Using Meta-Transformers for Multimodal Clinical Decision Support and Evidence-Based Medicine

Sabah Mohammed, Jinan Fiaidhi and Abel Serracin Martinez

Abstract— The advancements in computer vision and natural language processing are keys to thriving modern healthcare systems and its applications. Nonetheless, they have been researched and used as separate technical entities without integrating their predictive knowledge discovery when they are combined. Such integration will benefit every clinical/medical problem as they are inherently multimodal - they involve several distinct forms of data, such as images and text. However, the recent advancements in machine learning have brought these fields closer using the notion of meta-transformers. At the core of this synergy is building models that can process and relate information from multiple modalities where the raw input data from various modalities are mapped into a shared token space, allowing an encoder to extract high-level semantic features of the input data. Nerveless, the task of automatically identifying arguments in a clinical/medical text and finding their multimodal relationships remains challenging as it does not rely only on relevancy measures (e.g. how close that text to other modalities like an image) but also on the evidence supporting that relevancy. Relevancy based on evidence is a normal practice in medicine as every practice is an evidence-based. In this article we are experimenting with meta-transformers that can benefit evidence based predictions. In this article, we are experimenting with variety of fine tuned medical meta-transformers like PubmedCLIP, CLIPMD, BiomedCLIP-PubMedBERT and BioCLIP to see which one provide evidence-based relevant multimodal information. Our experimentation uses the TTi-Eval open-source platform to accommodate multimodal data embeddings. This platform simplifies the integration and evaluation of different meta-transformers models but also to variety of datasets for testing and fine tuning. Additionally, we are conducting experiments to test how relevant any multimodal prediction to the published medical literature especially those that are published by PubMed. Our experimentations revealed that the BiomedCLIP-PubMedBERT model provide more reliable evidence-based relevance compared to other models based on randomized samples from the ROCO V2 dataset or other multimodal datasets like MedCat. In this next stage of this research we are extending the use of the winning evidence-based multimodal learning model by adding components that enable medical practitioner to use this model to predict answers to clinical questions based on sound medical questioning protocol like PICO and based on standardized medical terminologies like UMLS.

***Index Terms*—**Meta-Transformers, Multimodal Learning, Evidence-Based Medicine

I. Introduction

Meta-Transformers have demonstrated significant promise for computer multimodal learning tasks involving variety of data from natural language, 2D images, 3D point clouds, audio, video, time series and tabular data [1]. Multimodality learning is the new AI challenge to develop models that have the ability to learn simultaneously from different sources of information [2]. In recent years models such as Next-GPT [3], CLIP [4], Flamingo [5], VLMO [6], OFA [7] and BEiT-3 [8] reported promising progress in processing text and image inputs compared to single-modality model. However, there are a lot of work still remains to be done to extend multimodal learning models to different domains as well as to enhance its accuracy. There are many reasons hindering the progress towards having unified learning network for processing various modalities. Such reasons include the difficulty of integrating of the attention mechanisms [9], the difficulty to identify good fine-tuning mechanisms [10] and lack of providing evidence-based predictions [11]. Most of the current research investigations to overcome these difficulties are focused on identifying generic techniques that can associate text and images via variety of embedding techniques as text and images are the most common forms to describe clinical cases. These generic learning techniques are trained using a contrastive learning approach that aims to unify text and images, allowing tasks like image classification to be done with text-image similarity. The core architecture of all these generic techniques consist of a text encoder and an Image encoder where they are jointly trained to predict the correct pairings of a batch of training

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(image, text) samples without being trained for a specific domain and may requires little fine-tuning to improve its accuracy. However, generic learning models like CLIP trained using 400 million (text and image) pairs from the ImageNet has not shown promising results in the medical domain [12] and requiring intensive fine tuning to reach SOTA performance. Attempts to redefining the CLIP learning model for medical use has been divided into three groups: (1) Medical Knowledge Enhancement Approach for Subject and Domain Levels [13], (2) Supervision Focused Approach within particular modality and across modalities [14] and (3) Semantic-based Pre-Training Approach [15]. All these approaches aim to improve training the text-image training for medical domain but it does not necessary build the association and similarity utilizing evidence-based medical sources like PubMed [16]. In this article we are investigating meta-transformer generic learning technologies that can be used to support evidence-based medicine (EBM) where it can be used reliably in diagnosis and prognosis of described clinical cases.

II. Medical Meta-Transformers for EBM

Meta-transformers are special type of learning transformers tuned to work with multimodal medical data [17]. In this direction, the meta-transformers need to work with multimodal datasets like those listed in table 1.

Table 1: Common Medical Datasets

Dataset Title	Dataset in HF Format
Alzheimer-MRI	https://huggingface.co/datasets/Falah/Alzheimer_MRI
chest-xray-classification	https://huggingface.co/datasets/trpakov/chest-xray-classification
LungCancer4Types	https://huggingface.co/datasets/Kabil007/LungCancer4Types
skin-cancer	https://huggingface.co/datasets/marmal88/skin_cancer

However, we can extend the list of datasets by uploading other datasets from the Hugging Face hub[2] or by uploading your own dataset to the Hugging Face hub then import it:

https://huggingface.co/docs/datasets/en/share#create-the-repository

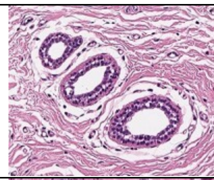
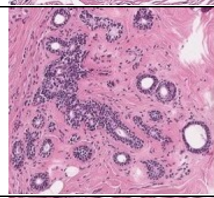
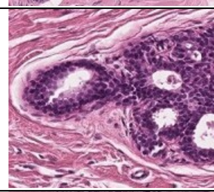
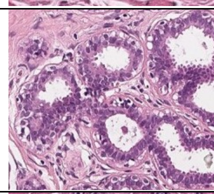
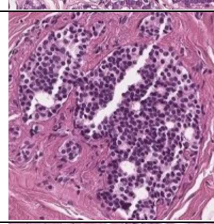
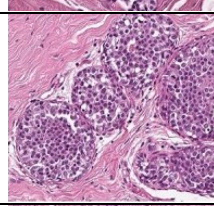
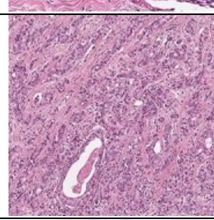
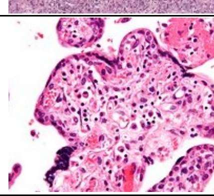
Actually the Hugging Face Hub hosts many machine learning models and datasets for a broad range of tasks across textual narratives (NPL), imaging (Computer Vision), and Audio. Not all models are pre-trained for medical domains nor they are built from transformers. For this purpose, there is a need to select models that are pre-trained on medical domains as well as follows similar encoding standard like the Open AI CLIP[3] where these models have the ability to connect textual narratives via a text encoder and pair it with related images based on image encoder. This type of text-image pairing is not only important for multimodal learning but also important to answer clinical questions [18]. The following Python snippet illustrates using Open AI CLIP and the BRACS[4] dataset [19] to list the different histological disorders.

```
import numpy as np
import torch
import open_clip
open_clip.list_pretrained()
import os
import histolab.data
import IPython.display
import matplotlib.pyplot as plt
from PIL import Image
import numpy as np
from collections import OrderedDict
import torch
%matplotlib inline
%config InlineBackend.figure_format = 'retina'
descriptions = {
    "N": "Normal Tissue",
    "PB": "Pathological Benign",
    "UDH": "Usual Ductal Hyperplasia",
    "FEA": "Flat Epithelial Atypia",
    "ADH": "A Typical Ductal Hyperplasia",
    "DCIS": "Ductal Carcinoma in Situ",
    "IC": "Invasive Carcinoma",
    "UN": "Unknown"
}
original_images = []
images = []
texts = []
plt.figure(figsize=(16, 5))
for filename in [filename for filename in
os.listdir(bracs.data_dir) if filename.endswith(".png") or
filename.endswith(".jpg")]:
    name = os.path.splitext(filename)[0]
    if name not in descriptions:
        continue
    image = Image.open(os.path.join(bracs.data_dir,
filename)).convert("RGB")
    plt.subplot(2, 4, len(images) + 1)
    plt.imshow(image)
    plt.title(f"{filename}\n{descriptions[name]}")
    plt.xticks([])
    plt.yticks([])
    original_images.append(image)
    images.append(preprocess(image))
    texts.append(descriptions[name])
plt.tight_layout()
```

The result from this simple code snippet illustrates associating tissue disorders with their textual label (see Table 2).

[2] https://huggingface.co/docs/hub/en/index
[3] https://openai.com/index/clip/
[4] https://www.bracs.icar.cnr.it/

Table 2: Different Histological Tissue Conditions.

N	Normal Tissue	
PB	Pathological Benign	
UDH	Usual Ductal Hyperplasia	
FEA	Flat Epithelial Atypia	
ADH	A Typical Ductal Hyperplasia	
DCIS	Ductual Carcinoma in Situ	
IC	Invasive Carcinoma	
UN	Unknown Tissue Disorder	

However, training learning models on any given medical dataset like BRACS requires that these models which are originally pre-trained on general medical domain data need to be fine-tuned on the specific medical given domain like the skin-cancer. In this direction, the Hugging Face hub contains models that are general trained on medical domains like:

- **Pubmed CLIP:** https://huggingface.co/flaviagiammarino/pubmed-clip-vit-base-patch32
- **ClipMD:** https://huggingface.co/Idan0405/ClipMD
- **BiomedCLIP-PubMedBERT:** https://huggingface.co/microsoft/BiomedCLIP-PubMedBERT_256-vit_base_patch16_224
- **BioCLIP**: https://huggingface.co/imageomics/bioclip

These pre-trained models can perform very well on specific tasks and datasets, but they do not generalize well. They cannot handle new classes or images beyond the domain they have been trained with [20]. Retraining and fine-tuning is an option, as training requires significant time and capital investment for gathering a classification dataset and the act of model training itself [21]. There are a few reasons:

- **Saves resources:** Training a large model from scratch requires significant computational resources and time. By using a pre-trained model, we can leverage the patterns it has already learned, reducing the resources required.
- **Leverages transfer learning:** This is a big part of fine-tuning. The idea is that the knowledge gained while solving one problem can be applied to a different but related problem.
- **Deals with limited data:** In many cases, we might not have a large enough dataset for our specific task. Fine-tuning a pre-trained model on a smaller dataset can help prevent overfitting, as the model has already learned general features from the larger dataset it was initially trained on.

Fortunately, OpenAI's CLIP models have proved itself as incredibly flexible learning models that often require zero retraining. Models like Pubmed CLIP and BioCLIP are called "*many-shot*" learning models because we need many training samples to reach acceptable performance during that final fine-tuning step. Many-shot learning is only possible when we have compute, time, and data to allow us to fine-tune our models. Ideally, we want to maximize model performance while minimizing N-shot requirements. *Zero-shot* is the natural best-case scenario for a model as it means we require zero training samples before shifting it to a new domain or task [22]. Moreover, OpenAI's CLIP models are initially trained on a dataset called WebImageText (WIT)[5]. WIT contains 400 million (image, text) pairs from publicly available internet data including those covering medical domains. However, OpenAI CLIP models may not be breaking SotA performance benchmarks on specific datasets but still, it is proving to be a massive leap forward in zero-shot performance across various tasks in both image and text modalities [23].

[5] https://github.com/google-research-datasets/wit

To facilitate experimentation with these medical OpenAI CLIP models, we will need a platform that enables the flexible models changing as well as the flexibility to add or delete datasets. In this direction we found the TTi-Eval Embedding API providing a flexible platform to test the performance of variety of OpeAI CLIP models and datasets:

https://github.com/encord-team/text-to-image-eval?tab=readme-ov-file

All what we need to install this platform is two libraries:

!pip install poetry

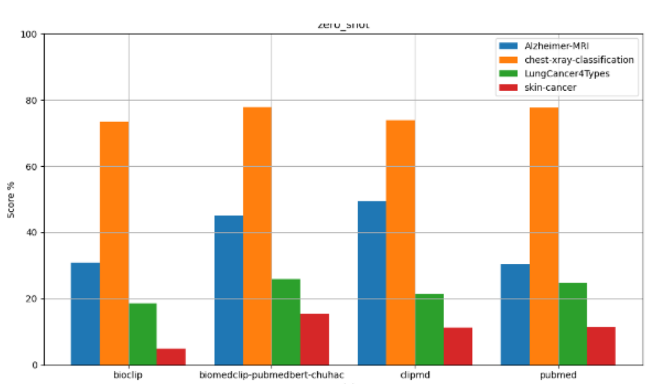
!poetry run tti-eval list –all

Algorithm 1 illustrates how we can use the TTi-Eval platform with the four types of transfer learning across different medical datasets.

Algorithm 1 Train and Evaluate Models and Datasets

Datasets: Alzheimer-MRI, chest-xray-classification, LungCancer4Types, etc.
Models: apple, bioclip, BioMEDCLIPBERT-pubmedbert, etc.
Training Commands:
For each model with each dataset, run: `!poetry run tti-eval build --model-dataset {model}/{dataset}`
Evaluation:
Collect raw data using: `!poetry run tti-eval evaluate {model_dataset_pairs}`
Saving resulting evaluations:
Create columns for zero_shot, linear_probe, wKNN, I2IR
Create CSV files for each model with each dataset and their results.
Save results to CSV:
Save each section's data into a CSV file.
Read results and Plot:
Read each section's CSV file and plot the performance for each category.

Actually the TTi-Eval platform enable us not only to accommodate different OpenAI CLIP medical models and medical datasets, it also provide us with four basic transfer learning mechanisms that can be used across different datasets including Zero-Shot, Linear-Probe, wKNN and I2IR. Basic to all these transfer learning models are the image encoders and the text encoder. The first image encoder uses the ResNet-50 as base model. The second image encoder considered is Vision Transformer, ViT. The text encoder is a Transformer. Figure 1 describe the performance results of running four OpenAI CLIP models (BioCLIP, CLIPMed, PubmedCLIP and BioCLIP-PubmedCLIP) across four medical datasets (Alzheimer-MRI, chest-xray-classification, LungCancer4Types and skin-cancer).



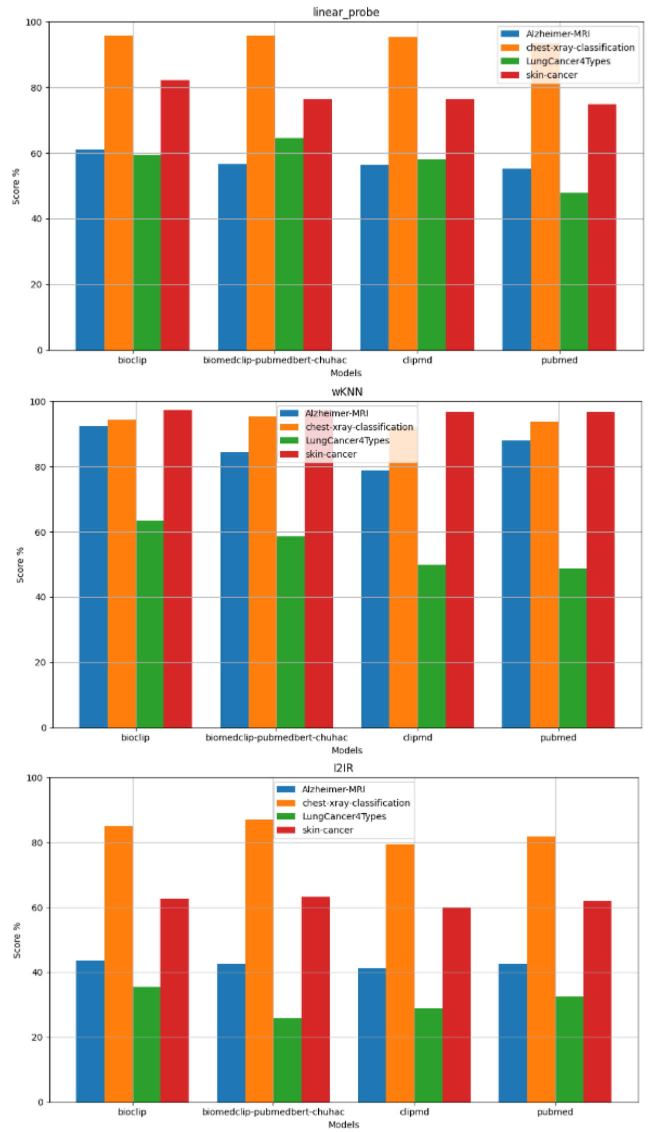


Fig. 1: Testing the Performance of Four OpenAI CLIP Models across Four Datasets.

From figure 1, we can see that the overall best performing models is the BiomedCLIP-PubMedBERT over mainly two datasets; the chest-xray-classification and skin-cancer dataset. Further justifications for the wining BiomedCLIP-PubMedBERT model are listed below:

1. **Balanced Across Multimodal Tasks:** While some of the other models may excel in specific medical tasks but falter in others, BiomedCLIP-PubMedBERT maintains a consistently high level of performance across multiple modalities.
2. **Zero Shot Capabilities:** Even in zero-shot scenarios, where the model has not been fine-tuned on the specific medical domain downstream tasks, BiomedCLIP-PubMedBERT performs very well.
3. **Provides Evidence Based Authenticity:** BiomedCLIP-PubMedBERT uses multimodal data from high-quality clinical research that is centerlly publish in the PubMed platform. PubMed is very

popular Evidence-Based publication platform and hence BiomedCLIP-PubMedBERT model provides better likelihood of good evidence-based embeddings compared to the other models.

However, we attempted to test the BiomedCLIP-PubMedBERT model further by performing another randomized test using ten cases (images + captions) from the ROCO V2 dataset [24]. Figure 2 illustrates the cosine similarity of testing BiomedCLIP-PubMedBERT on ten cases listed in table 2. Figure 2 prove that the BiomedCLIP-PubMedBERT can reliably identify which caption matches the correct image with higher reliability than other cases. Algorithm 2 illustrates how are testing the different meta-transformers using randomized samples from ROCO V2.

Algorithm 2 BioMEDCLIPBERT Model Evaluation

Require: BioMEDCLIPBERT model, tokenizer, test dataset
Ensure: Cosine similarity heatmap, image-caption pairs
1: Load the BioMEDCLIPBERT model and preprocessing functions
2: Load the tokenizer
3: Load test dataset from the specified files
4: Sample 10 random indices from the dataset
5: Create a subset of the test dataset using sampled indices
6: Initialize device as `cuda` if available, otherwise `cpu`
7: Load and preprocess images using the model's preprocessing function
8: Tokenize captions using the model's tokenizer
9: Compute image features, caption features, and logits using the model
10: Compute cosine similarity matrix between image and caption features
11: Prepare image and caption labels
12: Plot cosine similarity heatmap using the prepared labels and similarity matrix
13: For each of the 10 samples:
14: Load the image and display it with its corresponding caption
15: Repeat steps 6-13 for the researched samples from multiple other papers

Table 2: Randomized Cases of Images and their Captions from ROCO v2 Dataset.

	Caption	Image
0	CT scan showed a large stone causing gastric-o...	ROCOv2_2023_test_000357.jpg
1	CT scan with axial view showing a heterogenous...	ROCOv2_2023_test_009531.jpg
2	Non-contrast computed tomography of the head w...	ROCOv2_2023_test_008028.jpg
3	Computerized tomography scan of the abdomen an...	ROCOv2_2023_test_007965.jpg
4	Inferior facial angle (IFA) measurement.	ROCOv2_2023_test_009484.jpg
5	Imaging findings from whole body PET CT. On fu...	ROCOv2_2023_test_000558.jpg
6	From a parasternal short-axis view, the transt...	ROCOv2_2023_test_003880.jpg
7	(Case 1) Contrast-enhanced computed tomography...	ROCOv2_2023_test_000337.jpg
8	V Flow ultrasound image of a canine femoral ar...	ROCOv2_2023_test_008248.jpg
9	Contrast-enhanced 3D MR angiography. Forty-yea...	ROCOv2_2023_test_006850.jpg

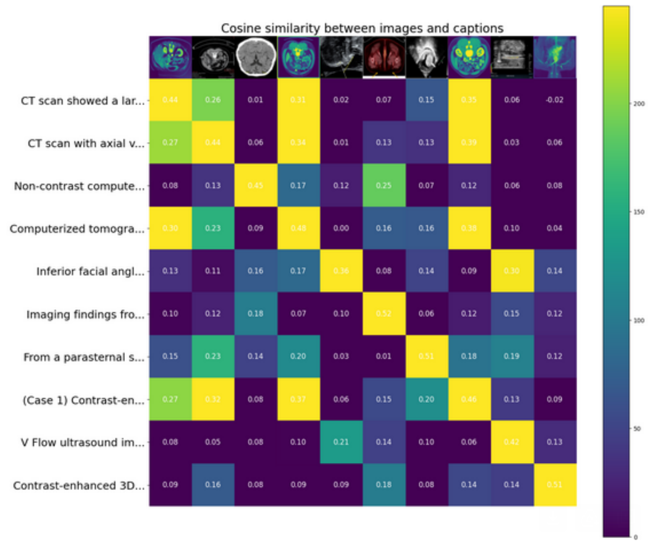


Fig. 2: BiomedCLIP-PubMedBERT model Performance Evaluation using Cosine Similarity between Images and Captions from ROCO V2.

However, since BiomedCLIP-PubMedBERT model is tested in ROCO V2 cases, one may point that this model is a variant of PubMedCLIP [25] which originally trained on ROCO and thus the similarity results may be bias. For this reason we collected random ten images and their captions from ten published articles from PubMed and run the similarity between captions and images using our BiomedCLIP-PubMedBERT model. Table 3 list the ten cases from PubMed and Figure 3 shows the similarity

Table 3: Ten Test Cases from PubMed Articles for BiomedCLIP-PubMedBERT,

	Caption	Paper/Article	Figure No.	PMID
0	Radiograph of wrist showing ABC of the distal ...	Bone cysts Unicameral and aneurysmal bone cyst	Fig. 6. Section a.	25579825
1	Ear scapha squamous cell carcinoma. Patient ph...	Skin cancer: findings and role of high-resolut...	Fig. 4.	31069756
2	A 49-year-old female COVID-19 patient presenti...	Chest CT manifestations of new coronavirus dis...	Fig. 6.	32193638
3	63-year-old woman with advanced adenocarcinoma...	Imaging of Precision Therapy for Lung Cancer: ...	Fig. 2a.	31385753
4	Patient 16. Pre- and post-treatment images in ...	Diffusion imaging in obstructive hydrocephalus	Fig. 4. A.	12812949
5	Hip joint MRI of a patient with first-time fem...	Femoral neck fracture after femoral head necro...	Fig. 3. Every section, want to test for multip...	37907913
6	Histology of orthotopic colon tumors. (A) One ...	Magnetic Resonance Imaging and Bioluminescence...	Fig. 5. All sections again	30988343
7	Unoperated “congenitally corrected” transposit...	Imaging congenital heart disease in adults	Fig. 4. a.	22723533
8	A man in his 60s with gastric cancer (well-dif...	Characteristics and Early Diagnosis of Gastric...	Fig. 2. D.	32321202
9	An 8-year-old boy on steroids with cough and n...	Tuberculosis revisted: classic imaging finding...	Fig. 1	37217783

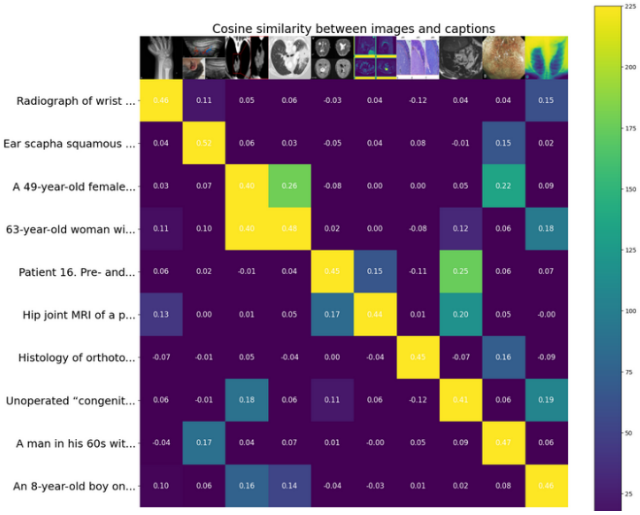


Fig.3: BiomedCLIP-PubMedBERT Performance Evaluation using Cosine Similarity between Images and Captions from Figures Published in PubMed.

III. Harnessing The full potential of Clinical data Analysis

Understanding and analyzing multimodal clinical data like the electronic healthcare records (EHR) requires not only wider evidence-based support but also the connectivity to the mainstream standards as applied in healthcare systems. Actually analyzing and understanding data requires linkage to the medical concepts repositories like UMLS or SNOMED as well as the support of popular medical vocabulary like MedMentions[6] corpus which consists of 4,392 papers (Titles and Abstracts) randomly selected from among papers released on PubMed. Additionally the power of understanding and analyzing clinical data requires the power to allow practitioners to interact with the clinical data seamlessly based on sound clinical questioning protocol like PICO[7] as well as to receive annotations and generate case reports. These added value capabilities for understanding and analyzing clinical data necessitate expanding the machine learning capability of the models used. This means that a machine learning model like our BiomedCLIP-PubMedBERT winning multimodal learning model should prove its applicability beyond the ROCO V2 dataset as well as to integrate the other three non-machine learning capabilities. In this direction we find MedCaT [26] dataset and environment can enable us to achieve this type of integration. MedCat dataset adds on top of 25 K images and captions of ROCO v2, 217,060 figures from 131,410 open access papers as well as 7507 subcaption and subfigure annotations for 2069 compound figures. The wide coverage of evidence-based dataset of MedCat provide another interesting question whether our winning model can span successfully to recognize text and images relationships from MedCat. For this purpose we took another randomized sample from MedCat (see table 4) to test the power of BiomedCLIP-PubMedBERT.

[6] https://github.com/chanzuckerberg/MedMentions?tab=readme-ov-file
[7] https://www.nlm.nih.gov/oet/ed/pubmed/pubmed_in_ebp/02-100.html

Table 4: Random Sample from MedCat.

	PDF_Hash	Image_URI	Caption	Image
0	26491ab76c6e8d6acc582e71bb6b3b5f5601ccc2	3-Figure4-1.png	Figure 4. Nuclear magnetic resonance scan demo...	26491ab76c6e8d6acc582e71bb6b3b5f5601ccc2_3-Fig...
1	57c9ad0f4aab133f96d40992c46926fabc901ffa	2-Figure1-1.png	Figure 1. (A) Barium enema and (B) endoscopic ...	57c9ad0f4aab133f96d40992c46926fabc901ffa_2-Fig...
2	57c9ad0f4aab133f96d40992c46926fabc901ffa	2-Figure3-1.png	Figure 3. Surveillance colonoscopy 1 year afte...	57c9ad0f4aab133f96d40992c46926fabc901ffa_2-Fig...
3	57c9ad0f4aab133f96d40992c46926fabc901ffa	2-Figure2-1.png	Figure 2. Complete resolution of the colonic o...	57c9ad0f4aab133f96d40992c46926fabc901ffa_2-Fig...
4	57c9ad0f4aab133f96d40992c46926fabc901ffa	2-Figure4-1.png	Figure 4. Endoscopic images 4 years after colo...	57c9ad0f4aab133f96d40992c46926fabc901ffa_2-Fig...
5	b362a19e4c4b1854f7cbe246a19502a56f52c2b5	3-Figure2-1.png	Figure 2. Abdominal CT image of a rabbit revea...	b362a19e4c4b1854f7cbe246a19502a56f52c2b5_3-Fig...
6	e19039cd42f72102389f811643cd3036f8db5182	2-Figure3-1.png	Fig 3. Control computed tomography (CT) angiog...	e19039cd42f72102389f811643cd3036f8db5182_2-Fig...
7	e19039cd42f72102389f811643cd3036f8db5182	2-Figure1-1.png	Fig 1. Computed tomography (CT) angiogram with...	e19039cd42f72102389f811643cd3036f8db5182_2-Fig...
8	5f2d2f2ffbd20c7ff3ac30d514da54ee5bd825b4	1-Figure1-1.png	Fig. 1. Brain CT (A) and MR diffusion images (...	5f2d2f2ffbd20c7ff3ac30d514da54ee5bd825b4_1-Fig...
9	5f2d2f2ffbd20c7ff3ac30d514da54ee5bd825b4	2-Figure2-1.png	Fig. 2. Mid sagittal (A, C) and axial MRI (B, ...	5f2d2f2ffbd20c7ff3ac30d514da54ee5bd825b4_2-Fig...

Figure 4 illustrates the cosine similarity of the images and captions using the MedCat random sample. The BiomedCLIP-PubMedBERT model has successfully correlated all the images with their descriptions.

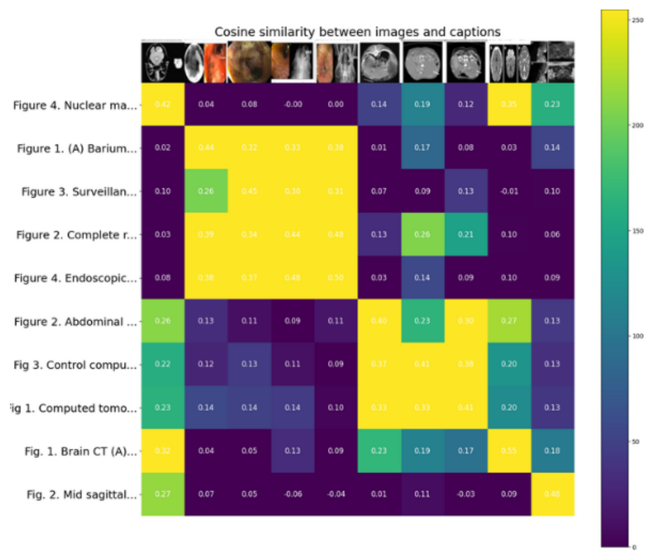


Fig.4: BiomedCLIP-PubMedBERT Performance Evaluation using Cosine Similarity between Images and Captions from MedCat..

IV. Conclusion

Multimodality has emerged as the primary form of information resource in the paradigm of medical knowledge cognition and reasoning because they can contributes to capturing the underlying complex relationships among clinical and medical elements due to the synergy between the diverse sources [27]. Machine learning based data fusion strategies based on the new wave of meta-transformers are becoming popular approach for modeling these nonlinear relationships echoed from the synergy between the information multimodalities. Although important meta-transformers has been fine-tuned for medical general medical domain, their fine-tuning embeddings can sourced from wide range of publically available data including social media [28]. Hence, these fine-tuned medical meta-transformers cannot be reliably used for evidence-based practice [29]. In our previous research we proved also that evidence-based learning based on normal text analytics transformers that are fine-tuned on evidence-based data cannot provide high accuracy [30]. However, this research article focuses on multimodal learning with Meta-Transformers and their use for clinical support evidence-based medicine. We utilized the TTi-Eval platform to evaluate different fine-tuned medical meta transformers like PubmedCLIP, CLIPMD, BiomedCLIP-PubMedBERT and BioCLIP and found that performance of BiomedCLIP-PubMedBERT outperforms the other models not only in identifying relations between the different medical modalities like clinical narratives assertions and medical imaging but also to support evidences from sound clinical research as published by PubMed. Our overall approached used in this research is illustrated in Figure 4. The dotted parts represent our ongoing research to support more evidence-based mechanisms for clinical support purposes. The current implemented evidence-level focuses on choosing the effective pre-trained medical meta-transformer that provide robust evidence based information. The dotted line is our extension to add a wrapper to enable practitioner's posses questions around a clinical case using a protocol like PICO and then the learning model help to generate relevant answers based on knowledge from scholarly medical articles. Our initial attempts stated with expanding the use of the MedCat environment that is used for concept annotation [31] and expand it to generate clinical case reports in response to PICO Queries. The full Python implementation details of our first level investigation are given in the Github of this project where the link is available at the acknowledgment of this article.

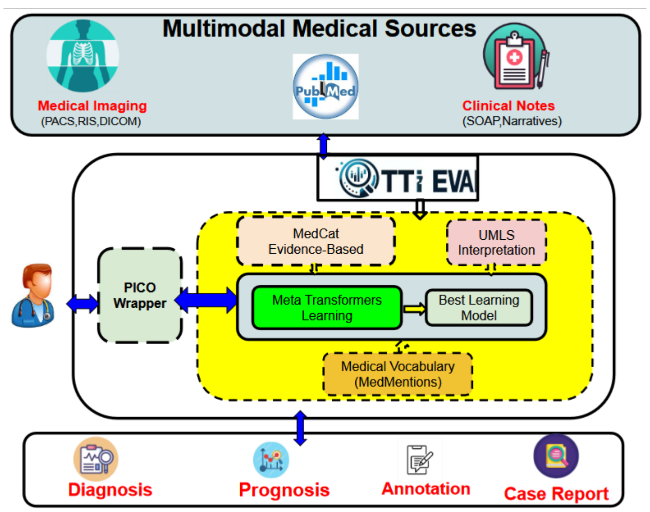


Fig. 4: The Overall Platform for Medical Meta-Transformers Learning for Evidence-Based practice.

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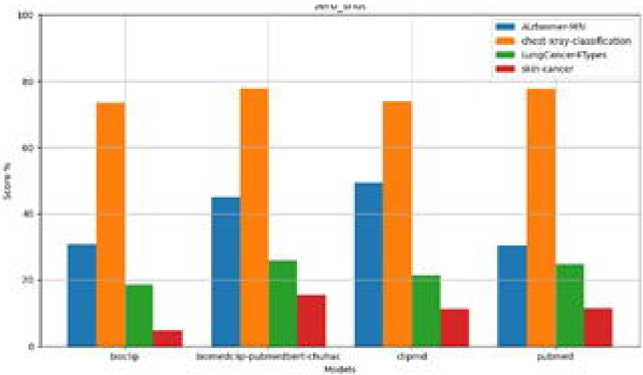

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skin-cancer
pubmed
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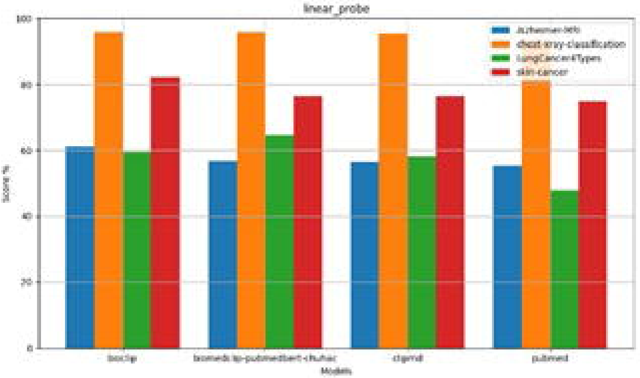
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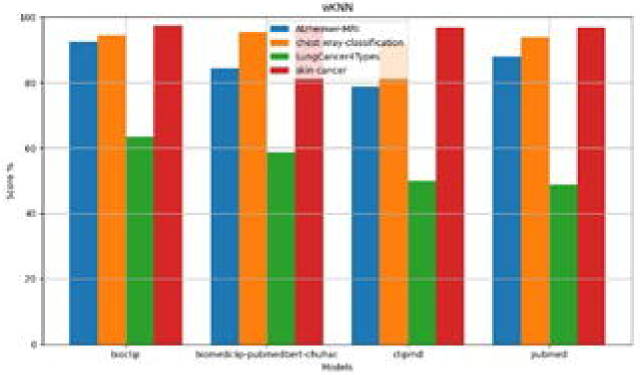
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skin cancer
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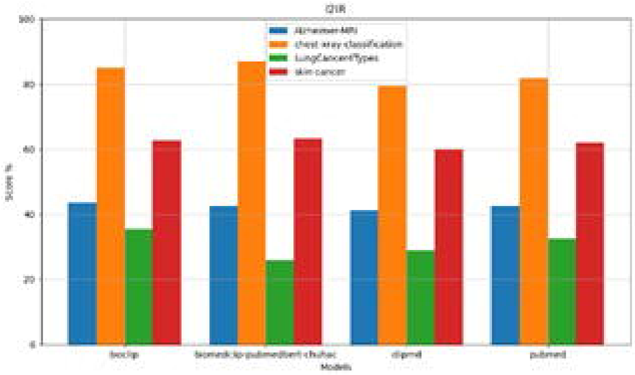
Score %
bioclip
clipmd
pubmed
Models



LungCancerTypes
skin cancer
Score %
Models
clipmd
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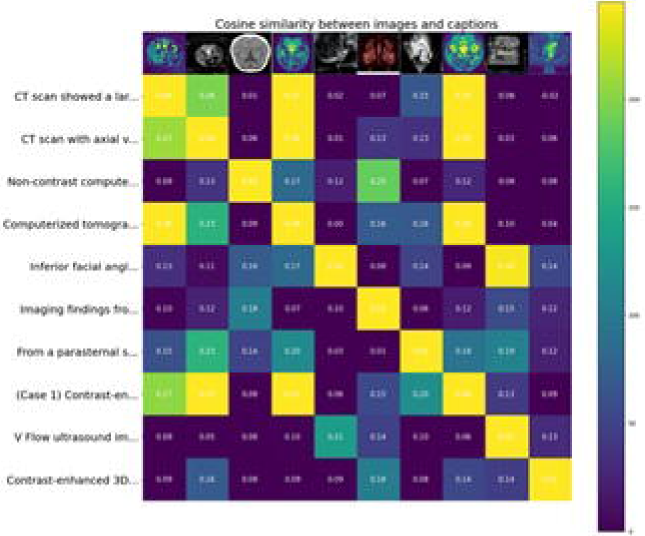

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CT scan with axial v...
Non-contrast compute...
Computerized tomogra...
Inferior facial angi...
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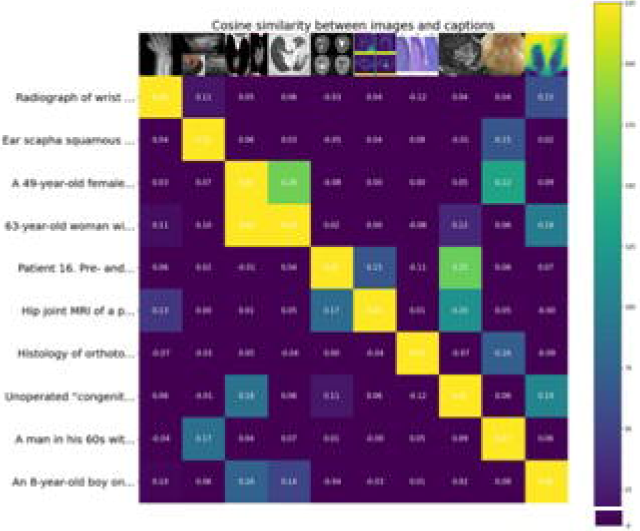
Cosine similarity between images and captions
Radiograph of wrist ...
Ear scapha squamous ...
A 49-year-old female...
63-year-old woman wi...
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Hip joint MRI of a p...
Histology of orthoto...
Unoperated "congenit...
A man in his 60s wit...
An 8-year-old boy on...

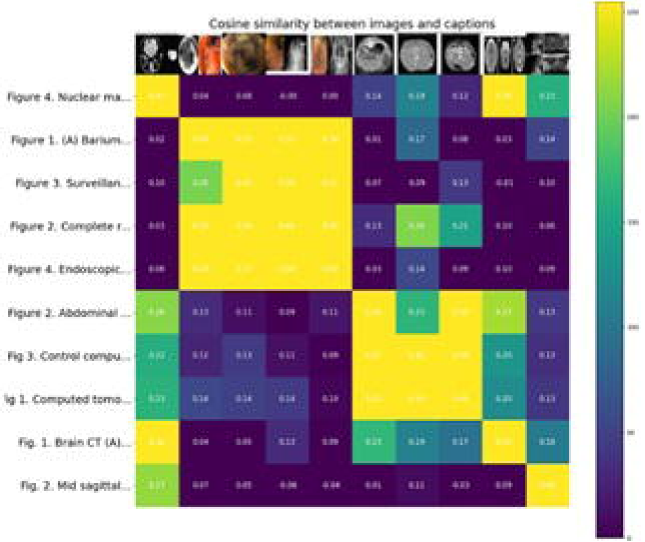
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Figure 4. Nuclear ma...
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Figure 4. Endoscopic...
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Fig. 1. Brain CT (A)...
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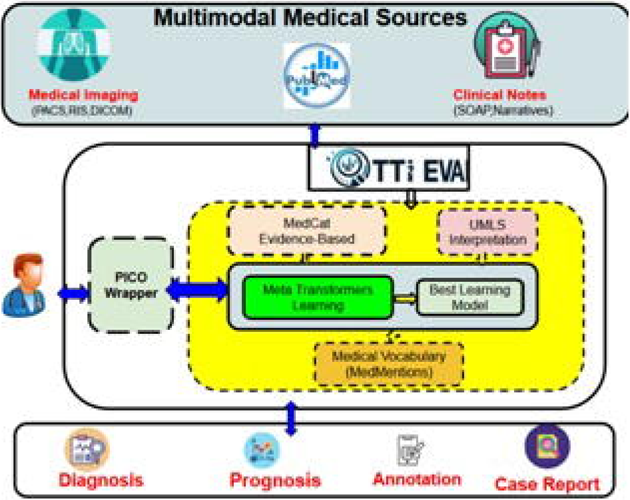

Multimodal Medical Sources
Medical Imaging
(PACS,RIS,DICOM)
Clinical Notes
(SOAP,Narratives)
TTi EVA
MedCat
Evidence-Based
UMLS
Interpretation
PICO
Wrapper
Meta Transformers
Learning
Best Learning
Model
Medical Vocabulary
(MedMentions)
Diagnosis
Prognosis
Annotation
Case Report