MLD Advance Project Phase 4

Topic: Weather Classification using ML

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Abstract

Our project topic is weather classification based on a dataset assembled by Harvard database archives [1] containing a total of **6,862** image samples in 11 different folders wherein each folders have images of specific weather types such as dew, rain, rainbow frost, lighting, smog etc. The fourth phase incorporates the PEFT4VISION package [6] to effectively adapt Google SigLip[7] and further embedding has been fed to df-analyze[2] for our weather-related dataset and notice the differences between weather conditions.

The Siglip[7] PEFT model achieved a remarkable accuracy of **94-96%** with **RF with pred** and **SGD** with **none** being the top learning models noted by df-analyze[2]. This is nearly **49%** more accurate than the Resent50[5] pre-trained model accuracy implemented in X-vision helper[3] which was implemented in previous phase 3. These results therein demonstrate a significant improvement compared to earlier PEFT implementation in our 3rd phase highlighting the robustness and efficiency of the SigLIP[7] PEFT approach. A literature comparison is done where we have compared the results with our 4th phase result and has seen slightly better accuracy than the paper which is directly published on our selected dataset and is discussed further in the report.

Introduction

Weather Classification is a critical and very important task in methodology with implications based on agriculture, disaster management and climate research[8]. Accurate weather classification can help in early warnings and better planning to mitigate adverse impacts[8]. Using our dataset, which has different weather conditions, this project's 4th phase would study and evaluate the effectiveness of the PEFT model using siglip[7] with df-analzye[2] package and analyzing advanced machine learning models to determine accuracy in classifying weather classification.

We have employed Google's SigLip model [7] with the PEFT4VISION package[6] developed by John Kendall to extract image embeddings and analysis using various models using df-analzye[2] too. According to our hypothesis and the professor's feedback, we compared SigLip's results against ResNet50[5], which was our previous package model by the X-Vision Helper[3] package. This phase 4 does experimental conditions on our same weather dataset and runs an analysis segmented by specific weather categories to identify patterns and pre-train model sensitiveness. Therefore, the outcomes not only will highlight the differences in performance but also contribute to giving decisions to the weather and methodical authorities which can be used to predict weather and would have a clearer understanding of which model should be preferred to have more accurate predictions

1. Discussion

For this phase, We have removed the snow folder as it was undersampled in our test set for df-analzye containing only 11 image samples, where df-analzye requires at least 20 samples. Discussing the analysis of results in this phase, the most interesting finding which has been seen is the performance model of **RF with pred** and **SGD with none** models which are leading techniques of the dataset. Both of these models have been learning machine learning techniques on this dataset. Both of these models have shown an accuracy of approximately **96.7% and 96.5%** respectively. The result is noteworthy as it is aligned with the hypothesis that if peft had been implemented using siglip[7], we could see an increase in accuracy compared to peft with resnet50[5] and it would have also impacted the overall performance of the model which is compared to the previous phase and happens to be true as the accuracy has been increased more than the in the previous phase. This work highlights the value and importance of different-trained models and their sensitivity towards datasets which can provide insights into the robustness limitations of predicting weather with Machine learning.

1.2 Hypothesis: Full Dataset [PEFT-Google SigLip]

Based on the feedback received from phase 3, we hypothesize that utilizing siglip[7] with PEFT will yield superior results compared to RESNET50[5], which has been previously implemented and demonstrated a significant drop in accuracy to 49.7% using Xvision Helper[3]. We hypothesize that the integration of SigLip[7] with peft4vision[6] is expected to enhance the model's predictive capability, and accuracy, addressing the limitation of pre-trained model performance in an earlier phase. The Results obtained in this phase show improvements in accuracy by up to 49% and are explained further in subsequent sections. The findings validate our hypothesis that PEFT tuning with SigLip[7] will outperform the previously implemented conventional deep-learning model ResNet50[5] in our weather classification project dataset.

1.3 Literature Comparison

We have compared our findings with the existing literature which used the same dataset we utilized for this project. The work is presented by Xiao, Haixia. 2021 [5], which focuses on classifying weather phenomena using a MeteCNN machine-learning technique. In their study, MeteCNN were employed which has achieved a classification accuracy of **92.68%** which is outstanding compared to traditional models and various mainstream models available such as VGG16, ResNet34, and EfficientNet-B7.

For our approach, we have leveraged Google Siglip[7] with PEFT4Vision[6] and later evaluated with DF-Analyze[2]. This result showcases an overall accuracy across various ML models on the dataset in the test set has been reported as achieving **94%-96%** (excluding dummy), rf with pred being the best, which is slightly better than the reported accuracy of the already existing paper which is **92.68%** using the METECNN model. This discrepancy may showcase multiple factors including robust validation and preprocessing steps. But one thing which is to be noted here is that the snow class folder has been removed from our dataset run; it might not create a major difference but has to be taken into consideration while the literature review is compared.

Furthermore, for this phase, our work demonstrated that combining PEFT using SigLip[7] with Df-Analzye[2] can surpass performance benchmarks which were set by the deep learning architectures, such as ResNet50[5] used in the previous phase which didn't perform well at all.

2. Conclusions.

In this 4th phase, and so far the last phase of this advanced project, our application of parameter-efficient fine-tuning (PEFT) using Google SigLip[7] by PEFT4Vision[6] and DF-Analyze[2] demonstrated substantial performance improvements compared to the earlier phase. While our previous methods were implemented, which is Resnet50[5] which is integrated with X-vision helper[3], which struggled with accuracy and dropped as low as **49%**, compared to this phase, the PEFT adapted with siglip has significantly achieved high accuracy in **94-96%** range. This improvement not only highlights the value of PEFT but also showcases that optimizing model parameters in Siglip[7] can be more efficient and indicates that the advanced techniques can enhance predictive capability in complex tasks such as weather classification; which is a multi-class classification use-case. Comparing the results with the related literature review shows that our approach is a bit better compared to it. These results emphasize the importance of the adaption of advanced fine-tuning pre-trained model strategies and robust evaluation with various ML models being performed using df-analzye[2] and using such a tool, we can provide accurate efficient and adaptable solutions for weather classification and enhance the predicting capabilities in its domain for future use cases.

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3. References

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8. Hannah Ritchie (2024) - “Weather forecasts have become much more accurate; we now need to make them available to everyone” Published online at OurWorldinData.org. Retrieved from: 'https://ourworldindata.org/weather-forecasts' [Online Resource]

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Files Included

1. Results Files

- **no_snow_dfanalyze.zip**
  Includes the results from phase 2 which was the downsampling of the original dataset.
- **no_snow_split**
  Contains files like test_image_target.parquet and train_image_target.parquet, which we used to train and test the dataset using Siglip. Commands are provided in 'commands.sh'.

2. Analysis Scripts

train_image_target.parquet

- A parquet file was created when we ran peft4vision, which contains the train images in the parquet format.

test_image_target.parquet

- A parquet file was created when we ran peft4vision, which contains the testing images in the parquet format.

no_snow.parquet

- A Parquet file was created at the end that was given as input to the df-analyze

3. Python Script

create_parquet.py

- Python file that creates the parquet file using the dataset folder.

commands.sh

- Contains the commands that need to be run for all workflows.