Few-Shot Lung Cancer Classification Using Prototypical Networks

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***Abstract*—Lung cancer is a devastating global health issue that can be fatal if not detected early. To increase the chances of successful treatment and prevent the loss of lives, doctors need to identify the type of the lung cancer.Currently, CT scans are commonly used in medical practice to detect and diagnose lung tumors.However, implementing deep learning models to identify the lung cancer types poses a significant challenge. Because acquiring many medical images for each type of lung cancer can be difficult.The challenge of requiring a large amount of data samples for each category in traditional deep learning models was addressed in this research by implementing a prototypical network, which is a few shot learning technique. This method requires only a few samples per category, and it was used in conjunction with a pre-trained model to extract features from lung CT scans. The accuracy of the model was analysed based on the number of samples per category.This method achieves an accuracy of 98% after 15 epochs.Overall, the results of the study demonstrate that implementing a prototypical network for lung cancer type detection is feasible.**

***Index Terms*—Prototypical Networks, Few-shot Learning, Lung Cancer Classification, CT Scans**

I. Introduction

Lung cancer is an imposing worldwide health emergency, claiming the existence of roughly 422 individuals consistently across the world. Deplorably, lung cancer ranks among the deadliest and most prevalent types of cancer, principally originating within the lung tissues.Identifying the cancer type can significantly impact a patient's prognosis, highlighting the need for additional precise diagnostic tools and treatments.

The American Cancer Society has identified two main classifications of lung cancer: non-small cell lung cancer (NSCLC) and small cell lung cancer (SCLC) [1].Within the domain of NSCLC, there are three significant subgroups: Adenocarcinoma, Squamous cell carcinoma, and Large cell carcinoma [1].On the other hand, SCLC represents a distinct classification. Understanding the differences among these types is urgent for tailoring effective treatment strategies and improving patient endurance rates.

However, instances for each of these types are infrequent in practical scenarios and might appear in training datasets as singular example or just a few examples.Collecting medical images for each kind is infeasible.In certain situations, researchers will most likely be unable to obtain the necessary extensive data that they expect for their examinations ,because of confidentiality and security concerns.

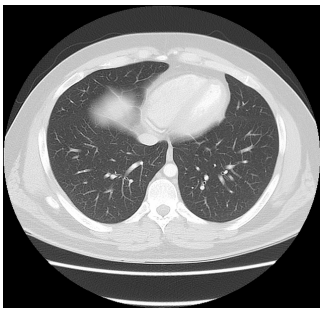


Fig. 1: CT scan of a healthy person

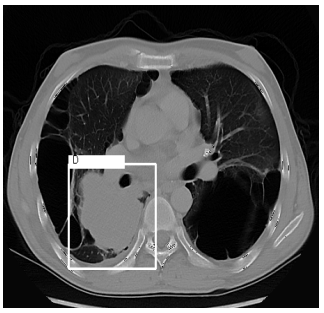


Fig. 2: CT scan of a patient with Large Cell Carcinoma

Computer-aided design (CAD) frameworks are the preferred methodology for lung cancer diagnosis because of their wide availability, cost-effectiveness, and fast image acquisition capacities. It gives exceptionally point-by-point cross-sectional images of the chest, allowing for the visualization of even little nodules and abnormalities within the lung tissue. Many of these frameworks are fundamentally trained on datasets that predominantly feature nodal types of lung cancer. While this approach might be effective for identifying and classifying nodules, it doesn't completely align with the clinical and radiological variety of lung cancer types.

In the field of image processing and deep learning, there have been many impressive breakthroughs in medical image analysis to diagnose diseases using medical images. Deep learning strategies for lung cancer identification utilizing CT images have been proposed by inspired researchers with a lot of labeled data [2], [3], [4], [5], [6].

Applying deep learning for the identification of lung cancer type poses a challenging task. To conquer this challenge, there has been an increasing sub-region in machine learning called few-shot learning. The point of this approach is to accomplish great learning results despite having a restricted amount of marked data in the training dataset, which contains instances of inputs matched with their respective results.

In few-shot classification, there are two datasets known as the support set and query set. The support set is utilized to

support the model and comprises a small number of examples or ”shots” In a 4-way 5-shot setting, for instance, if a model involves four classes, each with five examples, it means there are five instances or ”shots” available for each of the four classes.Query set used for testing the model's generalization performance. It contains examples that the model has not seen during training, and the model's task is to correctly classify these unseen instances based on what it learned from the support set.

Prototypical Networks, introduced by Snell et al [7] play had a significant impact in advancing few-shot learning. This model excels in the classification of limited sample sizes. In this model, the prototype is derived by computing the mean of features within the same class. Predictions are then made based on the similarity between the class prototype and a new instance. This approach has found applications in different domains, including image recognition, natural language processing, and medical image analysis [8], [9], [10], [11], [12].In this study, the Prototypical Network is employed, as it effectively addresses the primary challenge of managing an extensive number of examples per class.

II. Background

Few-shot learning, a subset of machine learning, has arisen as a compelling way to deal with addressing the challenges presented by restricted data availability and improving the generalization capacities of models in different domains. Few-shot learning models can be broadly categorized into two groups known as non-meta learning and meta-learning.A Prototypical Network is a famous meta-learning approach for few-shot learning that utilizes a nearest neighbor strategy, eliminating the need for hyper-parameters in the meta-test stage and resulting in practically insignificant inference time.

Prototypical Networks, introduced by Snell et. al. [7] aims to enable models to generalise and perform well even when only a few instances or examples are available for each category or class.This method has shown guarantee in the field of medical image analysis, as evidenced in the concentrate by Keshani et. al. [12].Their work centres around glaucoma diagnosis using a small measured dataset of high-resolution fundus images, emphasising the potential of few-shot learning techniques in addressing challenges related with restricted medical image data.

Yifan Jian et. al. [9] have introduced an innovative way to deal with Coronavirus CT diagnostics, leveraging regulated domain adaptation techniques.This technique offers significant advantages when only a predetermined number of named CT images are accessible, a common challenge in medical imaging applications.

Ahuja et. al. [8] proposed an implementation of P-shot n–ways Siamese network, based on deep learning principles combined with prototypical nearest neighbour classifiers. Their approach was to accurately classify COVID-19 infection in lung CT scan slices and the technique investigated that different pre-trained network CNN models affect the performance of multi-class classification of Siamese based networks.

Domain	Dataset	Performance
Siamese network based model [9]	Covid-19 CT segmentation from https://medicalsegmentation.com/covid19	Accuracy 0.8040±0.0356 F1-score 0.7998±0.0384
Prototypical closest neighbors' classifiers combined with a P-shot N-ways Siamese network [8]	Chest CT scans from 1110 patients in medical hospitals from Moscow, Russia	Accuracy 98.07% F1-Score 95.10%
A model based on a few-shot U-Net architecture [13]	Lung-PET-CT-DX dataset in TCIA database. PET/CT scans from 87 patients	Accuracy 99% Precision 70.62%
Comparison using both Zero-shot learning and Few Shot Learning [14]	LC25000 dataset. 25,000 color images in 5 classes	99.87% of accuracy from few-shot setting

TABLE I: Results from prior research involving few-shot learning applied to medical image analysis

Nicholas et. al. [13] have introduced an innovative dynamic few-shot learning framework custom-fitted for lung cancer lesion segmentation. This framework consistently integrates the force of few-shot learning with the U-Net architecture, presenting a novel way to deal with lung cancer detection and classification. What sets their procedure separated from existing methodologies is the worldwide neighbourhood PET/CT methodology fusion, a technique that veers off from conventional strategies, which regularly exploits separate PET and CT features or performs restricted fusion using CNN structures.

Meldo et. al. [5] has implemented an aggressive methodology to enhance the differential diagnosis of various lung conditions and create a comprehensive classification system for a broad spectrum of lung cancers. Their approach involves the development of a Computer-Aided Diagnosis framework, utilising a Siamese neural network. This network undergoes training on a specific dataset that includes meticulously segmented and labelled abnormal lung objects, with a focus on tumours. The dataset is carefully categorised into distinct groups such as ”typical” peripheral lung cancer (LC), ”abnormal” LC, and ”not cancer,” based on discernible CT image patterns. Notably, the dataset comprises only confirmed tissues validated through precise examinations, ensuring a high level of data integrity.But their

Fu-Ming Guo et. al. [14], employed a pre-trained Vision Transformer (ViT) model for the classification of lung cancer on histologic slices with multiple labels. They conducted evaluations in both Zero-Shot and Few-Shot settings, comparing the performance of ViT in terms of accuracy, precision, recall, sensitivity, and specificity. Their study revealed that the pre-trained ViT model exhibited excellent performance in the Zero-Shot setting. In the Few-Shot setting with just one epoch, it demonstrated competitive accuracy at 99.87%, and with five epochs, it achieved optimal results with 100.00% accuracy on both the validation and test sets.

The aforementioned research has made a significant contribution to the field by employing a few-shot learning method for the identification of lung cancer. However, the existing reviews have not sufficiently emphasized the utilization of a prototypical network and the impact of applying various feature extraction methods. Addressing these aspects is crucial for a comprehensive understanding of the research landscape in the context of lung cancer identification. Therefore, this review aims to fill this gap by thoroughly exploring and evaluating the role of prototypical networks and the implications of employing four pre-trained feature extraction methods in the context of few-shot learning for lung cancer identification.

III. Methodology

A. Dataset

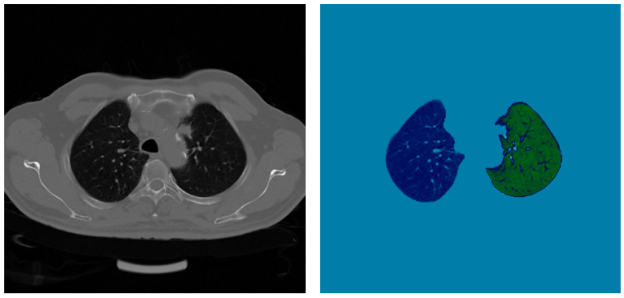
The implementation of this study used CT scan images obtained from the Lung-PET CT-Dx dataset in The Cancer Imaging File (TCIA), an invaluable asset laid out by the National Cancer Institute [15]. These images were complemented by XML Annotation documents that gave vital information regarding the localization of growths through bounding boxes. The dataset was curated retrospectively, focusing on individuals under suspicion of lung cancer who had undergone both a standard-of-care lung biopsy and PET/CT imaging.

This dataset includes CT images for a sum of 355 subjects, with each subject's data represented as a progression of DICOM images. In a request to lay out class marks within this dataset, a naming convention was utilized in light of the initial letter of the patient or subject name. Subjects designated with the letter 'A' were identified as having adenocarcinoma, 'B' as little cell carcinoma, 'E' as huge cell carcinoma, and 'G' as squamous cell carcinoma.

B. Image Pre-processing

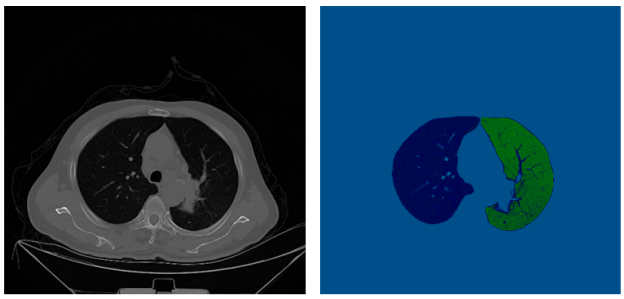
As the first step pixel information from the DICOM images was extracted. These pixels act as the fundamental units of a computerized image, capturing the brightness of this present reality scene they represent. Conversion of pixel representations into Hounsfield units is the next step. Hounsfield Units represent a standardized scale within the domain of medical imaging, serving as a universal reference for characterizing the radiodensity of explicit tissues or materials. This conversion enhances the likeness and analyzability of images, accordingly, enabling more precise and dependable diagnosis and treatment planning.

In the context of CT scan images, the presence of inherent noise can be especially dangerous, potentially leading to erroneous interpretations of the cancer type. Consequently, the evacuation of noise becomes basic to ensure the accuracy and unwavering quality of diagnostic results. In the implementation median filtering was applied to the images to reduce the noise. The median is calculated by first arranging all the pixel values in the correct numerical sequence in the neighborhood, and then replacing the middle pixel value for the one being assessed.



(a) Before Segmentation (b) After Segmentation

Fig. 3: The CT scan image depicting Squamous Cell Carcinoma before the application of the U-Net (R321) architecture for segmentation, followed by the post-segmentation result after applying U-Net.



(a) Before Segmentation (b) After Segmentation

Fig. 4: The CT scan image depicting Adenocarcinoma before the application of the U-Net (R321) architecture for segmentation, followed by the post-segmentation result after applying U-Net.

C. Image Segmentation

Image segmentation is fundamentally concerned with partitioning an image into discrete regions or classes, with every subset exhibiting internal homogeneity regarding explicit characteristics.

U-net is a modern architecture which has outstanding performance in medical image segmenting [13], [16].Johannes et. al. [17] introduced a changed version of the U-net architecture, which they trained using the R-231 Dataset.

In their research paper they have featured that at the hour of submission, the U-net(R-231) model attained the second-most elevated score among all participants in the LOLA11 challenge.In comparison, the U-net(R-231) model demonstrated better evaluation measures, including Dice similarity coefficient (DSC), Hearty Hausdorff distance (HD95), Mean Surface Distance (MSD), and cancer cross-over, when contrasted with other freely accessible algorithms.Furthermore, it covered more cancer volume.Because of the remarkable performance of the U-net(R-231) model,it was applied as the segmentation method for preprocessed CT images.

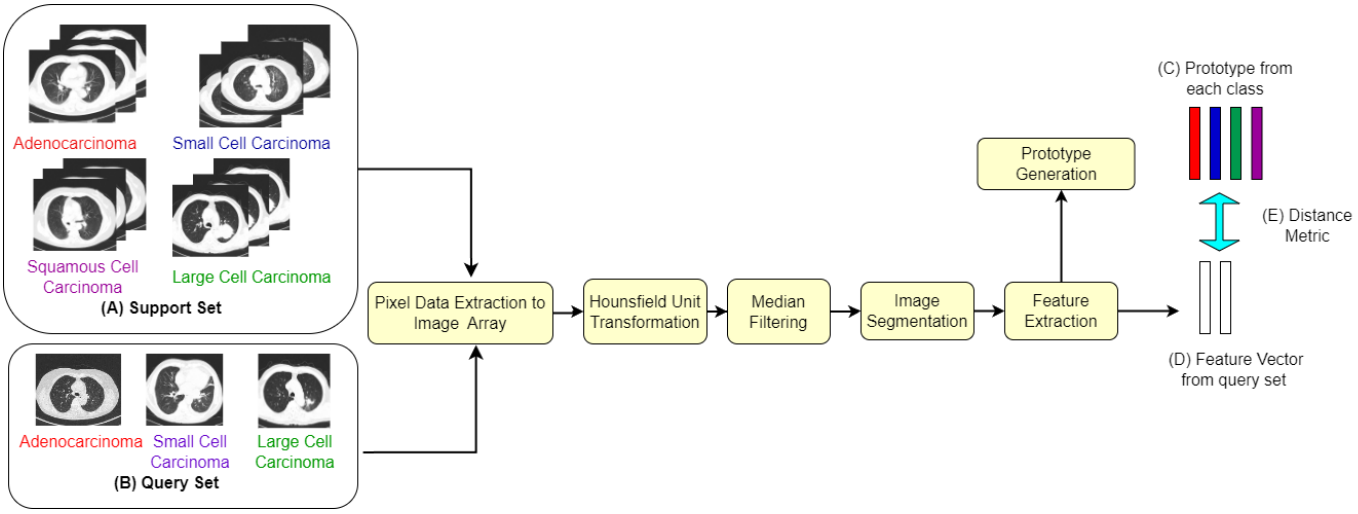


Fig. 5: Overall architecture of the prototypical network.(A) Support set has four classes with a limited number of shots.(B) Query set consists of the samples from the classes.(C) Prototype feature vector for each class is generated.(D) Feature vector from each query images.(E) Similarity between each prototype and the query image is calculated using the Euclidean distance.

D. Feature Extraction

Pre-trained CNNs in the feature extraction phase of medical image analysis stands as a significant advancement, enabling the programmed acquisition of intricate image features and leveraging the progressive representations learned during training.

Utilization of pre-trained CNNs conveys the benefit of these models having been trained on different sets of images, promoting generalization, and mitigating the risks of overfitting, particularly when confronted with restricted medical data.Four distinct pre-trained CNNs, namely VGG16 [18], ResNet50 [19],DenseNet [20] and CNN, were harnessed for the feature extraction process in the analysis of lung CT images in this methodology.

E. Prototypical Network

In a few shot classification, a small support set of N labeled examples will be given. The D-dimensional feature vector of each example will be output by a pre-trained feature extraction model. To create a prototype for each lung cancer type ,the average of all feature vectors in a class label will be calculated. This prototype serves as a representative for the label and is used to compare with the features of new examples during inference.

Next key component in prototypical network is calculation of distance matrix. The distance matrix is used to measure the similarity between the support set and the query set. It is shown that Euclidean distance performs better than cosine similarity when calculating distance [7].When Euclidean distance is applied, the model is equivalent to a linear model with a particular parameterization.

F. Episodic Learning

Episodic learning has been applied to improve the performance of the model. In this approach, a few shot classification tasks are directly tuned for the model. One Iterative cycle ,here considered as “Epoch”.

During each epoch, the whole training set is feeding forward and backward and it will be partitioned into several parts which are called “Batch”. Consequently, the number of iterations per epoch are all batches that feed into the model. The support set is in the form of N-way k-shot random samples, and the query set consists of q random samples for each of the N support set classes and these two data sets would be created during each episode. The prediction error over episodes is used to update the meta-learner. The meta-learner learns to learn from the limited dataset throughout a series of episodes. This stage is known as meta-learning.

For this development, the CrossEntropyLoss() function is used to define the loss criterion for the classification task. Adam() function is used to define the optimizer for updating the model’s parameters during training. The learning rate was set to 0.001,which determines the step size taken by the optimizer in the parameter space.

IV. RESULTS & DISCUSSION

The experiment involved the utilization of four pre-trained CNN models as the feature extractors. The performance evaluation of each pre-trained model is conducted by assessing metrics such as Precision, Recall, F-Score, and Accuracy score. This evaluation is conducted under varying conditions where the number of shots per class in the support set is altered. The purpose is to gauge how well the models perform when faced with different scenarios of data availability for each class. Table II present the Precision, Recall and F1-Score for four different pre-trained model, when applied to the prototypical network.

The results demonstrate how the model’s performance changes with the number of labeled example per class. Figure 4 displays the accuracy for each pre-trained model with the

Pre-trained model	Shots per class = K	Precision	Recall	F1-Score
VGG16	1-Shot	0.74	0.68	0.68
	2-Shot	0.82	0.81	0.81
	3-Shot	0.86	0.81	0.82
	4-Shot	0.77	0.75	0.74
	5-Shot	0.69	0.66	0.65
CNN	1-Shot	0.6	0.56	0.54
	2-Shot	0.88	0.87	0.87
	3-Shot	0.68	0.68	0.68
	4-Shot	0.95	0.93	0.93
	5-Shot	0.87	0.83	0.82
DenseNet	1-Shot	0.79	0.68	0.66
	2-Shot	0.95	0.93	0.93
	3-Shot	0.88	0.87	0.87
	4-Shot	0.87	0.83	0.82
	5-Shot	0.9	0.9	0.9
ResNet50	1-Shot	0.33	0.43	0.33
	2-Shot	0.22	0.31	0.25
	3-Shot	0.76	0.68	0.69
	4-Shot	0.71	0.62	0.6
	5-Shot	0.98	0.98	0.98

TABLE II: Performance metrics for Individual Pre-trained Models in a K-Shot 4-Way Setting.(Epochs=3)

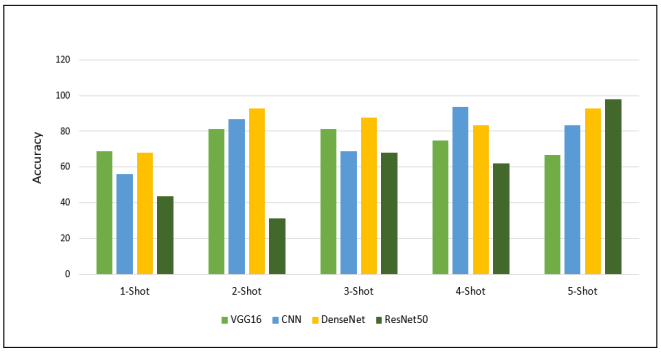


Fig. 6: Accuracy comparison for each pre-trained model before meta-training with 5-Shot 4-Way Setting.(Epochs=3)

number of lung CT images per class. The highest accuracy scores are attained for all models with more than 3-shot settings.

Notably, the highest accuracy observed as 98% for ResNet50 model with 5-Shot setting for each class.Shivan et al. [21] introduced a lung cancer detection method utilizing CT scan images and conducted experiments using the ResNet18 and ResNet50 models. Their approach involves integrating deep learning with pre-trained models.Shital et al [22] have devised a technique for classifying lung nodules, employing ResNet50 as the feature extractor and utilizing Support Vector Machine as the classification model. The table III compares the results obtained by them with the outcomes from our study.

Overall, the models achieve their best performance when there are more shots per class, especially with 4 or 5-Shot classes, indicating the importance of having sufficient training examples to achieve higher accuracy and F1-Scores. The findings underline the importance of considering both the decision of model and the availability of marked data when aiming for ideal few-shot learning results.Figure 7 show the

Method	Accuracy
Convolutional Neural Network with RestNet50 [21]	97.05%
Support Vector Machine with ResNet50 [22]	97.53%
Prototypical Network with ResNet50	98%

TABLE III: Comparison of the accuracy between existing methods utilizing ResNet50 for feature extraction and the proposed Prototypical Network.

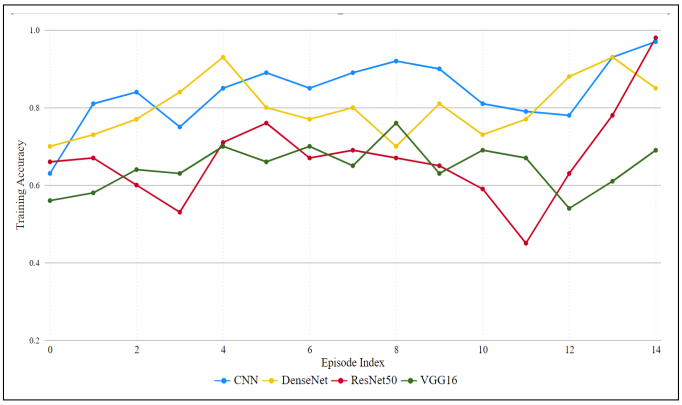


Fig. 7: The graphs compares the training accuracy over 15 epochs for each feature extraction model. The chosen configuration utilized five shots per class and a learning rate of 0.001.

training accuracy and training loss were tracked over multiple episodes for each model. Model was set to learn for 15 episodes.

When examining the training progress for each pre-trained model from Figure 7, which was completed 15 episodes with 4 shots for every class, interesting patterns arise. Looking at the VGG16 model, the training accuracy fluctuates all through the episodes. This indicates that the model's learning cycle isn't totally steady, because of variations in the accessible data or the intricacy of the task.

For the ResNet50 model, the training accuracy initially wavers around 0.6 prior to showing improvement in episodes two and three. In any case, the accuracy is inconsistent across episodes, and a declining trend is seen towards the end of the training. Conversely, the training loss begins higher however diminishes with slight fluctuations. The CNN model, in contrast, displays consistent advancement regarding training accuracy, with consistent improvement throughout the span of the episodes.

This indicates a steady learning process, potentially owing to the model's architecture and data distribution. Likewise, the training loss shows a consistent decline, indicative of effective learning.Finally, the DenseNet model shows an initially fluctuating training accuracy, however it balances out as training advances. The training loss diminishes, with minor fluctuations, suggesting that the model is adapting to the data effectively. These findings recommend that different pre-

trained models display assorted training ways of behaving. While certain models demonstrate sporadic patterns, others show more steady and consistent learning trends.

These observations feature the mind-boggling nature of training neural networks, influenced by factors like model architecture, data distribution, and convergence dynamics. In the conducted study, the most noteworthy accuracy was achieved by both ResNet50 and Convolutional Neural Networks (CNNs) as the feature extractors when the number of epochs was increased to 15.The experiment encompassed 15 training episodes, where every episode consisted of 5 support images from each class and 3 query images from each class. The models attained an impressive accuracy of 98

In this study, we conducted our research using only one dataset obtained from TCIA. While this dataset provided valuable insights into the use of the prototypical network architecture for lung cancer classification, the reliance on a single dataset may impact the generalizability and applicability of our results. Future research endeavors could benefit from incorporating diverse lung CT image datasets labeled with specific lung cancer types. This approach would enhance the reliability and broader relevance of the findings.

V. CONCLUSION & FUTURE WORK

The entire postulation project spun around identifying four main types of lung cancer using CT scan images, with an essential spotlight on determining the most fitting image processing philosophy for medical images when it is restricted to train data. The project basically used the prototypical network, a notable few-shot learning model, to accomplish this objective. Different pre-trained models and a CNN model were utilized to extract a superior feature space from lung CT images.

The insights generated by this research give a foundation to additional exploration and refinement in the field of lung cancer identification using CT scans and few-shot learning techniques. An intriguing avenue for future review is the combination of Siamese Neural Networks and Prototypical Networks. This fusion can possibly yield an additional strong and precise model for classifying types of lung cancer. Siamese Networks [23] succeed in discerning differences, while Prototypical Networks are proficient at categorization using models. Combining their strengths could address challenges that each network faces in isolation. Mastering the specialty of consistently integrating these networks and addressing any challenges that might arise represents a captivating issue to be settled.

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