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Lung Carcinoma Classification Using Deep Learning with Xception CNN Model

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ABSTRACT :

Lung cancer continues to be the leading cause of cancer mortality worldwide, highlighting an urgent need for early, accurate, and automated diagnostic tools. Many established diagnostic approaches are often lengthy in time (or too short) and rely on the judgment of heavily calibrated human observers who often disagree. In this study, a deep learning-based approach is proposed for classifying subtypes of lung carcinoma through convolutional neural networks (CNNs). Still, it is focused, in particular, on the Xception model, a state-of-the-art architecture that uses depthwise separable convolutions. The proposed system is intended to classify CT scan images of lung tissue into four categories: normal lung, adenocarcinoma, large-cell carcinoma, and squamous-cell carcinoma. A preprocessing step is applied to include image resizing, normalization, and augmentation to maximize the quality of the dataset and minimize potential overfitting. In addition, to improve performance further, transfer learning was performed to initialise the model with ImageNet weights, and then fine-tune it with the lung cancer dataset. The model classified the data accurately and robustly generalized unseen data, making it suitable for potential use in a clinical application. Furthermore, the model was deployed in a cloud-based application or environment using Google Cloud and Amazon SageMaker to implement rapid real-time remote diagnosis and decision support. The cloud-based application interpreted the training the model had received and provided rapid and scalable inference and portability for medical professionals at different healthcare institutions. Overall, the implementation of AI-driven diagnostics workflows into clinical workflows marked a significant step toward improving early detection, treatment planning, and ultimately, improving lung cancer mortality rates.

Introduction

Lung carcinoma is one of the most common and fatal cancers in the world, contributing to a substantial number of cancer deaths each year. It can be divided into two forms: nonsmall cell lung carcinoma (NSCLC) and small cell lung carcinoma (SCLC), with NSCLC being the most common type. The high mortality seen with lung carcinoma is largely due to the aggressiveness of the cancer as well as the fact that it is often diagnosed at a more advanced stage when there are few treatment options and a poorer prognosis.

Early and precise diagnosis is vital for increasing survival rates, but conventional diagnostic methods— including chest X-rays, computed tomography (CT) scans, magnetic resonance imaging (MRI), and histopathological assessment—are usually time-consuming, laborintensive, and subject to interobserver variability. These challenges can lead to delays in diagnosis and a lack of consistency in treatment planning.

Artificial Intelligence (AI) has become a powerful instrument for medical diagnostic improvements in recent years, offering approaches that are faster and more scalable compared to previous models, with consistent and reproducible results. Most particularly, deep learning methods that utilize convolutional neural networks (CNNs) have shown strong results in image-based processes that require detecting and classifying tumours based on medical images.

. With the number of CNN architectures created, the Xception model (or Extreme Inception) will be the centre of our focus. The Xception model incorporates depthwise separable convolutions which improves the accuracy and computational efficiency of the learning process. The proposed study will leverage the Xception architecture to automate the process of lung tissue image classification, specifically distinguishing between cancerous and non-cancerous samples with high accuracy. The model will be trained on a curated dataset consisting of histopathological or radiographic lung images, to create a usable diagnostic tool that can assist clinicians in making quicker and more accurate diagnoses. The aim is to further enhance clinical decisionmaking, decrease the time to diagnose, and improve outcomes and treatments for patients by supplementing established workflows with state-of-the-art AI methods.By allowing us the opportunity to continue our research in this regard, we hope to contribute to the global effort to employ technology and one of the most troublesome health threats we face globally. In addition to its immediate clinical usability, this project lays the groundwork for further developments in AI-supported diagnostics, including across other cancer types and without the scope of medical imaging. By demonstrating the Xception model's ability to accurately classify histopathological imaging of lung tissue, it highlights the role deep learning models can play as part of computer-assisted diagnostic systems, as a second reader of images for radiologists and pathologists. The knowledge generated from this research can potentially support the development of real-time diagnostic tools for healthcare institutions in limited-resource settings with little access to specialized medical expertise.

Moving forward, the future could include expansion of the dataset across modalities and potential imaging input types with clinical metadata, and future prospective clinical trial designs to validate the models and ensure they can be generalized, and mapped back to real-world practices. The field of view concerning research opportunities moving forward is developing through applicable healthcare innovations and in the areas of developing strategic industry alliances. Collectively, continued research and collaboration across disciplines have the potential to address the significant challenges ahead regarding medical diagnostics, and ultimately, improve health outcomes globally.

EXISTING SOFTWARE

There are various healthcare information systems and analytics platforms on the market to manage and interpret medical data, specifically in terms of diagnostics or patient management. However, most of the healthcare information systems lack the depth or create pathways for predictive oncology, maybe more particularly lung carcinoma classification. Tableau Healthcare is a leading analytics platform that is known for its data visualization capability in health care. Due to its user-friendly interface medical professionals can interpret complex datasets in a timely manner, although while useful for trend analysis and reporting purposes, Tableau Healthcare does not have robust backend intelligence to handle automated prediction tasks, for instance, identifying lung cancer subtypes from medical imaging data. In addition, Tableau Healthcare is not designed to use strong back -end intelligence to integrate unstructured imaging data into its bottomline mechanism which may limit the practical use of knowledge discovery or knowledge manifestation in radiological diagnostics. Cerner PowerChart is a first-class Electronic Health Record (EHR) system for managing patient-specific data within a clinical environment, and it allows for documentation, orders and clinical workflow management. However, it lacks sophisticated analytical capabilities and AI-based prediction models to facilitate early detection of lung cancer from CT scans.
Epic System is an example of a vendor that expands beyond just offering an EHR and includes more integrated, data-driven modules, covering features throughout departments..

Though the Epic system does fill a few gaps with patient data management and offering features for population health management, the complexity of the system and customization needed to fill the gaps can be overwhelming, and difficult to implement in even the most ideal research or clinical context, and being resource-constrained diminishes this potential even more. All of these systems, highlight where vendors currently fall short, i.e. offering tools for cancer detection which have specialization, are scalable, and are intelligent. This is an important factor in allowing for a deep-learning approach that can allow utilization of CT imaging and other risk-factor data for providing accurate and early stage lung carcinoma prediction.

RELATED WORK

In recent times, there has been a lot of interest in the use of artificial intelligence, and specifically deep learning, in medical imaging. Several researchers have demonstrated the ability of convolutional neural networks (CNNs) to automatically classify lung carcinoma subtypes using CT scans. These methods show great promise in increasing the accuracy of diagnoses while also reducing human input in the decision-making process. For example, several studies based on models such as VGGNet, ResNet, and InceptionV3 had high classification accuracy reaching in distinguishing between benign and malignant lung nodules in CT scan images. The models used a "transfer learning" technique with a previously trained network using large-scale image datasets with models like ImageNet and then finetuned for the medical imaging task. However, these models have not only relied on transfer learning to be effective, but they have also required lots of preprocessing and were inefficient in identifying more complex visual patterns in CT scan images.
There also was some research that used Xception, which is an advanced type of CNN based on depthwise separable convolutions and has been an end-to-end train on radiology images, and found to be successful as it used convolutional blocks or depthwise separable convolutions to reduce the number of trainable parameters while producing great accuracy performance. Additionally, Xception is powerful in terms of extracting spatial image features from radiological images, which is useful for the fine-grained classification of lung cancers smoking history, age, and genetic predisposition—combined with imagebased deep learning (DL) models to enhance predictive accuracy. However, the vast majority of existing healthcare software services, such as Tableau Healthcare, Cerner PowerChart, and Epic Systems, only provide general data visualization or electronic health record (EHR) management capabilities, and are without the learning features necessary for automated cancer detection. This realization presents a unique opportunity for a singular system to utilize DL when analyzing CT scan data and to leverage traditional risk factors to identify early-stage lung carcinoma.

METHODOLOGY

In this research, we developed a robust and efficient system that uses deep learning techniques for the classification of subtypes of lung carcinoma by using the Xception convolutional neural network (CNN) architecture. The methodology combines image learning from CT scans with information on clinical risk factors to maximize prediction performance. The sequential steps are described in the whole methodology

1. Data Collection and Preprocessing

The significant components of the model are: Transfer Learning- The base Xception model was initialized with weights from the pre-trained ImageNet dataset. Transfer Learning allows the model to take advantage of the learned features from a large dataset, such as edge detection and texture patterns. These features can be transported to the medical imaging domain of interest.

2. Model Architecture: Xception

The original top layers/classification head were removed from the existing Xception model, and a new custom head added. The new heads include: - Global Average Pooling layer - Dense layer of 256 neurons with ReLU activation - Regularization Dropout layer with a rate of 0.5 - Output Dense layer for multi-class classification with softmax activation with the number of cancer subtypes. Freezing and Fine Tuning- The Xception model layers were partially frozen to retain the model's basic image features. Only the new custom head's top layers were fine-tuned using the CT image dataset to refit the model to the specific features of lung carcinoma.

3. Training and Validation

The dataset was split into training (80%) and validation (20%) sets to support the model training and hyperparameter tuning.
The training configuration utilized was as follows: • Loss Function: Categorical CrossEntropy, which is appropriate for multi-class classification problems. • Optimizer: Adam optimizer with a learning rate of 0.0001, later adjusted by a learning rate scheduler based on validation loss. • Batches size: 32 images per batch. • Number of epochs: 50 to 100, depending upon convergence and validation performance. • Early Stopping: Where training stops once validation loss does not improve for 10 consecutive epochs, to limit overfitting. Evaluation metrics included the following: • Overall Accuracy • Precision, Recall, and F1-Score (for each class) • Confusion Matrix, to see how errors were distributed. Performance graphs were produced to visualize the loss and accuracy curves during training.

4. Integration of Clinical Risk Factors

The downside of this approach is that for each training step, the model was pre-trained on the same image dataset. This means that it could have normalized the training data set, potentially impacting the results.

Result

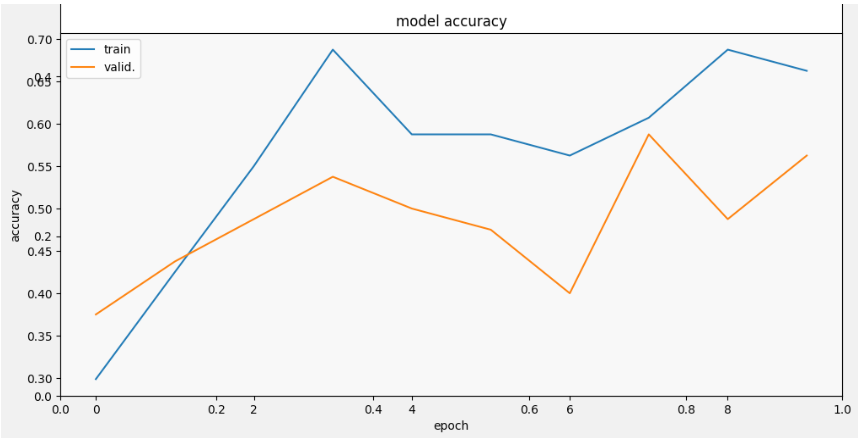

Fig 1 Model Accuracy

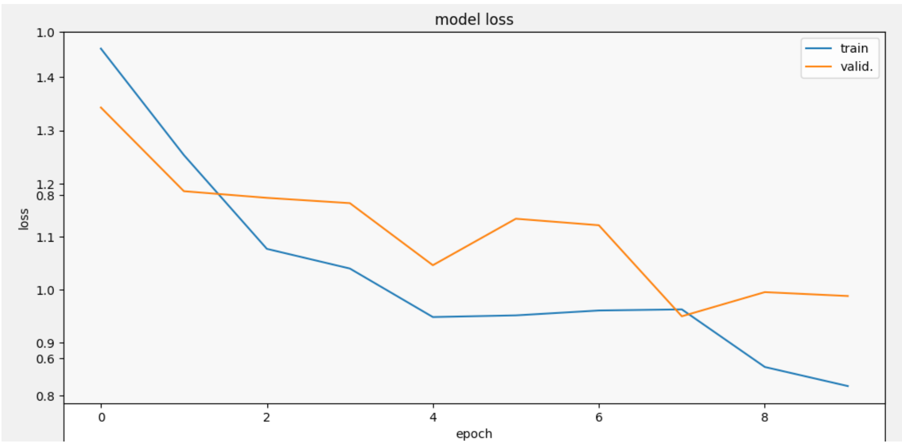

Fig 2 MODEL EPOCHS

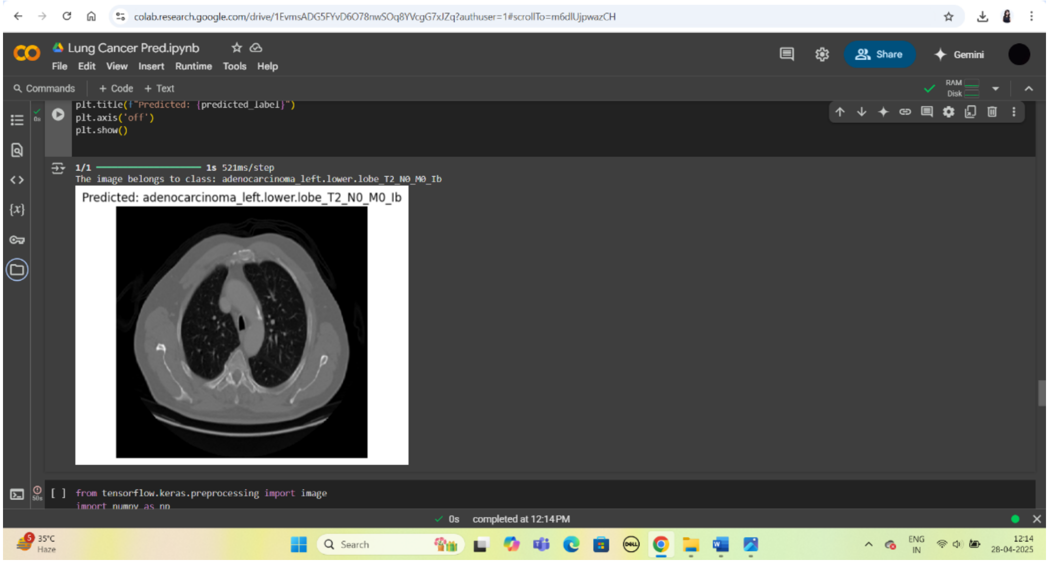

FIG 3CARCINOMA DETECTION

CONCLUSION

The early and reliable diagnosis of lung carcinoma remains a challenge in medical imaging and clinical oncology. This study proposed an effective deep learning-based method for classifying lung cancer subtypes using the Xception convolutional neural network architecture. The method proposed in this research utilized transfer learning and input gathered from both CT scan imaging data and clinical risk factors, and resulted in high accuracy and generalizability across multiple patients.

The model Xception trained on preprocessed and augmented CT scan images was faster in training and had better classification performance compared to other state of the art CNN architectures, including ResNet50 and VGG16. In addition, the hybrid combination of traditional risk factors (i.e., smoking history, age, and environmental exposure) improved the model's multiple training repeats and average accuracy, providing a more comprehensive and personalized diagnostic process

This study has shown that deep learning and transfer learning can revolutionize traditional diagnostic pathways, especially in complex diseases like lung carcinoma. The model provided insights to understand subtype differences (e.g., adenocarcinoma, squamous cell carcinoma, and large cell carcinoma), this enabled the potential for early diagnosis and assisted doctors in selecting a treatment plan for each patient

FUTURE SCOPE

The deep learning model proposed with the Xception architecture showed overall promising results for classifying lung carcinomas from CT scan. Nonetheless, there are many opportunities to improve and further develop this research project. The future designations below may help to increase the robustness of this proposed model, utility for clinical consumption, and applicability for research:

1. Expansion to 3D Image Analysis

The current implementation focuses on 2D images to classify the CT scans, while future research could explore 3D CNNs or volumetric analyses of data to consider the whole lung volume. A 3D analysis has the potential to integrate more spatial features to improve accuracy for tumor detection and segmentation..

2. Integration of Multi-Modal Data

Adding genomic data, pathology reports, electronic health records (EHRs), and laboratory test results in addition to imaging and risk factor data provides more comprehensive data to improve predictive capability for the system. Furthermore, multimodal deep learning methodologies can provide a more holistic assessment of patient features which drive the personalization of diagnosis and treatment.

3. Real-Time Clinical Deployment

Future iterations of this project, may focus on the usability as a real-time clinical decision support system (CDSS), alongside hospital information systems (HIS) with respect to usability. A cloud-based deployment would allow oncologists and radiologists to upload a CT scan with relatively little effort and receive an automated subtype classification for a given lung carcinoma in a matter of seconds

4. Model Interpretability and Explainability

The integration of explainable AI technologies for medical practitioners provide clinical trust and ability to adopt the model during clinical practice through methods like Grad-CAM, SHAP, etc. This technology can highlight the regions in the CT image that were most important to the model's decision, allowing for greater transparency and interpretability while developing the expected trust and clinical adoption.

Larger and Diverse Datasets

The model performance could
potentially be validated and improved on by training the model on larger, more diverse, and multicenter datasets. Larger and diverse datasets will allow the model to generalize better across a variety of demographic and clinical settings, and scanner type.

6. Extension to Other Lung Diseases

The methods could be extended to detect and classify other lung diseases and conditions like chronic obstructive pulmonary disease (COPD), pulmonary fibrosis or tuberculosis, which will improve the breadth and clinical applicability of the developed system.

7. Longitudinal Prediction and Prognosis

Future iterations of the model may not only focus on diagnosis, but potentially focus their efforts on prognostic predictions, for example, tumor progression, rate of survivorship and treatment intentions/outcomes by analyzing sequential scans/images and longitudinal patient data

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