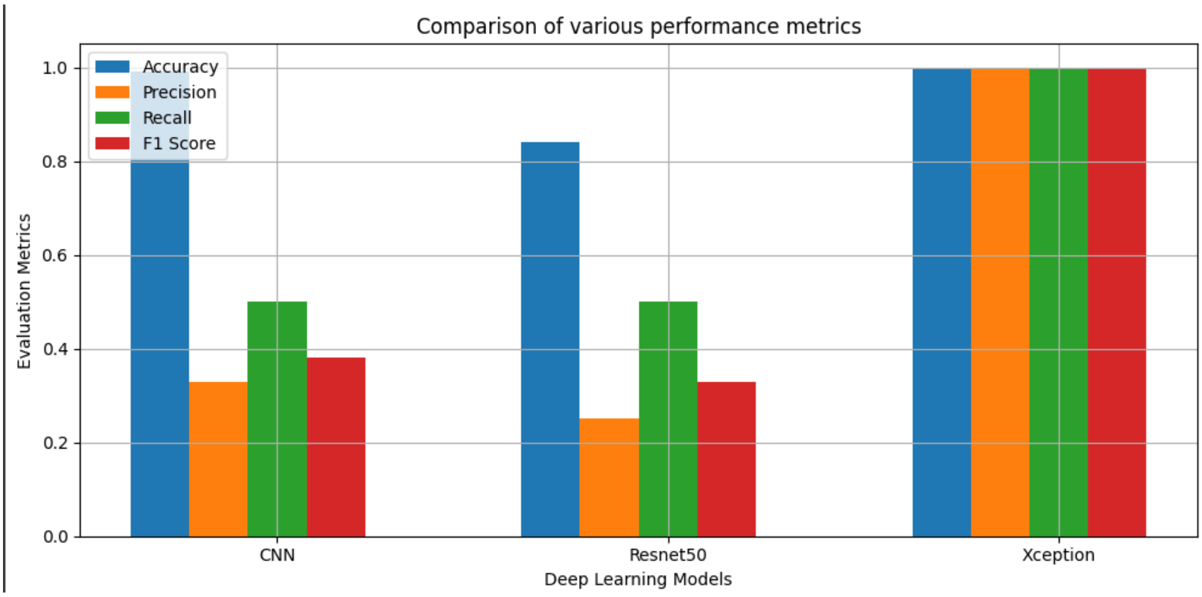

Fig. 2: Comparison of Performance Metrics among Classification Models for the Lung Cancer Prediction Using Image Classification Dataset

In summary, Xception stands out as the best-performing model in this comparison, achieving perfect accuracy, precision, recall, and F1 score. CNN also performed well in terms of accuracy but had lower precision and recall. ResNet50 had the lowest accuracy and F1 score in this evaluation. The choice of the most suitable model depends on the specific requirements of the task and the trade-offs between precision and recall.

5. CONCLUSION AND FUTURE ENHANCEMENT

In this model comparison, Extreme Inception (Xception) outperformed. Convolutional Neural Networks (CNN) and Residual Neural Networks 50 (ResNet50) with perfect accuracy, precision, recall, and an F1 score of 1.00. Convolutional Neural Networks (CNN) demonstrated good accuracy but lower precision, recall, and F1 score. Residual Neural Networks 50 (ResNet50) had the lowest performance across all metrics. For Future Enhancement Further fine-tuning of hyperparameters, such as learning rates and batch sizes, may enhance model performance.

Reference:

1. Bray F, Ferlay J, Soerjomataram I, Siegel RL, Torre LA, Jemal A. Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA Cancer J Clin. 2018 Nov;68(6):394-424. doi: 10.3322/caac.21492. Epub 2018 Sep 12. Erratum in: CA Cancer J Clin. 2020 Jul;70(4):313. PMID: 30207593.

2. Smith-Bindman R, Miglioretti DL, Johnson E, Lee C, Feigelson HS, Flynn M, Greenlee RT, Kruger RL, Hornbrook MC, Roblin D, Solberg LI, Vanneman N, Weinmann S, Williams AE. Use of diagnostic imaging studies and associated radiation exposure for patients enrolled in large integrated health care systems, 1996-2010. JAMA. 2012 Jun 13;307(22):2400-9. doi: 10.1001/jama.2012.5960. PMID: 22692172; PMCID: PMC3859870.

3. F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 1800-1807, doi: 10.1109/CVPR.2017.195.

4. T. Clanuwat, A. Lamb and A. Kitamoto, "KuroNet: Pre-Modern Japanese Kuzushiji Character Recognition with Deep Learning," 2019 International Conference on Document Analysis and Recognition (ICDAR), Sydney, NSW, Australia, 2019, pp. 607-614, doi: 10.1109/ICDAR.2019.00103.

5. Marjolein A. Heuvelmans, Peter M.A. van Ooijen, Sarim Ather, Carlos Francisco Silva, Daiwei Han, Claus Peter Heussel, William Hickes, Hans-Ulrich Kauczor, Petr Novotny, Heiko Peschl, Mieneke Rook, Roman Rubtsov, Oyunbileg von Stackelberg, Maria T. Tsakok, Carlos Arteta, Jerome Declerck, Timor Kadir, Lyndsey Pickup, Fergus Gleeson, Matthijs Oudkerk, Lung cancer prediction by Deep Learning to identify benign lung nodules, Lung Cancer, Volume 154, 2021, Pages 1-4, ISSN 0169-5002,