NATIONAL UNIVERSITY OF COMPUTER AND EMERGING SCIENCES

PROJECT REPORT

ON

AI-POWERED LUNG CANCER SCREENING

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0.1 PROJECT OVERVIEW

Lung cancer is a major worldwide health threat, accounting for one of the main causes of cancer-related death. The stage at which the cancer is identified is a crucial factor influencing patient survival. Hence, early identification is a challenge as it broadens therapy choices and improves patient outcomes. This project revolves around classification of 25,000 histopathological images of lung tissue from a diverse dataset into five distinct categories. A Vision Transformer (ViT) model and a hybrid Xception + MobileNet architecture are the models used for this task.

0.2 PROBLEM STATEMENT

The project's goal is to use Convolutional Neural Networks (CNNs) and Vision Transformer to solve the essential issue of early lung cancer diagnosis. Despite advances in medical imaging, early detection of lung cancer remains difficult. Our objective is to provide a CNN-based and ViT based system capable of detecting probable malignant spots in lung scans reliably and rapidly, thereby improving patient outcomes through early intervention.

0.3 OBJECTIVES

1. **Detect Lung Nodules:** The primary objective is to develop a model that can accurately detect and classify lung nodules from medical images such as CT scans.

2. **Improve Sensitivity and Specificity:** Enhance the sensitivity (the ability to detect true positives) and specificity (the ability to correctly identify true negatives) of the model for early and accurate lung cancer detection.

3. **Early Detection:** Detect lung cancer at an early stage when it is more treatable and has a higher chance of successful outcomes.

0.4 METHODOLOGY

0.4.1 *Dataset Description*

The dataset contains 25,000 histopathological images with 5 classes. All images are 768 x 768 pixels in size and are in jpeg file format. The images were generated from an original sample of HIPAA compliant and validated sources, consisting of 750 total images of lung tissue (250 benign lung tissue, 250 lung adenocarcinomas, and 250 lung squamous cell carcinomas).

0.4.2 *Prepprocessing*

1. **Image Resizing:** All the images were resized to the size of 224x224.

2. **Rescaling:** All image pixels were rescaled between -1 and +1.

0.4.3 *Model Architecture*

Xception and MobileNet

1. **Description:** A hybrid model combining the Xception and MobileNet architectures was employed for image classification. This model use the depth wise distinct convolutional layers from MobileNet for productivity and the component extraction force of Xception.

2. **Training Parameters:** The Adam optimizer and a categorical cross-entropy loss function were used to train the model. In order to improve training efficiency, learning rate schedules and early stopping were implemented.

3. **Transfer Learning:** Pre-trained weights were used from the ImageNet dataset to initialize the model, facilitating transfer learning.

4. **Learning Rate Adjustment**:In order to adjust the learning rate in response to the training and validation data, a specialized learning rate function was implemented.

5. **Training Duration:** The model was trained for 15 epochs.

Vision Transformer

1. **Description:** For the purpose of image classification, the Vision Transformer (ViT) model was utilized. ViT replaces conventional convolutional layers with self-consideration components, permitting the model to catch long-range conditions in the pictures.

2. **Training Parameters:** The Adam optimizer and a categorical cross-entropy loss function were used to train the model. In order to improve training efficiency, learning rate schedules and early stopping were implemented.

3. **Tokenization & MultiHead Attention:** For efficient feature extraction, the images were broken up into patches through the tokenization process, and multi-head self-attention mechanisms were used.

4. **Learning Rate Adjustment:** In order to adjust the learning rate in response to the training and validation data, a specialized learning rate function was implemented.

5. **Training Duration:** The model was trained for 100 epochs.

0.4.4 *Training*

1. **Data Split:** The dataset was parted into training (80%), validation (10%), and test sets (10%). The preparation set was utilized to prepare the models, the approval set for hyperparameter tuning, and the test set for assessing the final model performance.

2. **Metrics:** The model's performance on the validation and test sets was evaluated using evaluation metrics like accuracy, precision, recall, and the F1 score.

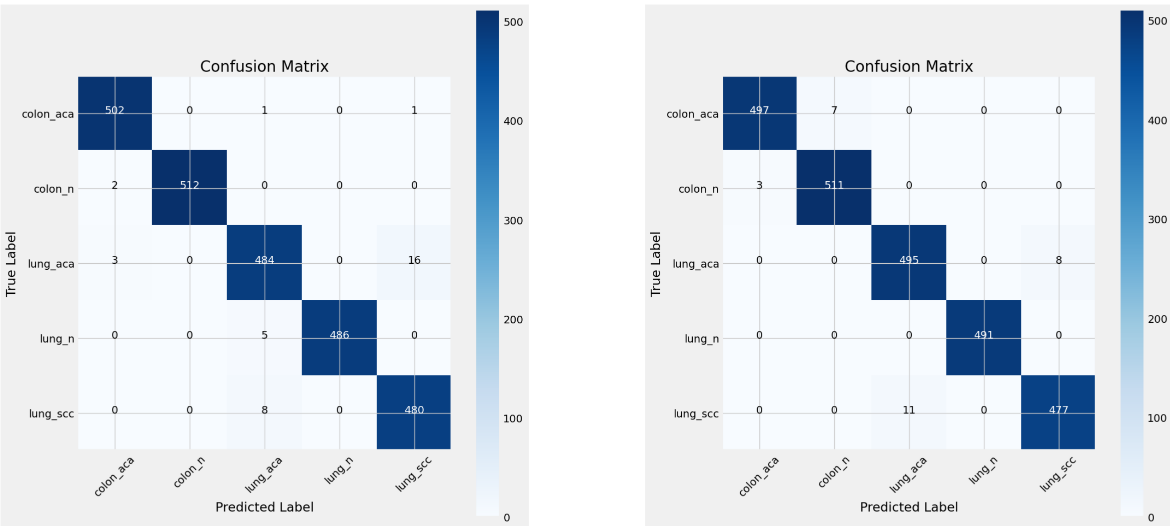
0.4.5 *Model Evaluation*

1. **Quantitative Analysis:** The trained models were evaluated on the test set to quantify their performance in classifying histopathological images.

   (a) Xception+MobileNet Accuracy on Test Data is 98.54%.

   (b) Vision Transformer Accuracy on Test data is 98.84%.

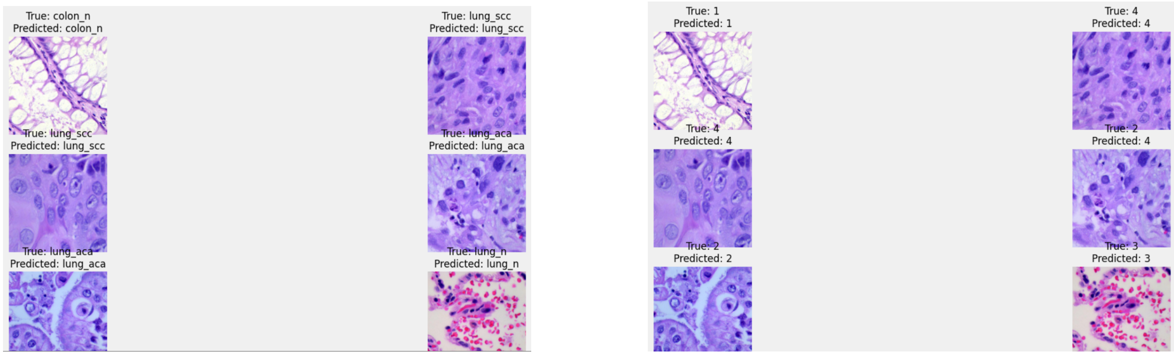
2. **Confusion Matrix:** A confusion matrix was generated to visualize the model's performance across different classes.



(a) Xception+MobileNet **(b)** Vision Transformer

Figure 1: Confusion Matrix

0.4.6 *Results*



(a) Xception+MobileNet **(b)** Vision Transformer

Figure 2: Prediction on Test Data

0.5 FUTURE WORK

1. **AI-Powered Imaging:** Artificial intelligence (AI) algorithms will continue to improve the accuracy of lung cancer detection through medical imaging. Radiologists will be aided by AI systems that can quickly and accurately analyze chest X-rays and CT scans, potentially catching tumors at an earlier, more treatable stage.

2. **Personalized Treatment:** Advances in genomics will enable the tailoring of lung cancer treatments to the specific genetic profile of each patient's tumor. Targeted therapies and immune-therapies will become more effective, with fewer side effects.

3. **Minimally Invasive Surgery:** Surgical techniques for lung cancer removal will continue to evolve. Minimally invasive procedures like robotic-assisted surgery will become more common, reducing recovery times and complications.

0.6 CONCLUSION

In conclusion, the hybrid Xception + MobileNet and Vision Transformer (ViT) models had varying degrees of success in classifying histopathological images due to to a specialized learning rate adjustment function. The near examination gives important bits of knowledge to utilizing progressed designs in clinical picture order, establishing the groundwork for future refinements and headways in symptomatic applications.
