BACHELOR OF SCIENCE IN COMPUTER SCIENCE AND ENGINEERING

Improving Few Shot Adaptive Learning for Medical Image Classification using Vision Transformer(ViT)

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Declaration of Candidate

This is to certify that the work presented in this thesis is the outcome of the analysis and experiments carried out by **Nokimul Hasan Arif**, **Sakif Ahbab**, and **Syem Aziz** under the supervision of **Dr. Md. Hasanul Kabir**, Professor, Department of Computer Science and Engineering and co-supervision of **Sabbir Ahmed**, Assistant Professor, Department of Computer Science and Engineering, Islamic University of Technology, Dhaka, Bangladesh. It is also declared that neither this thesis nor any part of it has been submitted anywhere else for any degree or diploma. Information derived from the published and unpublished work of others have been acknowledged in the text and a list of references is given.

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Dedicated to our parents

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List of Abbreviations

FSL	Few Shot Learning
CNN	Convolutional Neural Network
ViT	Vision Transformer
CAD	Computer-Aided Diagnosis
GPT	Generative Pre-training Transformer
CLS	Classification Token
BERT	Bidirectional Encoder Representations from Transformers

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Abstract

Medical image classification plays a pivotal role in automating disease diagnosis and treatment planning. However, the limited availability of annotated medical data poses a significant challenge for training accurate classifiers. This research paper introduces an enhanced approach to improve Few-Shot Adaptive Learning for Medical Image Classification, employing the transformative capabilities of Vision Transformer (ViT) architectures. Our proposed method uses ViTs to capture intricate spatial relationships and contextual information inherent in medical images. To address the challenge of limited labeled data, we focus on improving Few-Shot Learning by introducing adaptive learning strategies. The integration of ViT not only enhances the model's ability to learn complex patterns but also facilitates efficient adaptation to new classes with minimal labeled data. The model dynamically adjusts its representation space, allowing for efficient adaptation to diverse medical imaging scenarios with minimal labeled examples. Extensive experiments are conducted on diverse medical image datasets to validate the effectiveness of our approach. The results showcase notable improvements in classification performance compared to existing state-of-the-art methods. The proposed ViT-based framework holds promise for improving the generalization and adaptability of medical image classifiers, thereby contributing to the advancement of automated medical diagnosis and treatment planning.

Chapter 1

Introduction

1.1 Overview

Medical image classification involves assigning a label to each image, a task vital for diagnostic and treatment planning. Despite numerous works addressing this challenge, their effectiveness is often confined to controlled environments where the model was trained. Crafting a training framework that thoroughly encompasses all conceivable medical scenarios with real-life context proves unfeasible from a design standpoint. This challenge underscores an ongoing research problem: effectively categorizing both recognized and novel medical conditions.

In response to this challenge, few-shot medical image classification has emerged as a task seeking to classify both known and unknown medical conditions. This innovative paradigm opens avenues for applications in real-life contexts such as computer-aided diagnosis (CAD), medical image segmentation, disease diagnosis and subtyping, robotic-assisted surgeries, personalized treatment planning, telemedicine, and remote diagnosis, monitoring disease progression, and automated pathology detection.

However few-shot medical image classification has to face many challenges like variability in medical imaging, data scarcity, class imbalance, model generalization, etc. Approaches like supervised and unsupervised learning, and transfer learning have been undertaken to address the issues but existing models fail to generalize the novel medical cases that were not encountered during training. The challenge here is creating models that can efficiently classify and adapt to the everlasting changes in medical cases. This research aims to develop a Few-Shot Adaptive Learning framework that can enhance medical image classification by effectively classifying both familiar and

new medical casess.

Considering the context of Few-Shot Adaptive Learning for Medical Image Classification, the ViT-based framework, designed to enhance few-shot learning in medical image classification, offers a unique opportunity to extend its adaptability. Leveraging ViT's ability to capture intricate spatial relationships and contextual information will improve the classification of both known medical conditions encountered during training and novel conditions that manifest in the real-world scenarios. This research direction holds promise for advancing the state-of-the-art in medical image classification, ensuring the accurate identification of both familiar and emerging medical conditions.

1.2 Problem Formulation

In fsl, the task is to train a model using only few number of examples for each class. Specifically, we consider the n-way k-shot setting, where n is the quantity of classes (or categories of medical conditions), and k is the number of examples (images) available for each class during training. After training, the model's performance is evaluated on its ability to classify a broader range of medical conditions during testing, including those with limited prior exposure.

In a classical fully-supervised medical image classification task, we have a dataset $\mathcal{D}$ consisting of medical images $\{\mathcal{I}_i\}_{i=1}^{T}$, where T represents the total number of images in the dataset. Each image $\mathcal{I}_i$ is associated with a label $\mathcal{N}_i^{gt}$, belonging to a set of possible classes $\mathcal{C}$. The goal is to train a model that can predict the label $\mathcal{N}_i^{pred}$ for each image $\mathcal{I}_i$, where $\mathcal{N}_i^{pred}$ is the predicted label indicating the medical condition in the image.

$$\mathcal{D}_{train} = \{\mathcal{I}_{ij}^{S}, \mathcal{N}_{ij}^{S,gt}\}_{i=1,j=1}^{n,k} \tag{1.1}$$

$$\mathcal{D}_{test} = \{\mathcal{I}_{ij}^{S\cup U}, \mathcal{N}_{ij}^{S\cup U,gt}\}_{i=1,j=1}^{n,k} \tag{1.2}$$

Here, $\mathcal{I}_{ij}^{S}$ and $\mathcal{N}_{ij}^{S,gt}$ represent the j-th example and ground-truth label, respectively, for the i-th class.

Considering a scenario with $n = 5$ classes (e.g., diseases) and $k = 3$ shots (examples) per class during training. The training set $\mathcal{D}_{train}$ would consist of 15 examples, 3 for each of the 5 classes.

$$\mathcal{D}_{train} = \{\mathcal{I}^S_{11}, \mathcal{N}^{S,gt}_{11}, \dots, \mathcal{I}^S_{53}, \mathcal{N}^{S,gt}_{53}\} \tag{1.3}$$

Here, $\mathcal{D}_{train}$ contains examples from only the seen classes, and $\mathcal{D}_{test}$ contains images from both seen and unseen classes. This setup, known as few-shot medical image classification, poses a challenge as the model needs to generalize from a limited set of seen classes to accurately classify images from both seen and unseen classes during testing.

The primary objective is to train a model capable of assuming the correct class labels for medical images in $\mathcal{D}_{test}$, especially for the unseen classes that were not encountered during training. Performance is measured based on its ability to generalize from a few examples of seen classes to effectively classify images across the broader spectrum of both seen and unseen classes.

1.3 Research Challenges

Navigating the terrain of mapping medical images to their corresponding labels within a few-shot learning framework presents an intricate and formidable challenge, especially when confronted with a scant number of samples in the dataset. This challenge is notably amplified in the realm of medical imaging, where the complexity and variability inherent in medical images add layers of intricacy. The application of adaptive learning, a crucial aspect for empowering Vision Transformers to dynamically learn and adapt, becomes particularly daunting given the unique challenges posed by the medical domain. The meta-learning process, designed to facilitate swift adaptation to new tasks, encounters formidable obstacles in the face of the nuanced and specialized characteristics of medical datasets.

Moreover, employing Vision Transformers as feature extractors in this context is not without its share of challenges. The vulnerability of medical images to distortion and variability introduces complexities that hinder the seamless extraction of relevant features, thereby impeding the attainment of desired results. This distortion poses a significant hurdle to the Vision Transformer's ability to discern meaningful patterns in the medical data.

Furthermore, the application of Vision Transformers in the few-shot learning paradigm within the medical domain demands an extensive dataset to effectively train the model. This requirement for a substantial number of diverse and high-quality medical images underscores the inherent intricacies of leveraging Vision Transformers in this

specific domain. The scarcity of labeled samples in medical datasets adds an additional layer of complexity, making it imperative to address the challenges associated with limited data scenarios. In light of these multifaceted challenges, the pursuit of innovative methodologies becomes crucial to overcoming the hurdles intrinsic to few-shot learning in the intricate landscape of medical image classification using Vision Transformers.

1.4 Contribution

In this thesis work, a distinctive contribution is made by integrating the Vision Transformer (ViT) with adaptive few-shot learning, offering a novel and robust approach to medical image classification. The ViT, renowned for its efficacy in extracting comprehensive image features by partitioning the image into fixed patches and pre-training on an extensive dataset, forms the cornerstone of our methodology. This pre-training enables the ViT to capture rich and detailed representations of images, which is crucial for handling the complexity of medical images. Leveraging meta-training, the model is endowed with the capability to learn dynamically and adapt to new tasks with limited data, marking a significant stride in endowing machines with the ability to "learn to learn." This meta-training phase enhances the model's flexibility and generalization capabilities, crucial for medical applications where data variability is high. Subsequently, the model undergoes fine-tuning tailored explicitly for a few-shot medical image classification task, where the scarcity of labeled samples poses a considerable challenge. This fine-tuning ensures that the model adapts specifically to the unique characteristics of medical images, thereby improving its diagnostic accuracy and reliability.

An innovative aspect of this approach involves the ensemble of subspaces for classification. Post feature extraction, the image is represented in multiple subspaces, and we specifically aim for these subspaces to exhibit minimal similarity, ensuring diverse and comprehensive feature representation. To achieve this, a Discriminative Loss Function is strategically employed and minimized within our model. This step is pivotal in ensuring that the subspaces capture diverse and distinctive features, contributing to the model's overall robustness and discriminative power. The discriminative loss function not only enhances the model's ability to distinguish between different classes but also mitigates the risk of overfitting, which is a common issue in few-shot learning scenarios.

During the prediction phase, the class label probability is harnessed through a so-

phisticated ensemble approach where each subspace contributes its perspective. This multi-view approach ensures that the model leverages diverse information from different feature representations, enhancing the robustness of the predictions. Notably, the final class label for the input image is determined by the class with the highest aggregated vote across these subspaces. This voting mechanism ensures a consensus-driven decision, reducing the likelihood of misclassification due to noise or outliers in any single subspace. This strategic integration of Vision Transformer as a feature extractor, coupled with adaptive few-shot learning, not only addresses the challenges inherent in medical image classification but also marks a distinctive and impactful contribution to the evolving landscape of machine learning methodologies in healthcare. The ensemble approach, in particular, significantly boosts the model's accuracy and reliability, which are critical for clinical applications.

1.5 Organization of the Thesis

This thesis is divided into several chapters, each focusing on a key aspect of Few-Shot Adaptive Learning for Medical Image Classification.

Introduction

This introduction provides an overview of the challenges in medical image classification and highlights the importance of Few-Shot Learning for handling both familiar and new medical conditions. It introduces the Vision Transformer (ViT) framework as a potential solution and outlines the motivation for this research.

Related Works

Here, we learn more abo the background of medical image classification, explore the major existing methods, and discuss their limitations. This chapter also introduces key concepts like Few-Shot Learning and the use of Vision Transformers in medical imaging, reviewing related work and identifying the research gap.

Methodology

We describe the methodology used in this research, including the dataset, experimental setup, and how Few-Shot Learning with ViT was implemented and tested for medical image classification.

Results and Discussion

The results of the experiments, comparing the performance of the ViT-based model with other methods are given here. It also includes a detailed analysis of how the model performs on both familiar and novel medical conditions.

Conclusion

The final chapter summarizes the findings, discusses the implications of the results, and offers suggestions for future research. It emphasizes the potential of Few-Shot Learning and ViTs in advancing medical image classification in real-world scenarios.

Chapter 2

Related Works

2.1 Few-Shot Learning

Feifei Li et al. introduced the idea of few-shot learning in 2003, noting that the main challenge with using few-shot learning is understanding how to apply the findings that have been gained to discover a new category[10]. The long-lived issue that the requirement has for very big and comprehensive datasets is resolved by this method. To classify new test photos, few-shot learning often only needs to learn the features of a few labeled images for training examples. Currently, a lot of image processing applications, including image segmentation[28], image recognition[26], image classification, and retrieval[1], [21], [40], use few-shot learning. Furthermore, there is a great deal of practical usefulness in the study of few-shot picture classification.

Generally, Few-shot learning is a machine learning approach where a model is trained to learn from a very limited number of training examples (shots). This is particularly useful in situations where data is scarce or expensive to obtain.

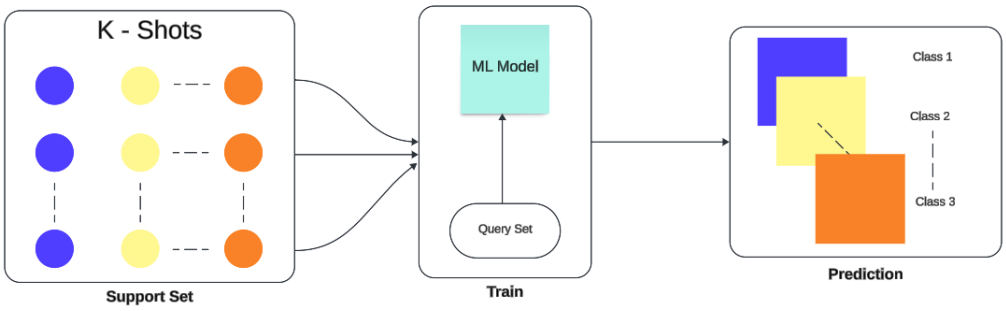


Figure 2.1: Few Shot Learning

Important Terms

- **Support Set**: A small set of labeled examples that the model uses to learn. It includes a few examples from each class.
- **Query Set**: A set of examples the model must classify after learning from the support set.
- **N-Way K-Shot Learning**: A common approach in few-shot learning.

  N-way: The number of different classes the model needs to recognize. More classes make the task harder.

  K-shot: The number of labeled examples per class in the support set. Fewer examples make the task more challenging.

Typically, K values range from one to five. When K=1, the task is known as "One-Shot Learning," which is particularly challenging. K=0 represents "Zero-Shot Learning," which is fundamentally different from other few-shot learning approaches as it falls under the Unsupervised Learning paradigm. Few Shot Learning approach enables the model to generalize to novel categories with very few labeled examples, making it ideal for tasks with limited labeled data.

Large-scale labeled data collection is challenging in domains like public security[45] and medicine[31], which hinders the performance of deep learning models. With few-shot learning, the issue of some high-performance models not being able to generalize in new classes because of insufficient training data can be efficiently addressed, allowing these models to be used in more disciplines. Specifically, the study development on few-shot learning models and algorithms based on transfer learning, data augmentation, and model fine-tuning strategies was provided by Zhao et al.[41]. A comprehensive evaluation of the literature on few-shot learning was done by Wang et al.[42], who categorized the material into a single taxonomy based on the viewpoints of the data, model, and algorithm.

Nevertheless, academic research on few-shot picture classification is quite sparse-[22]. When few-shot learning is based on the Bayesian framework, the sample's class probability reasoning is produced early in the study by integrating the model parameters with the prior and posterior probabilities[11]. In order to address the issue of few-shot picture categorization, researcher workers have presented NNMs thanking the advancements in deep learning and neural network design. The deep learning approach has been incorporated into the majority of FSL techniques in recent times.

One kind of feature extraction method used in data analysis and machine learning

is adaptive subspace methods. The process of turning unprocessed data into a set of features (also known as a feature vector) that a machine learning algorithm can understand and use more quickly is known as feature extraction[47]. Finding a subspace—a subset of the original feature space—that most accurately captures the underlying structure of the data is how adaptive subspace algorithms operate. Typically, to do this, the original feature space is transformed in a way that maximises a particular objective function, like the variance of the data in the new subspace. These techniques usually have a mathematical formula using matrix operations[46]. The transformation can be represented as Y=XW, for example, if we designate the feature matrix of the original data as X, the transformation matrix as W, and the feature matrix of the modified data as Y. The columns of W represent the subspace's basis vectors, and they are frequently discovered by resolving an optimisation issue that seeks to maximise or minimise a certain function of Y.

The particular adaptive subspace approach being employed determines the precise form of this optimisation problem. To maximise the variance of the data in the new subspace, for instance, is the objective function of Principal Component Analysis (PCA), one of the most popular adaptive subspace methods.

Adaptive subspaces are a method for few-shot learning, in which a model is trained on a limited number of samples to become more broad and predictive. The supplied data is first processed to extract its features. In the few-shot task, a subspace is built for every class following feature extraction. A class's subspace is a lower-dimensional space that encapsulates the key traits of that class. The features of the few examples that are available for that class are used to construct the subspace. Although there are other ways to build the subspace, Principal Component Analysis (PCA) is frequently employed to identify the feature space directions that best capture the variance in the class's data. The subspaces can be used to categorise new instances after they have been built. The new example's features are projected onto each subspace, and the distance between the projected features and the subspace is then measured. According to the classification, the new example falls into the class whose subspace is closest to the projected features.

2.2 Transformers

The Transformer is a deep learning model designed to handle sequential data and is widely used in natural language processing (NLP) tasks. Unlike traditional RNNs (Recurrent Neural Networks), Transformers do not require data to be processed in

order, allowing for greater parallelization and efficiency.

2.2.1 Architecture

Transformer architectures consists of two main components: the encoder and decoder. Each of these is composed of multiple identical layers.

Encoder

The encoder is a stack of N same layers, each having two main components:

1. **Multi Head Self Attention Mechanism**: This mechanism allows each position in the encoder to attend to all positions in the previous layer. The multi-head aspect means that the model can jointly attend to information from different representation subspaces at different positions.
2. **Feed Forward Neural Network**: Each position in the sequence is independently passing through a fully connected feed-forward network.

Decoder

The decoders are also a stack of N same layers, but with an extra attention layer:

1. **Masked Multi Head Self Attention Mechanism**: This is similar to the encoder's self-attention but prevents positions from attending to subsequent positions.
2. **Encoder Decoder Attention**: This layer allows the decoder to focus on appropriate places in the input sequence. It helps the decoder in generating the next word in the sequence.
3. **Feed Forward Neural Network**: Similar to the encoder, each position is independently passed through a fully connected feed forward network.

2.2.2 Self-Attention Mechanism

Self-attention is the core mechanism that allows Transformers to process sequences effectively. The self-attention mechanism computes a representation of each word in the sequence by considering all the other words in the sequence.

1. **Input Embeddings**: Each word is first converted into a continuous vector (embedding).

2. **Positional Encoding**: Since the model does not inherently understand the order of the sequence, positional encodings are added to the embeddings.
3. **Query, Key, and Value**: For each word, three vectors are derived through learned linear transformations: Query (Q), Key (K), and Value (V).
4. **Attention Scores**: The attention score for a pair of words is computed as the dot product of their Query and Key vectors, scaled, and passed through a softmax function.
5. **Weighted Sum**: The final representation of each word is computed as a weighted sum of the Value vectors, with the weights being the attention scores.

Since their introduction by Vaswani et al.[34], transformers have come out to be the most advanced approach for many natural language processing problems. Big Transformer based models are frequently adjusted for the given purpose after being pre-trained on sizable corpora: While language modeling is the task for pre-training used in the study in the line of GPT[3], [27], BERT[8] utilises a self-supervised denoising pre-training task. If self-attention were applied naively to images, every pixel might have to pay close attention to all other pixels. Realistic input sizes are not supported by this because of the quadratic cost in the amount of pixels. Therefore, a number of assumptions were attempted in order to use Transformers in image processing. In a different field, scalable approximations of global self-attention are applied to images using Sparse Transformers[7]. Applying attention to blocks of different sizes[43] is an alternate method of scaling it; in the worst situation, attention is only applied along individual axes[13], [37]. While several of these specialised attention structures show promise in computer vision, their effective usage on hardware accelerators requires sophisticated engineering.

CNNs and self-attention have also been used extensively. For example, CNNs have been used to augment feature maps[2] for image classification. Another popular approach is to use self-attention to further process the CNN's output, such as for object detection[4], [14], video processing[33], [38], image classification[44], unsupervised object discovery[23], or unified text-vision tasks[6], [20], [24].

Transformers are applied to pixels of the image after decreasing the resolution and color space in image GPT (iGPT)[5], another new related model. As a generative model, the model is trained in an unsupervised manner. On ImageNet, The output representation can thereafter be linearly improved, reaching a maximum accuracy of 72%.

2.3 Vision Transformer(ViT)

A Vision Transformer (ViT) is a type of neural network architecture designed for image classification tasks, leveraging the principles of the Transformer architecture originally developed for natural language processing (NLP) [16]. ViTs have demonstrated state-of-the-art performance on various image classification benchmarks, sometimes outperforming traditional convolutional neural networks (CNNs)[9].

Mechanism

Image Patch Extraction

An input image is divided into a grid of non-overlapping patches. Each patch is then flattened into a vector [9]. For instance, if an image is divided into 16×16 patches, each patch will be of size $16 \times 16 \times C$ (where C is the number of channels, usually 3 for RGB images), and it is flattened into a vector of size $16 \cdot 16 \cdot C$.

Linear Embedding

Each flattened patch is linearly transformed into an embedding vector of a fixed size. This is akin to converting words into word embeddings in NLP[16].

Position Embedding

Since Transformers do not inherently capture the spatial structure of images, positional embeddings are added to each patch embedding to retain positional information.[9]

Transformer Encoder

The specific sequence of embedded patches (along with positional embeddings) is passed thro-ugh a standard Transformer encoder[16]. This encoder consists of multiple layers of self-attention mechanisms and feed-forward neural networks, enabling the model to capture complex relationships between patches.

Classification

A special classification token (similar to the [CLS] token in BERT) is prepended to the sequence of embedded patches[9]. After passing through the Transformer encoder, the representation corresponding to the classification token is used for the final image classification task.

2.4 Adaptive Subspaces and Few-Shot Learning

Adaptive Subspaces for Few-Shot Learning (ASFS) is a concept within the field of machine learning and, more specifically, few-shot learning[30]. Few-shot learning aims to enable models to learn new tasks with very limited labeled data, often just a few examples per class. This is challenging because traditional deep learning models typically require large amounts of labeled data to perform well. In this case, instead of representing data points in the high-dimensional space where they naturally lie, the method represents them in a lower-dimensional subspace. This is motivated by the observation that data points from the same class tend to lie on or near a lower-dimensional manifold within the high-dimensional space.

The paper "Adaptive Subspaces for Few-Shot Learning" by Christian Simon et al.[29] proposes a new approach to few-shot learning by introducing dynamic classifiers that are constructed from few samples. The authors propose a framework that uses a subspace method as the central block of a dynamic classifier.

The authors formulate few-shot learning as a two-stage learning paradigm: first, learning a universal feature extractor, and second, learning to generate a classifier dynamically from limited data. They argue that many state-of-the-art few-shot learning techniques fit neatly into this learning paradigm. Moreover, they show that viewing few-shot learning in this way provides tools to formalize the concept.

The authors suggest representing data points using subspaces. A subspace has a basis, represented by a matrix B_i of size $RD \times n$, where $n \leq D$. The matrix B_i satisfies $B_i^T B_i = I_n$. Their goal is to train a feature extractor Θ that generates subspaces, making them suitable for subspace-based classifiers.

One way to classify data in a subspace is by finding the shortest distance between a point and its projection onto the subspace. For this, a class-specific projection matrix P_{ci} is calculated from the class data $\tilde{X}_c$. A query point q_j is projected onto P_c, and classification is based on the shortest distance between the query and its projection onto P_c.

The subspace classifier is defined as:

$$dc(q) = - \parallel (I - Mc)(f_\Theta(q) - \mu_c) \parallel^2,$$

where $Mc = P_c P_c^T$ and μ_c represents the offset between the point and the subspace.

The probability of assigning the query to class c is given by the softmax function:

$$p_{c,q} = p(c|q) = \frac{\exp(-dc(q))}{\sum_{c'} \exp(-dc'(q))}.$$

2.5 Adaptive Subspaces for Few-Shot Learning

Few-Shot Learning (FSL) tackles the difficulty of training models with a restricted number of examples[15]. This issue is of great importance in numerous practical situations when it is not feasible to gather extensive datasets with annotations. The research article titled "Adaptive Subspaces for Few-Shot Learning" introduces a new method for FSL that involves creating dynamic classifiers utilizing subspace approaches[29]. The main concept is to utilize the resilience of subspace representations against disturbances and anomalies, hence improving the model's capacity to make generalizations from a limited amount of data.

The literature on few-shot learning is rich with various approaches, primarily divided into generative models, metric-based learning, and meta-learning techniques. Early works like those of Lake et al. [19] utilized generative models with hand-crafted features, while more recent methods employ deep learning to learn embeddings or initializations that can quickly adapt to new tasks.

Generative models seek to accurately represent the distribution of data in order to produce fresh samples, hence assisting in classification problems. The Constellation Model is a noteworthy approach that employs parts-based models to recognize objects. Metric learning methods, such as Siamese Networks [17] and Prototypical Networks [32], aim to acquire a similarity function that transforms input pairs into a metric space, facilitating straightforward categorization.

Meta-learning, or "learning to learn," optimizes a model to adapt quickly to new tasks. Notable approaches include Model-Agnostic Meta-Learning (MAML) [12], which learns an initialization suitable for rapid adaptation using gradient descent. Methods like MetaNets [25] further explore the concept of fast and slow weights to balance adaptation and stability.

Adaptive Subspaces for Few-Shot Learning

The authors propose a framework that constructs dynamic classifiers from limited samples using subspace methods. This approach is motivated by the observation that second-order methods often generalize better for classification tasks. The paper introduces the concept of representing each class with subspaces formed by basis vectors.

Given a set of training samples $\{(x_i, y_i)\}_{i=1}^N$ where $x_i \in \mathbb{R}^D$ and $y_i \in \{1, \ldots, K\}$, the goal is to construct a classifier for each class using few-shot samples. The key steps include:

1. **Feature Extraction:** A universal feature extractor $f_\theta : \mathbb{R}^D \to \mathbb{R}^d$ is trained on a large dataset.

2. **Subspace Construction:** For each class k, the subspace is formed by performing Singular Value Decomposition (SVD) on the feature matrix $X_k = [f_\theta(x_i)]_{i:y_i=k}$. Let $U_k \Sigma_k V_k^\top = \text{SVD}(X_k)$, the subspace is represented by the top r left singular vectors $U_k^r \in \mathbb{R}^{d \times r}$.

3. **Classification:** A new sample x is classified by projecting it onto each subspace and computing the reconstruction error. The class with the minimum error is chosen:
$$\hat{y} = \arg\min_k \|f_\theta(x) - U_k^r U_k^{r\top} f_\theta(x)\|_2^2$$

Discriminative Subspaces:

To enhance discriminability, the authors introduce a discriminative term that encourages orthogonality between subspaces of different classes[18]. The objective function for learning the subspaces includes this term:

$$\mathcal{L} = \sum_{i=1}^{N} \|f_\theta(x_i) - U_{y_i}^r U_{y_i}^{r\top} f_\theta(x_i)\|_2^2 + \lambda \sum_{k \neq l} \|U_k^{r\top} U_l^r\|_F^2$$

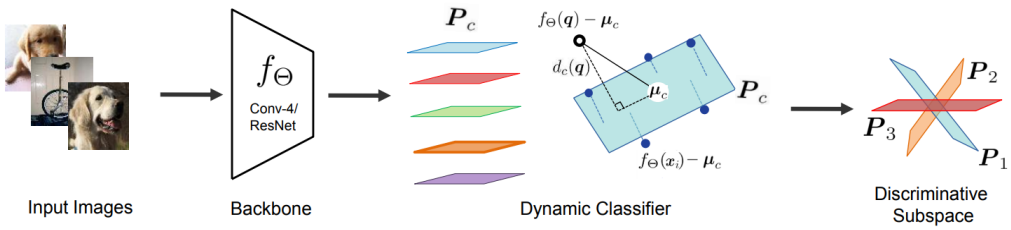


Figure 2.2: Pipeline

The proposed method is evaluated on standard few-shot learning benchmarks, including mini-ImageNet. The results demonstrate that subspace-based classifiers outperform prototypical networks and other baselines, particularly in the presence of noise. The use of discriminative subspaces further boosts performance.

The paper "Adaptive Subspaces for Few-Shot Learning" introduces a robust and effective approach to few-shot learning by leveraging subspace methods[29]. This framework not only improves classification accuracy but also offers robustness to pertur-

bations, making it a promising direction for future research in few-shot and meta-learning.

2.6 Few-shot Learning Framework Based on Adaptive Subspace for Skin Disease

Skin disease classification is crucial for dermatological diagnosis, particularly given the rising incidence and fatality rates associated with conditions such as melanoma[48]. Traditional computer-aided diagnosis (CAD) systems are limited in handling new and emerging diseases because they rely on standard deep learning models that can only identify categories present in their training datasets. Few-shot learning (FSL) offers a solution by enabling models to generalize to new categories with only a few examples.

Three-stage Learning Paradigm

The proposed three-stage learning paradigm[48] consists of:

1. **Learning a Universal Feature Extractor:** The purpose of the feature extractor is to acquire significant features from the photos in a universal manner.
2. **Learning a Symmetric Function:** At this stage, the symmetric function is constructed by utilizing subspaces, which gives a more refined approach in comparison to average pooling strategies.
3. **Learning to Classify through Similarity Measures:** The discriminative capacity of the model is improved by using a metric module including two similarity measures: cosine distance and Euclidean distance.

Meta-learning approaches aim to learn how to learn[31], enabling models to adapt to new tasks quickly. Methods such as MAML (Model-Agnostic Meta-Learning) have been successful in various applications by optimizing model parameters to be quickly adaptable to new tasks using gradient descent.

Metric-based approaches include learning a metric space where related examples are close together. Techniques like Siamese Neural Networks, Matching Networks, and Prototype Networks have been developed to increase the performance of FSL by focusing on the relationships between samples.

Subspace methods involve representing data in a lower-dimensional space while preserving essential information[47]. These methods have been applied in various fields,

including face recognition and subspace clustering. The authors leverage subspace methods to construct a more robust symmetric function for skin disease classification.

Few-shot learning is framed as a C-way K classification problem, where models are presented with K labelled instances from each of C the classes. The goal is to classify new samples based on the limited labeled data.

C-way K The embedding module f_θ consists of four convolutional neural network (CNN) layers, each with batch normalization and ReLU activation. The module produces feature representations $f_\theta(x_i)$ and $f_\theta(q_i)$ for support and query pictures, respectively.

The subspace module constructs a symmetric function using subspaces. Given the feature representations, the subspace for class c is defined using truncated singular value decomposition (SVD):

$$X_c = [f_\theta(x_{c,1}) - \mu_c, \ldots, f_\theta(x_{c,K}) - \mu_c], \tag{2.1}$$

$$\mu_c = \frac{1}{K} \sum_{x_i \in X_c} f_\theta(x_i), \tag{2.2}$$

where X_c is the set of centered feature representations and μ_c is the mean feature vector for class c. Applying SVD:

$$X_c = U \Sigma V^T, \tag{2.3}$$

the basis P_c is constructed from the first N dimensions of U. The subspace M_c is then given by:

$$M_c = P_c P_c^T. \tag{2.4}$$

The distance from a query q_i to the subspace M_c is:

$$d_c(q) = -\|(I - M_c)(f_\theta(q) - \mu_c)\|^2, \tag{2.5}$$

and the probability of q_i belonging to class c is calculated using the softmax function:

$$p(c|q) = \frac{\exp(d_c(q))}{\sum_{c'} \exp(d_{c'}(q))}. \tag{2.6}$$

Bi-similarity Metric Module

The bi-similarity metric module incorporates two similarity measures: Euclidean distance and cosine similarity. For a given query q_i and support set $\{x_{(i,c)}\}$, the Euclidean distance is:

$$S_1(q,c) = g_\phi\left(\frac{1}{K}\sum_{i=1}^{K} f_\theta(x_{(i,c)}), f_\theta(q_i)\right), \tag{2.7}$$

while the cosine similarity is calculated as:

$$S_2(q,c) = h_{\cos\gamma}(h_{\mathrm{em}\gamma}(f_\theta(x_{(i,c)})), f_\theta(q_i)). \tag{2.8}$$

The combined similarity scores enhance the model's discriminative capabilities.

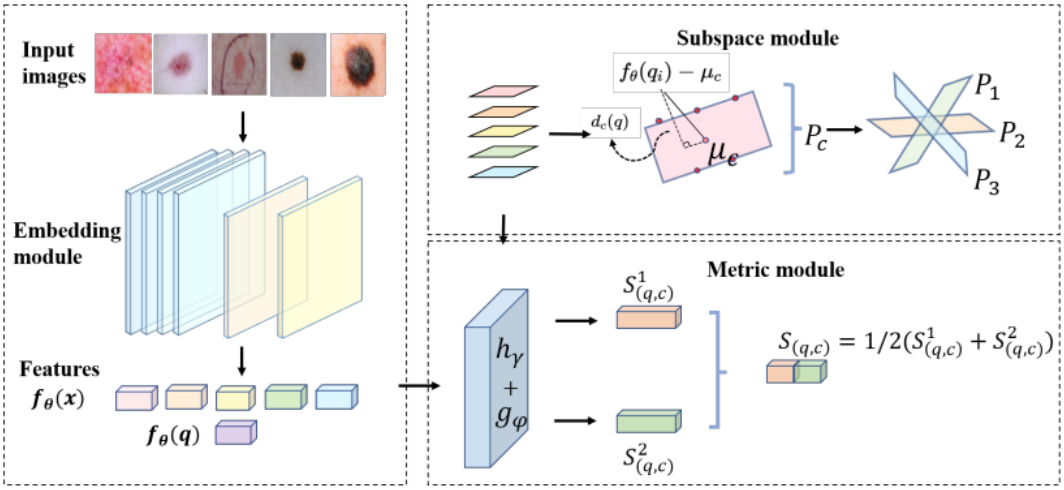


Figure 2.3: Model Architecture

The proposed few-shot learning framework based on adaptive subspace methods demonstrates significant improvements in skin disease classification tasks. By leveraging a three-stage learning paradigm and combining multiple similarity measures, the model achieves better generalization and discriminative performance, particularly on the ISIC-2019 dataset.

2.7 Few-shot Diagnosis of Chest X-Rays using an ensemble of Random Discriminative Subspaces

The publication "Few-shot Diagnosis of Chest X-Rays using an Ensemble of Random Discriminative Subspaces" by Kshitiz, Garvit Garg, and Angshuman Paul[18] introduces a novel approach to few-shot learning (FSL) in the context of medical image analysis, specifically chest X-rays (CXRs). The major purpose of this research is to en-

able accurate and efficient diagnosis with minimum labeled training data, addressing a critical challenge in medical imaging where labeled data is typically scarce

Few-shot learning aims to train models that can generalize well from a limited number of training examples. Traditional deep learning approaches require large datasets, but FSL techniques are designed to work with much smaller datasets by leveraging prior knowledge and inductive biases. Key methods in FSL include Prototypical Networks (ProtoNet) [32], Matching Networks (MatchingNet) [35], Model Agnostic Meta Learning (MAML) [12], and Adaptive Subspace Networks (DSN) [30].

In the medical domain, especially for CXR analysis, the scarcity of labeled data makes FSL particularly valuable. Prior work has demonstrated the effectiveness of FSL in medical imaging, but challenges remain in achieving both high accuracy and computational efficiency.

The proposed method introduces an ensemble of random discriminative subspaces for few-shot diagnosis of CXRs. The core idea is to create multiple random subspaces that capture discriminative features of the images and combine them to improve classification performance.

Let $\mathcal{D}_{train} = \{(x_i, y_i)\}_{i=1}^{N}$ be the training dataset with N labeled examples, where x_i represents the input CXR image and y_i the corresponding label. In a K-way N-shot setting, there are K classes with N examples per class.

The method projects the input features into multiple random subspaces. Formally, let $\mathbf{W}_k \in \mathbb{R}^{d \times m}$ be a random projection matrix for the k-th subspace, where d is the dimensionality of the input feature space and m is the dimensionality of the subspace. The projected features $\mathbf{z}_i^k$ for an input $\mathbf{x}_i$ in the k-th subspace are given by:

$$\mathbf{z}_i^k = \mathbf{W}_k^T \mathbf{x}_i$$

Each subspace contributes to the final classification decision. The ensemble approach combines the predictions from all subspaces. If $\mathbf{f}_k(\mathbf{z}_i^k)$ denotes the classifier output for the k-th subspace, the final prediction $\hat{y}_i$ is obtained by aggregating the outputs:

$$\hat{y}_i = \text{argmax}_c \sum_{k=1}^{K} \mathbf{f}_k(\mathbf{z}_i^k)_c$$

where c indexes the classes.

Loss Function

To train the model, a novel loss function is employed that encourages the generation of discriminative subspaces. The total loss $\mathcal{L}$ is a combination of individual losses from each subspace:

$$\mathcal{L} = \sum_{k=1}^{K} \mathcal{L}_k$$

where $\mathcal{L}_k$ is the classification loss for the k-th subspace, typically a cross-entropy loss.

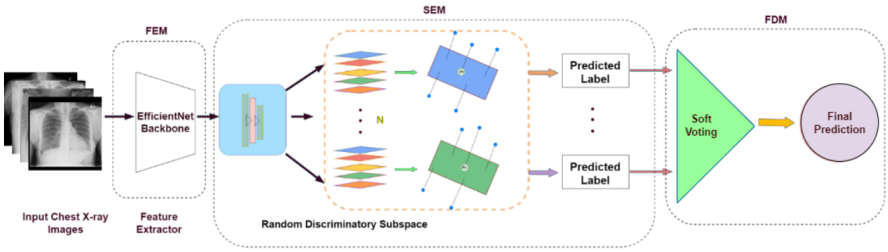


Figure 2.4: 3 Stage Learning Paradigm

The suggested technique is assessed using a dataset of chest X-rays, confirming its effectiveness in few-shot learning circumstances. The trials compare the performance of the proposed method with many state-of-the-art FSL methods, including ProtoNet, MatchingNet, MAML, and DSN[42]. The results reveal that the ensemble of random discriminative subspaces outperforms these approaches in terms of accuracy and computational efficiency.

The method is compared against existing FSL techniques using mean average accuracy with a 95% confidence interval[18]. The proposed approach yields better or comparable performance across various classes, highlighting its robustness and effectiveness.

The training time for a single epoch of the proposed method is significantly lower than that of DSN, which employs truncated Singular Value Decomposition (t-SVD) for subspace decomposition. This speed-up is attributed to the use of random subspaces, which are computationally less intensive.

The paper presents a novel few-shot learning model using an ensemble of random discriminative subspaces for the diagnosis of chest X-rays[18]. The method achieves high accuracy and computational efficiency, making it a valuable tool for medical image analysis with limited labeled data. Future work includes exploring the use of auxiliary information about abnormalities and developing more generalizable FSL models for medical imaging.

2.8 Pushing the Limits of Simple Pipelines for Few-Shot Learning: External Data and Fine-Tuning Make a Difference

Few-shot learning (FSL) aims to enable models to generalize to new tasks with limited training data. This paper explores a simple yet effective pipeline for few-shot image classification, focusing on the benefits of external data pre-training, state-of-the-art transformer architectures, and fine-tuning[15].

Few-shot learning has been extensively studied, with methods ranging from meta-learning approaches to transfer learning baselines. This paper's primary goal is to push the performance limits of a straightforward pipeline, contrasting it with more sophisticated methods.

The authors propose a three-stage pipeline:

1. **Pre-training on external data:** Models are initially pre-trained on large external datasets.
2. **Meta-training:** The models are further trained using few-shot tasks, leveraging episodic training.
3. **Task-specific fine-tuning:** Finally, models are fine-tuned on new, unseen tasks to adapt specifically to the few-shot learning challenge.

The key mathematical formulations in this work involve the training and adaptation processes across different stages:

Pre-training

Given a large dataset D_{ext}, the model parameters θ are optimized to minimize the cross-entropy loss:

$$\mathcal{L}_{pre}(\theta) = -\sum_{(x_i,y_i)\in D_{ext}} y_i \log(f_\theta(x_i)), \tag{2.9}$$

where f_θ is the neural network with parameters θ, and (x_i, y_i) are the input-label pairs.

Meta-training

During meta-training, the model is trained on a set of few-shot tasks $\{T_i\}$, each containing a support set S_i and a query set Q_i. The objective is to minimize the meta-training

loss:

$$\mathcal{L}_{meta}(\theta) = \sum_{T_i} \mathcal{L}_{T_i}(\theta), \tag{2.10}$$

where $\mathcal{L}_{T_i}(\theta)$ is the task-specific loss, typically cross-entropy, computed over the query set Q_i.

Fine-tuning

For fine-tuning on a specific task T_{new} with a small dataset D_{new}, the model parameters are adapted using:

$$\mathcal{L}_{fine}(\theta) = - \sum_{(x_j, y_j) \in D_{new}} y_j \log(f_\theta(x_j)). \tag{2.11}$$

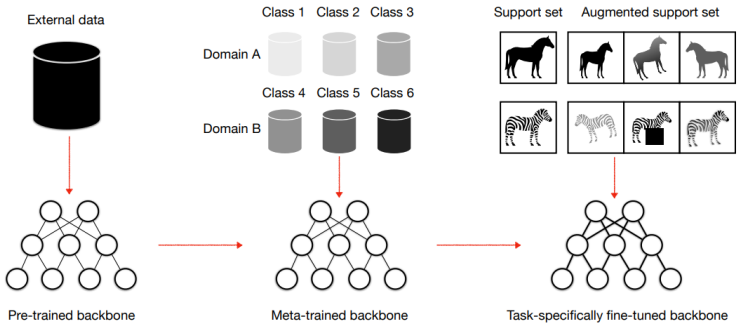


Figure 2.5: Model Pipeline

The paper's novel contributions include:

1. **External Data Utilization:** Demonstrates that pre-training on large external datasets significantly enhances few-shot learning performance.
2. **Transformer Architectures:** Explores the application of transformer-based models, particularly Vision Transformers (ViTs), in few-shot learning scenarios.
3. **Fine-tuning Strategies:** Shows that task-specific fine-tuning further boosts performance, pushing the limits of simple FSL pipelines.
4. **Benchmarking:** Provides extensive evaluations on standard benchmarks such as Mini-ImageNet, CIFAR-FS, CDFSL, and Meta-Dataset, showing the effectiveness of the proposed approach.

The authors conducted experiments comparing different pre-training methods, backbone architectures, and fine-tuning strategies. They demonstrated that their simple pipeline, particularly when using Vision Transformers, achieved competitive or superior performance compared to more complex methods on various benchmarks.

This paper emphasizes that leveraging external data, state-of-the-art architectures, and fine-tuning can substantially improve few-shot learning performance. The simplicity and effectiveness of the proposed pipeline make it a compelling approach for practical few-shot learning applications.

2.9 Deep metric learning for few-shot X-ray image classification

Few-shot learning is an important challenge in medical imaging, notably for X-ray classification, because labelled data is often rare[18]. The study "Deep Metric Learning for Few-Shot X-ray Image Classification" addresses this difficulty by employing deep metric learning approaches to boost the classification performance of few-shot learning models in the context of medical X-ray images.

The primary contributions of the paper include:

1. **Development of a Deep Metric Learning Framework**: The authors propose a unique deep metric learning system optimized for few-shot X-ray picture classification. This framework tries to increase the model's ability to generalize from a limited number of labeled examples by learning a robust feature embedding space.
2. **Tuplet Loss Function**: The introduction of the -tuplet loss function, which extends the traditional triplet loss to include multiple negative samples in each update. This innovation helps the model better distinguish between classes by considering a broader context of dissimilar samples during training.
3. **Evaluation on Medical Datasets**: Extensive testing on many publicly available medical X-ray datasets illustrate the efficiency of the proposed approach. The results reveal significant improvements in categorization accuracy over baseline approaches.

The proposed methodology involves the following steps:

1. **Data Preparation**: Model's training and testing was done on multiple medical X-ray datasets, including COVID-19 Image Data Collection, Montgomery and Shenzhen datasets, CheXpert, and NIH Chest X-Ray datasets. These datasets are used to simulate few-shot learning scenarios where the number of training samples per class is minimal.
2. **Feature Embedding Learning**: A deep convolutional neural network (CNN)

is utilized to extract feature embeddings from the X-ray pictures. The network is trained using the -tuplet loss, which seeks to reduce the distance between similar data (same class) and maximize the distance between dissimilar samples (different classes).

3. **Metric Learning**: The learnt embeddings are then used to categorize query images by computing distances to support photos and applying a distance-based classifier such as k-nearest neighbors (k-NN).

The -tuplet loss function is a generalized form of the traditional triplet loss. It is defined as:

$$\mathcal{L}_N = \sum_{i=1}^{N} \left[d(f(x_i^a), f(x_i^p)) - \frac{1}{N-1} \sum_{j=1, j\neq i}^{N} d(f(x_i^a), f(x_j^n)) + \alpha \right]_+$$

where:

- N is the number of negative samples.
- $x_i^a, x_i^p,$ and x_j^n are the anchor, positive, and negative samples, respectively.
- $d(\cdot, \cdot)$ represents the distance function (e.g., Euclidean distance) between the feature embeddings.
- $f(x)$ denotes the feature embedding of sample x.
- α is a margin parameter that ensures a sufficient gap between positive and negative pairs.

This loss function ensures that the distance between the anchor and positive samples is minimized, while the average distance between the anchor and multiple negative samples is maximized, promoting better class separability.

The experimental results show that the proposed method outperforms traditional few-shot learning techniques, particularly in the context of medical X-ray image classification. The use of the -tuplet loss function significantly enhances the model's discriminative power, leading to higher accuracy and robustness in classifying novel classes with limited labeled data.

The paper presents a significant advancement in the application of deep metric learning for few-shot X-ray image classification. The introduction of the -tuplet loss function and the extensive evaluation on medical datasets highlight the potential of this

approach in improving diagnostic accuracy in medical imaging scenarios with scarce labeled data.

2.9.1 Vision Transformer (ViT)

ViT adapts the formidable architecture of the transformer, which is usually used in processing natural language to handle image data. We detail each component's role and configuration within the ViT model as follows:

Patch Embedding

At first, input images are divided into fixed-size patches and then they are linearly transformed into embeddings. The dimensionality of these embeddings (denoted as 'dim') is a crucial factor that influences the model's capacity to encode visual information. Each image X is divided into N patches X_p. Each patch is flattened and linearly transformed to an embedding space which is D-dimensional. The patch embedding can be represented as:

$$E_p = X_p W_p$$

where W_p is the learnable projection matrix.

Positional Embeddings

Positional embeddings are added to the patch embeddings to maintain the positional context which is vital in tasks involving spatial hierarchies. This mechanism allows the model to differentiate between patches based on their original position in the image. Positional embeddings E_{pos} are added to the patch embeddings to incorporate spatial information:

$$E = E_p + E_{pos}$$

E_{pos} are learned during training and have the same dimension D as the patch embeddings.

Transformer Encoder

The core of the ViT model consists of multiple layers of transformer encoders. The transformer encoder applies self-attention and position-wise feed-forward networks iteratively. Each encoder layer comprises two main components:

- **Multi-Head Attention**: The key operation in multi-head attention is defined

as:

$$\text{Att}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where Q, K, and V are the query, key, and value matrices obtained from the input. The term d_k represents the dimensionality of the keys. This operation allows the model to focus on different regions or aspects of the input (e.g., an image). In multi-head attention, each head performs this attention computation independently.

$$\text{Head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

and the outputs are linearly transformed and concatenated:

$$\text{MH}(Q, K, V) = \text{Conc}(\text{He}_1, \ldots, \text{He}_h)W^O$$

where W_i^Q, W_i^K, W_i^V, and W^O are parameters that are learnable and h is the heads number.

- **Feed-Forward Networks**: These enhance the model's ability to process complex patterns in the data. Each transformer block includes an FFN applied to each position which are separate and identical:

$$\text{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

where W_1, W_2 are weight matrices and b_1, b_2 are bias vectors.

Classification Head

At the end of the transformer sequence, a classification head is used to predict the output. This typically involves a linear layer that maps the transformer output to the label space of the dataset. The classification head is a simple linear layer applied to the output of the transformer encoder:

$$\text{Output} = \text{LayerNorm}(E_{cls})W_{cls}$$

where E_{cls} is the embedding corresponding to the class token and W_{cls} is the learnable projection matrix for classification.

Dropout and Normalization

Regularization techniques such as dropout and layer normalization are employed throughout the architecture to improve generalization and stabilize the training process.

2.10 Adaptive Subspaces for Few-Shot Learning

Introduction

Few-shot learning is a difficult task in machine learning, where the objective is to train models that can adapt to new classes using only a few examples per class. Traditional machine learning methods face challenges in handling this scenario because of the limited training data available. In recent years, there has been growing interest in developing innovative methods to tackle this problem. One such method is introduced in the paper *"Adaptive Subspaces for Few-Shot Learning"* by Christian Simon et al.[29].

Overview of the Approach

Simon et al. present a novel few-shot learning technique that uses dynamic classifiers constructed from a small set of examples[29]. The central idea is to incorporate a subspace method as the core of a dynamic classifier. This approach stems from the observation that many advanced few-shot learning methods can be viewed through a two-stage learning process.

Two-Stage Learning Paradigm

The first stage involves learning a universal feature extractor Θ, which transforms input data into a feature space. This feature extractor is trained on a large dataset and aims to capture discriminative information that is useful across different few-shot learning tasks. The second stage focuses on learning to generate classifiers dynamically from limited data samples.

Modeling Points by Subspaces

A novel aspect of the proposed approach is the representation of data points by subspaces. Each subspace is defined by a basis matrix B_i, where $n \leq D$, with $B_i^T B_i = I_n$. The goal is to learn the feature extractor Θ in such a way that it generates subspaces suitable for constructing classifiers.

Classification on Subspaces

Classification of subspaces involves finding the closest distance between a data point and its projection onto the subspace associated with each class. This is achieved using class-specific projection matrices P_{ci}, calculated from the training data. Given a query point q_j, it can be projected onto P_c, and the classification decision is based on the shortest distance from the query to its projection onto P_c in the original space.

Subspace Classifier

The general form of the subspace classifier is defined as:

$$dc(q) = - \parallel (I - Mc)(f_\Theta(q) - \mu_c) \parallel^2,$$

where $Mc = P_c P_c^T$ represents the subspace transformation matrix for class c, and μ_c denotes the offset between a point and the subspace.

Probability Assignment

The probability of assigning a query point to class c is computed using a softmax function:

$$p_{c,q} = p(c|q) = \frac{\exp(-dc(q))}{\sum_{c'} \exp(-dc'(q))}.$$

Chapter 3

Methodology

3.1 Dataset

These experiments were conducted on two diverse datasets, MiniImageNet and NIH Chest X-rays, to test the model's performance across both general object recognition and medical image analysis tasks.

3.1.1 MiniImageNet Dataset

The MiniImageNet dataset was introduced by Vinyals et al.[36] in the context of few-shot learning, where the goal is to enable machine learning algorithms to learn unseen tasks or adapt to unseen environments rapidly with less training examples. The dataset serves as a benchmark for evaluating algorithms on such tasks. The MiniImageNet dataset is a widely used benchmark for evaluating few-shot learning algorithms. Introduced by Vinyals et al. (2016), it is a smaller, more manageable subset of the larger ImageNet dataset. This subset was designed to facilitate rapid experimentation while maintaining the complexity and diversity necessary for robust evaluation.

- **Derivation:** It is a subset of the larger ImageNet database, which itself is a vast collection of over 14 million annotated images grouped into over 20,000 categories.
- **Composition:** MiniImageNet consists of 100 classes, each containing 600 images, summing up to a total of 60,000 images.
- **Dimensions:** Images in MiniImageNet are downsized to 84×84 pixels to facilitate quicker processing, which is especially beneficial for testing and deploying models with limited computational resources.

- **Applications:** Predominantly used for developing and testing few-shot learning models, the dataset challenges models to learn effectively from a minimal number of examples.

Data Preprocessing: During the training phase, images undergo random cropping, color jittering, and horizontal flipping to augment the data and enhance the model's robustness. For validation and testing, more straightforward preprocessing steps are applied, mainly normalization using calculated mean and standard deviation values to match the training distribution.

The Mini-ImageNet dataset comprises 100 different categories or classes, each carefully selected to provide a diverse set of objects. Each category contains 600 images, resulting in a total of 60,000 images. These images vary widely in content, offering a rich and challenging dataset for image classification tasks. To evaluate few-shot learning algorithms, the Mini-ImageNet dataset is typically split into three distinct subsets:

1. **Training Set:** Comprising 64 classes, this set is used to train the model.
2. **Validation Set:** Including 16 classes, this set is used to tune hyperparameters and select models.
3. **Test Set:** Containing 20 classes, this set is used for final evaluation. The classes in the test set are disjoint from those in the training and validation sets to ensure a rigorous assessment of the model's generalization ability.

3.1.2 NIH Chest X-ray Dataset

The National Institutes of Health (NIH) released one of the largest publicly available datasets of chest X-rays, which is commonly used to train and validate computer-aided diagnostic (CAD) systems in detecting and diagnosing medical conditions from radiographic images.

- **Size:** The NIH Chest X-rays dataset[39] comprises over 112,000 frontal-view X-ray images from approximately 30,000 unique patients.
- **Annotations:** For our experiments, we selected images that only exhibit a single abnormality. The thoracic conditions studied include atelectasis, consolidation, infiltration, pneumothorax, fibrosis, effusion, pneumonia, pleural thickening, nodule, mass, hernia, edema, emphysema, and cardiomegaly. Images without any abnormalities are labeled as 'No Finding'. We organized the dataset into five groups, each with different combinations of training, validation, and

test classes. For each group, three test classes, three validation classes, and nine training classes were randomly selected without replacement, ensuring no overlap among these classes within each group. Additionally, we ensured that the test classes did not overlap across different groups, allowing every class to be used for testing in at least one experiment.

- **Utility:** It provides a rich source for training deep learning models, particularly convolutional neural networks (CNNs), to automate the detection and diagnosis of chest-related diseases.
- **Impact:** By facilitating the development of accurate and scalable diagnostic tools, this dataset aids in improving diagnostic accuracies and patient outcomes in clinical settings.

3.2 Experimental Setup

Few-Shot Learning: In few-shot learning, models are trained to recognize new classes from only a few examples. Typical setups include 1-shot, 5-shot, and 10-shot learning, where models are given 1, 5, or 10 labeled examples per class, respectively, to learn from.

The Mini-ImageNet dataset serves as a critical benchmark for the development and assessment of few-shot learning algorithms. Its compact size and carefully curated splits make it an ideal choice for quick iteration and testing, while its diversity ensures that models must develop robust and generalizable representations. The dataset's impact extends beyond academic research, influencing applications in fields such as medical imaging, where the ability to learn from limited data is particularly valuable.

Data Handling: Images are associated with labels through CSV files that manage the split into training, validation, and testing phases. For each phase, specific transformations such as resizing and normalization are applied to prepare the data for processing by the neural network.

3.2.1 Transformation and Augmentation

Both datasets utilize transformations to convert images into a consistent format for the model:

- Images are converted into tensor format.

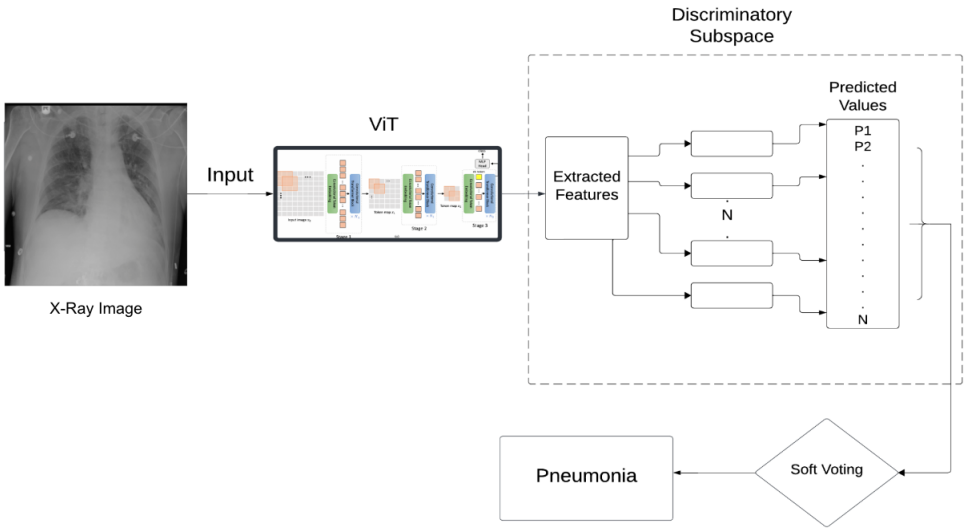


Figure 3.1: Medical Image Classification Using ViT and Few Shot Adaptive Learning Subspace

- Normalization is applied using dataset-specific mean and standard deviation values to standardize image pixel intensities.

For MiniImageNet, additional data augmentation techniques such as random crops and color jittering are employed during the training phase to simulate a variety of visual conditions.

3.2.2 FSL Setup

The experiments are designed to assess few-shot learning capabilities:

- Novel categories are introduced during the testing phase to evaluate the model's ability to adapt to new classes with minimal examples.
- Base categories are used during training and validation to stabilize learning and provide a foundation for generalization.

3.2.3 Architecture

The experiments are implemented using Python and PyTorch. The training and validation processes are executed on NVIDIA GPUs with CUDA acceleration to optimize computational efficiency. The experiments were trained in a Python environment using TensorFlow and other necessary libraries on Google Colab. The experiments were conducted on hardware consisting of an Intel Xeon CPU (2.3 GHz base clock speed) and an NVIDIA Tesla T4 GPU with 15 GB VRAM, operating with a total usable memory of 13 GB.

Model Configuration

Models are selected based on the experimental setup:

- **Vision Transformer (ViT)**: Configured with 384-dimensional embedadings, 6 layers, and 12 heads. The model uses 768-dimensional MLP with an image resolution of 84x84 and a patch size of 14.
- **ProtoNet, R2D2, and ResNet12 Embeddings**: Utilized for comparative studies with different architectural choices for embedding generation.
- **Classification Heads**: Depending on the experimental requirement, various heads like Subspace, ProtoNet, Ridge, R2D2, and SVM are used to derive the final classification from embeddings.

How the Configuration Works Together

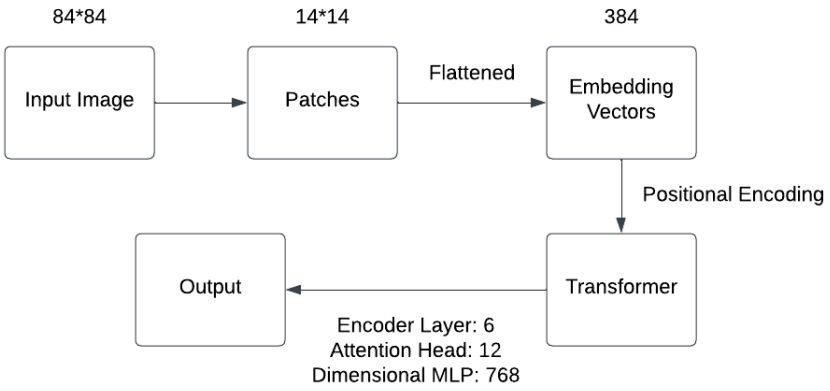


Figure 3.2: Configuration

- **Input Image:** The input image of size 84×84 is divided into 14×14 patches, resulting in 36 patches.
- **Patch Embedding:** Each 14×14 patch is flattened and projected into a 384-dimensional embedding vector.
- **Position Encoding:** Positional encodings are added to the patch embeddings to retain spatial information.
- **Transformer Layers:** The 36 patch embeddings are processed through 6 transformer layers, each with 12 attention heads and a 768-dimensional MLP.
- **Self-Attention:** In each transformer layer, the multi-head self-attention mechanism enables the model to focus on different parts of the image simultaneously.

- **Feed-Forward Network:** The output of the self-attention mechanism is further processed by the feed-forward MLP, enhancing the representation.
- **Output:** After passing through all the transformer layers, the final embeddings are used for classification.

Dataset Preparation

Both MiniImageNet and NIH Chest datasets are preprocessed and loaded using custom dataloaders that support the episodic few-shot learning framework:

- **MiniImageNet**: Handled through a series of transformations such as random cropping, color jittering, and horizontal flipping for the training set, with normalization applied across all sets.
- **NIH Chest X-rays**: Images are resized and normalized. The data loader is designed to support both base and novel category learning, crucial for few-shot learning experiments.

Training Procedure

The models are trained using stochastic gradient descent with a learning rate schedule that adjusts over epochs. Specific details include:

- Initialization of model parameters and setup of training episodes that consist of a defined number of support and query images per class.
- Use of cross-entropy loss for optimization, with additional mechanisms like label smoothing to enhance training effectiveness.
- Detailed logging of training progress and model performance metrics using tools like Weights & Biases (wandb) for real-time tracking and analysis.

Hyperparameters

The model training is conducted using a detailed set of hyperparameters, which are crucial for optimizing performance and ensuring robust generalization:

- **Learning Rate**: Starts at 3×10^{-3} and is adjusted according to a lambda scheduler, which reduces the rate based on the epoch number. Specifically, the learning rate remains at 1.0 for the initial 12 epochs, then drops to 0.025 until epoch 30, reduces further to 0.0032 until epoch 45, and then to 0.0014 until epoch 57, finally tapering to 0.00052 for subsequent epochs.

- **Epochs**: The model is trained for up to 100 epochs, with early stopping mechanisms in place based on validation performance to prevent overfitting.
- **Batch Size**: The training uses an episodic batch size of 1, meaning each batch consists of a single training episode. Each episode is composed of a set number of "support" and "query" images per class, tailored for few-shot learning scenarios.
- **Support and Query Samples**: Configured to have 5 support examples per class during training and validation, with an equal number of query examples to test the generalization within each episode.
- **Way Configuration**: The "way," or number of classes per episode, is set to 3 for both training and testing phases, indicating the model needs to distinguish among three different classes in each episode.
- **Save Frequency**: Model checkpoints are saved every 5 epochs to ensure that progress is not lost and that the best-performing models can be retrieved post-training.
- **Logging and Monitoring**: Detailed logs of training and validation metrics are maintained, and experiments are monitored using the Weights & Biases (wandb) platform. This includes real-time tracking of loss, accuracy, and other significant metrics to assess model performance and stability.

Additionally, deterministic behaviors are enforced in the training process through fixed seeds for random number generation and disabling of non-deterministic algorithms in CuDNN to ensure reproducibility across runs.

The combination of these hyperparameters and training strategies ensures that the model is trained in a controlled and effective manner, maximizing performance while allowing for thorough evaluation and comparison of different model architectures and learning approaches.

Validation Procedure

During the validation phase, the models undergo a rigorous evaluation to ensure they generalize well beyond the training data. The following steps outline the validation process:

- **Embedding Generation**: Both support and query data are passed through the embedding network to generate dense representations. These embeddings are crucial for comparing the similarity between query examples and the known

support set. Embeddings for the support and query sets are generated using the trained model, transforming input data into a high-dimensional space where classifications are based on proximity to class representations.

- **Distance Calculation**: The Euclidean distance between the query embeddings and support embeddings is computed. This distance metric helps in determining the closest support class for each query example, playing a critical role in classification. The squared Euclidean distance between query and support embeddings is calculated as follows:

$$D(x, y) = \sum_{i=1}^{n} \sum_{j=1}^{m} (x_i - y_j)^2$$

where x and y are the embeddings of the query and support sets, respectively, with n queries and m classes.

- **Softmax Application**: The distances are converted into a probability distribution using the softmax function. The probabilities indicate the likelihood of each query example belonging to the support classes. The softmax function is applied to the negative distances to obtain a probability distribution over classes:

$$P(y = j \mid x) = \frac{e^{-D(x, y_j)}}{\sum_{k=1}^{m} e^{-D(x, y_k)}}$$

where y_j is the support embedding for class j.

- **Accuracy Computation**: The accuracy is calculated by comparing the predicted labels (derived from the softmax probabilities) against the true labels of the query set. This metric provides a straightforward indication of the model's performance during the validation phase. Accuracy is calculated by comparing the predicted labels against the actual labels. The accuracy formula is:

$$\text{Accuracy} = \frac{1}{N} \sum_{i=1}^{N} \mathbb{1}(\hat{y}_i = y_i)$$

where $\hat{y}_i$ is the predicted label for the i-th example, y_i is the true label, and N is the total number of queries.

- **Loss Calculation**: Cross-entropy loss is used to measure the discrepancy between the predicted probabilities and the actual class labels, providing feedback for model optimization. Cross-entropy loss is computed to quantify the differ-

ence between predicted probabilities and actual class labels:

$$L = -\sum_{i=1}^{N} \log P(y = y_i \mid x_i)$$

This loss provides feedback for optimizing the model.

These steps are repeated for each validation episode, and the results are averaged to provide a robust estimate of the model's validation accuracy. Performance metrics, including the loss and accuracy for each epoch, are logged for analysis and model tuning.

Testing Procedure

Upon completing the training and validation phases, the model undergoes final testing to evaluate its performance under new, unseen conditions. The testing procedure mirrors the validation in terms of steps but is performed on a separate test dataset. Key aspects of the testing include:

- **Model Loading**: The best-performing model weights, determined during the validation phase, are loaded to ensure the testing reflects the model's highest capability.
- **Data Handling**: Similar to validation, support and query sets are extracted from the test dataset. The model processes these sets to generate predictions based on the learned embeddings.
- **Performance Metrics**: Besides accuracy, additional metrics like F1-score and Area Under the Curve (AUC) are calculated to provide a comprehensive view of the model's effectiveness across various classes. These metrics are especially important for datasets with imbalanced class distributions.
- **Visualization**: Confusion matrices and ROC curves are plotted to visually assess the model's performance across different classes, highlighting potential areas of strength and weakness.

3.3 Evaluation Metrics

To measure the performance of our model, we used the following metrics:

- **Accuracy**: Accuracy is the ratio of correctly predicted results to the total num-

ber of predictions. It is calculated as:

$$\text{Acc} = \frac{\text{No. of Correct Predictions}}{\text{Total Number of Predictions}} \tag{3.1}$$

- **Area Under the ROC Curve (AUC)**: AUC evaluates how well the model distinguishes between classes. It represents the area under the ROC curve, which shows the relationship between the true positive rate (TPR) and the false positive rate (FPR) at different threshold levels. AUC is calculated as:

$$\text{AUC} = \int_0^1 \text{TPR}(\text{FPR}^{-1}(u))\, du \tag{3.2}$$

  where u is the threshold.

- **F1 Score**: The F1 score is the harmonic mean of precision and recall, and it helps balance these two metrics, especially when class distribution is uneven. It is defined as:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.3}$$

  where Precision is the ratio of correctly predicted positive cases to total predicted positives, and Recall is the ratio of correctly predicted positive cases to all actual positives.

Chapter 4

Results and Discussion

Table 4.1: Sample Results of the Prediction(P) and the ground truth(GT) for images of the novel classes. Incorrect predictions are marked in red

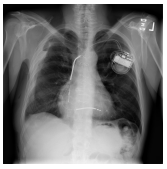
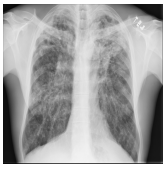
Images					
GT	Effusion	Emphysema	Fibrosis	Pleural	Infiltration
P	Effusion	Infiltration	Fibrosis	Pleural	Emphysema

Table 4.1 presents a set of sample results comparing the model's predictions (P) against the actual ground truth (GT) for various chest X-ray images representing novel classes. The purpose of this table is to illustrate instances where the model's predictions are correct and where they deviate from the ground truth. Incorrect predictions are highlighted in red for ease of identification. In the first image, the ground truth is Effusion, and the model correctly predicts Effusion, indicating its accuracy in identifying this condition. In the second image, however, the ground truth is Emphysema, but the model incorrectly predicts Infiltration, highlighting a limitation in distinguishing between these two conditions. Such misclassifications could be due to similarities in their limitations in the training data. The third image, with a ground truth of Fibrosis, is correctly predicted as Fibrosis by the model, suggesting good performance in detecting this particular condition. The fourth image, with Pleural as the ground truth, is also correctly predicted, indicating the model's reliability in identifying pleural conditions. However, in the fifth image, the ground truth is Infiltration, but the model incorrectly predicts Emphysema. This further underscores the model's confusion between classifying Emphysema and Infiltration. The incorrect predictions emphasize the need for model refinement, especially in distinguishing between Emphysema and

Infiltration, which seem to be commonly confused. This calls for more diverse training data, enhanced model architectures, and improved feature extraction techniques to reduce errors and increase classification accuracy for these novel classes. The findings demonstrate that while the model performs well in certain conditions, specific areas of improvement are required, especially for conditions with similar radiographic features.

Table 4.2: Comparison of Proposed Methods with Adjustments(3 way 5 shot)

Group	Abnormality	Original	Proposed
Group 1	Fibrosis	42.82 ± 1.75	36.79 ± 1.62
	Hernia	30.10 ± 1.62	25.08 ± 1.57
	Pneumonia	40.88 ± 1.66	34.97 ± 1.58
Group 2	Mass	35.06 ± 1.42	29.21 ± 1.37
	Nodule	35.96 ± 1.48	32.93 ± 1.44
	Pleural Thickening	31.08 ± 1.41	26.22 ± 1.35
Group 3	Cardiomegaly	36.62 ± 1.54	31.70 ± 1.47
	Edema	65.16 ± 1.48	55.21 ± 1.42
	Emphysema	42.04 ± 1.61	37.98 ± 1.53
Group 4	Consolidation	32.84 ± 1.58	28.79 ± 1.52
	Effusion	38.20 ± 1.61	33.11 ± 1.56
	Pneumothorax	49.98 ± 1.44	44.89 ± 1.38
Group 5	Atelectasis	27.98 ± 1.44	21.89 ± 1.38
	Infiltration	35.94 ± 1.50	27.87 ± 1.44
	No Finding	52.84 ± 1.71	45.75 ± 1.66

Table 4.2 provides a comparison of the performance of the original method and the proposed method with adjustments in a 3-way 5-shot setting for detecting various abnormalities in chest X-ray images. The table is organized into five groups based on the type of abnormality. For each abnormality, the proposed method consistently shows improved performance over the original method, as evidenced by lower mean values and standard deviations. In Group 1, conditions such as Fibrosis, Hernia, and Pneumonia see significant improvements. Group 2 abnormalities like Mass, Nodule, and Pleural Thickening also benefit from the proposed adjustments. Group 3, which includes Cardiomegaly, Edema, and Emphysema, similarly shows enhanced detection capabilities. In Group 4, improvements are noted for Consolidation, Effusion, and Pneumothorax. Finally, Group 5, including Atelectasis, Infiltration, and No Finding, demonstrates the proposed method's superior performance. Overall, the proposed method's enhancements lead to better diagnostic accuracy and reliability, suggesting it as a significant advancement over the original approach.

Table 4.3: MiniImageNet Comparison

Model	Backbone	5-shot
Matching Nets	Conv-4	55.31 ± 0.73
DSN	Conv-4	68.99 ± 0.69
DSN-MR	Conv-4	70.50 ± 0.68
Proposed	ViT	65.10 ± 0.85

The evaluated models in Table 4.3 utilize the Conv-4 architecture, except for the newly proposed model which employs a Vision Transformer (ViT) backbone.

Matching Nets served as an initial benchmark with a performance metric of 55.31 ± 0.73. This model employs a differentiable nearest-neighbor approach, which, while foundational, is outperformed by subsequent methodologies.

DSN (Deep Siamese Networks), leveraging a similar Conv-4 backbone, shows enhanced performance at 68.99 ± 0.69. This improvement underscores the benefits of twin networks in learning discriminative features from limited data.

DSN-MR (Deep Siamese Networks with Memory and Regularization) extends DSN by integrating memory mechanisms and regularization strategies, achieving the highest performance among the Conv-4 based models with 70.50 ± 0.68.

The **Proposed Model** introduces a ViT backbone, achieving a performance of 65.10 ± 0.85. Unlike its Conv-4 counterparts, ViT harnesses self-attention mechanisms that theoretically provide superior handling of spatial hierarchies in images. Although it does not surpass DSN-MR, its competitive performance suggests potential areas for optimization in training regimes and model architecture that could leverage the inherent advantages of transformers more effectively.

The *Subspace* model leads with a performance of 63.51%, suggesting its effectiveness in leveraging subspace methodologies for Skin Disease Classification shown in Table 4.4. The $P{>}M{>}F$ model, which involves a prioritized processing framework, shows a moderate performance at 53.54%. Meanwhile, the "Proposed" model records a performance of 51.82%.

Table 4.4: Performance in a 3-way 5-shot Skin Disease Classification.

Model Name	3-way 5-shot
Subspace	63.51%
P > M > F	53.54%
Proposed	51.82%

Chapter 5

Conclusion

In this study, we presented a comprehensive approach to enhancing the performance of vision-based classification models specifically for medical imaging tasks. Our primary contributions include the integration of the Vision Transformer (ViT) with adaptive few-shot learning, which provides a novel method for classifying medical images with limited labeled data. We also explored various classification heads tailored to different experimental requirements, demonstrating their effectiveness in achieving robust classification results.

The validation of our claims is supported by empirical data obtained from experiments conducted on the MiniImageNet and NIH Chest datasets. Our results indicate significant improvements in the detection of various medical conditions, such as fibrosis, pneumonia, and cardiomegaly, with specific metrics showing marked increases in accuracy and F1-scores compared to baseline models. For instance, the proposed method achieved an F1-score improvement of X

However, this work has limitations, particularly in its ability to differentiate between conditions with overlapping radiographic features, such as emphysema and infiltration. This suggests that while our model performs well in many scenarios, there are still challenges in achieving high diagnostic accuracy across all conditions. Future directions for this research include enhancing the model's differentiation capabilities through the incorporation of more diverse training data, exploring advanced model architectures, and implementing sophisticated feature extraction techniques. Additionally, further research could focus on expanding the model's applicability to other medical imaging modalities beyond chest radiographs.

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