Multi-Modal Electronics Recommendation System

Experience

2012-16	Undergraduate Biomedical Engineering Design a Biosignal Amplifier
2016-18	Masters Biomedical Engineering
2018-19	Biomedical Scientist Human Performance Lab Robotic Hand Development, Al-ML
2020-24	PhD Systems Design Engineering EMG-Biometrics
2023	PhD Research Intern - Huawei Human Machine Interaction Lab Wearable sensors
2024-Now	ML Research Scientist Eaigle Computer Vision, Al-ML

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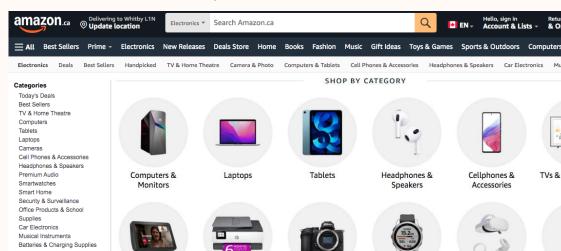
Introduction

- Al-Powered Recommendations Multi-modal (text & image) approach
- Use Case: Amazon electronic products 2023 (10k, Kaggle)
- **LLMs:** CLIP (OpenAI, 2021) + Sentence-BERT (2019)

Combining computer vision and natural language processing to build a smarter product recommender, specifically showcasing it on a large data set of Amazon electronics

Problem Statement

- Choice Overload: Many products, hard to find the right one
- Current Pain Point: Users struggle to find similar electronics
- Need: Recommend products by content (image & text)
- Further Need: Can the customized chatbot learn our specific needs?



RAG and Fine-Tuning

- RAG (Retrieval-Augmented Generation): Combination of retrieval of relevant documents and images and language generation to produce more accurate and contextaware responses.
- However, what if the chatbot needs to find very specific details. For example, the different classes of cameras, or, finding defects on products
- Need more specialized retrieval of information based on image/text query
- **Fine-tuning:** Customizes a pre-trained model on domain-specific data to improve performance on targeted tasks.

Project Objective

Prototype a multi-modal recommender for Amazon electronic products

- **Input:** User query (text or image) → Output: similar electronics
- Showcase: Use AI embeddings to match products by content and generate the response (RAG)
- Analysis: Improve the performance of the chatbot using Fine-tuning

Project Breakdown

Prototype a multi-modal recommender for Amazon electronic products

- Partl: Building the RAG Chatbot
- Part 2: CLIP model performance analysis
- Part 3: CLIP model fine-tuning



Part 1: Building a RAG Chatbot

- Identifying an Image Text dataset (Kaggle Amazon Electronics 2023 10k images-names)
- Building an Image Vector database (Chroma DB)
- Building Text database (Chroma DB)
- Knowledge Retrieval, given a text query, get top 5 image and text matches, given an image query get top 5 image matches (Langchain)
- RAG Chatbot. Given the top matches provide a response

Amazon Electronics 2023

The dataset consists of the following columns:

- **1. name:** The name of the electronic product.
- **2. image:** The link to a high-quality image representing the product.
- 3. link: The reference link to the product on the Amazon website.
- 4. ratings: The average ratings given by Amazon customers for the product.
- **5. no_of_ratings:** The number of ratings received by the product on Amazon.
- **6. discount_price:** The discounted price of the product.
- **7. actual_price:** The Manufacturer's Recommended Price (MRP) or original price of the product.

Part 1: Building a RAG Chatbot

Amazon Electronics 2023

* =	∆ name =	△ main_category =	△ sub_category =	∞ image =	∞ link =	△ ratings =	△ no_of_ratings =	△ discount_price =	△ actual_price =	
500	The name of the electronic product.	The main category to which the product belongs.	The sub-category specifying a more detailed classification of the product.	The link to a high-quality image representing the product.	The reference link to the product on the Amazon website.	the reference link to the Ratings of the Product [1- Controduct on the Amazon 4]		Count of ratings The discounted price of the product.		
0 9599	8800 unique values	1 unique value	1 unique value	8992 unique values	9600 unique values	4.3 14% 4.2 13% Other (7077) 74%	3456 unique values	(null) 5% ₹299 5% Other (8635) 90%	₹999 16% ₹1,999 5% Other (7554) 79%	
0	Redmi 10 Power (Power Black, 8GB RAM, 128GB Storage)	tv, audio & cameras	All Electronics	https://m.media- amazon.com/images/I/ 81eM151VcJLAC_UL80 0jpg	https://www.amazon.i n/Redmi-Power-Black- 128GB- Storage/dp/B09Y64HBV S/ref=sr_1_4? qid=1679133649&s=ele c	4.0	965	₹18,999	₹18,999	
ï	OnePlus Nord CE 2 Lite 5G (Blue Tide, 6GB RAM, 128GB Storage)	tv, audio & cameras	All Electronics	https://m.media- amazon.com/images/I/ 71AvQd3VzqLAC_UL80 0jpg	https://www.amazon.i n/OnePlus-Nord-Lite- 128GB- Storage/dp/B09WQYFLR X/ref=sr_1_59 qid=1679133649&s=ele c	4.3	113,956	₹18,999	₹19,999	
2	OnePlus Bullets Z2 Bluetooth Wireless in Ear Earphones with Mic, Bombastic Bass - 12.4 Mm Drivers, 1	tv, audio & cameras	All Electronics	https://m.media- amazon.com/images/I/ 51UhwaQXCpLAC_UL80 0jpg	https://www.amazon.i n/Oneplus-Bluetooth- Wireless-Earphones- Bombastic/dp/B89TVVG XWS/ref=sr_1_6? qid=16	4.2	90,304	₹1,999	₹2,299	
	2 2 2 2 22	1 1 1 1	244 941 31 3	122 12 12	122 122					

Knowledge Retrieval

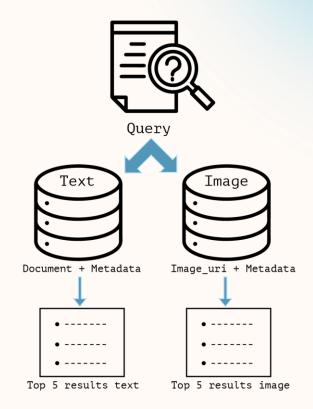
Two ChromaDB databases are created: text_db and image_db

Document = product name + rating + discount + price

Image_uri = uri of the downloaded image

Metadata = product_id, name, uri

 Given a query, get top 5 results from each database, based on distance



Prompt Engineering

System Template: Includes instructions on prioritization

- If brand name, discount, rating or price is mentioned in the query then prioritize the text query results
- If physical appearance (shape, color, size) is mentioned in the query then prioritize the Image query results
- If multiple descriptions are present then follow the sequence:
 Brand name > Physical appearance > Discount > Rating

```
# Create a custom prompt template

template = """

You are a helpful shopping assistant. Use the following product information to answer the question, while answering the question use metadate

If the query includes anything about the appearance (color size shape etc), then any other information such as rating, discount and price des

If the query is about the product/brand name, rating and discount, prioritize the text query results. Remeber the query results are sorted by

Give the answer in statements, not bullet points. make sure to include the product_id in the answer.

Question: {query}

Answer:

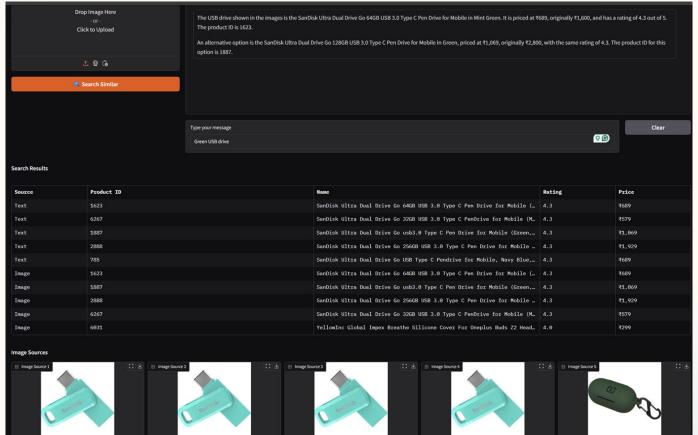
"""
```

Building QA chain

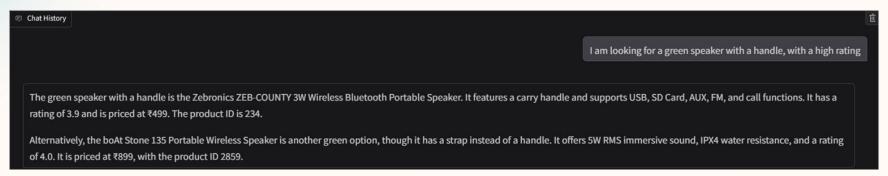
response = qa chain.invoke(query)

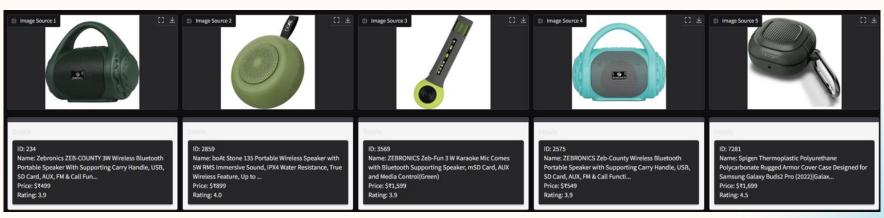
```
llm = ChatOpenAI(temperature=0.3, model="gpt-40")
parser = StrOutputParser()
qa_chain = prompt | llm | parser
```

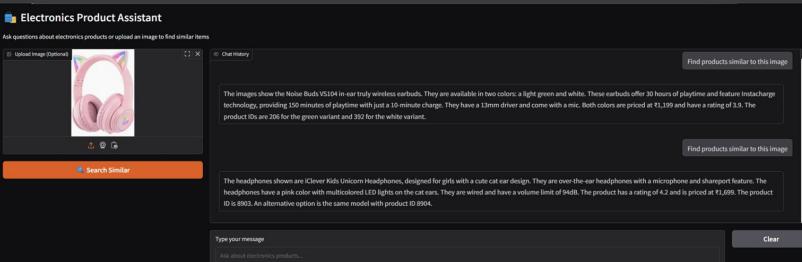
UI Design



Text Query







Search Results

Source	Product ID	Name	Rating	Price
Image	8903	iClever Kids Unicorn Headphones for Girl Over The Ear Headphone with ML	4.2	₹1,699
Image	8984	iClever Kids Unicorn Headphones for Girl Over The Ear Headphone with M	4.2	₹1,699
Image	8928	Infinity (JBL Glide 500, 20 Hrs Playtime with Quick Charge, Wireless O.	4.2	₹1,599
Image	795	Infinity (JBL Glide 510, 72 Hrs Playtime with Quick Charge, Wireless O.	4.2	₹1,699
Image	8108	ZEBRONICS Zeb Duke 101 Wireless Headphone with Mic, Supporting Bluetoo.	3.9	₹799

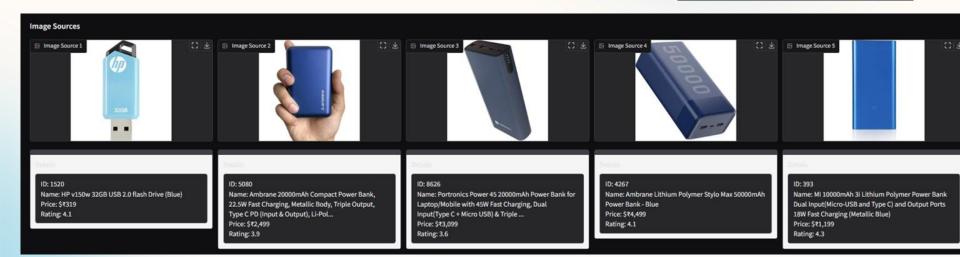
Image Sources



Observations

- The results are accurate in terms of text sources
- The image-query-from-text is correct, however, image-query-from-image has some mistakes
- Image-text dataset has no distinct relationship

blue power bank 50000 MAH



Part 2: CLIP Performance analysis

- Pseudo labels using OpenAl GPT-40 with the product name as the input
- Class_labels = {"camera", "headphones", "home appliance", "keyboard", "laptop", "monitor", "mouse", "phone case", "printer", "smartphone", "speaker", "tablet", "television", "tripod", "usb stick", "smartwatch", "earbuds", "phone charger", "power bank", "microSD card", "hard drive", "router", "wifi adapter", "calculator", "laptop charger", "stationery", "general accessory", "computer accessory", "phone accessory"}
- Select class labels for CLIP classification analysis (~25)

Pseudo-Labels Class Distribution

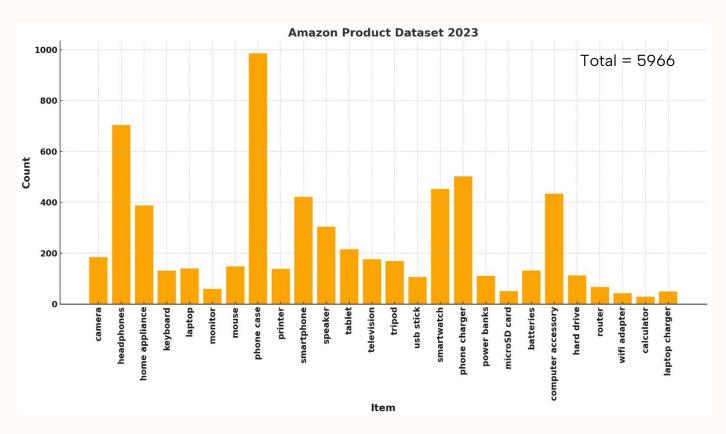
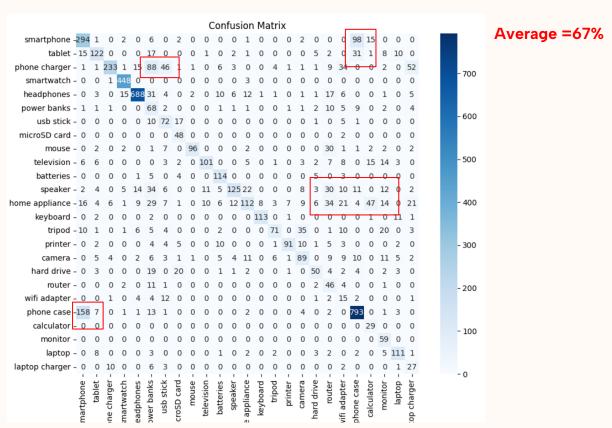


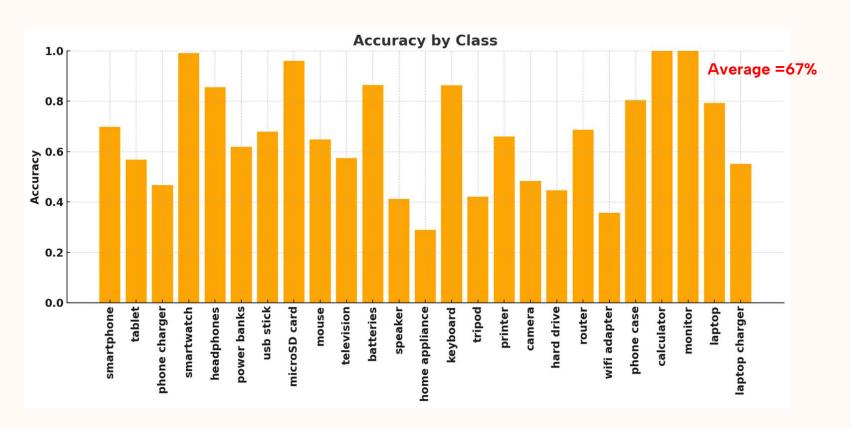
Image Classification Performance

- texts = [f"a photo of {class_label}" for class_label in class_label_list]
- Given an image, find the text with top similarity score
- Predicted_label is class_label in the text
- calculate_accuracy(predicted_labels, pseudo_labels)

Baseline CLIP Performance

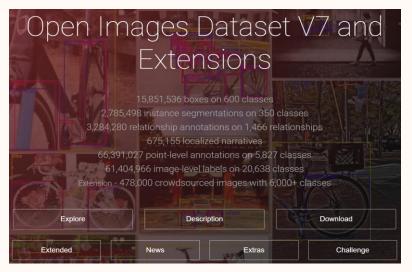


Baseline CLIP Performance

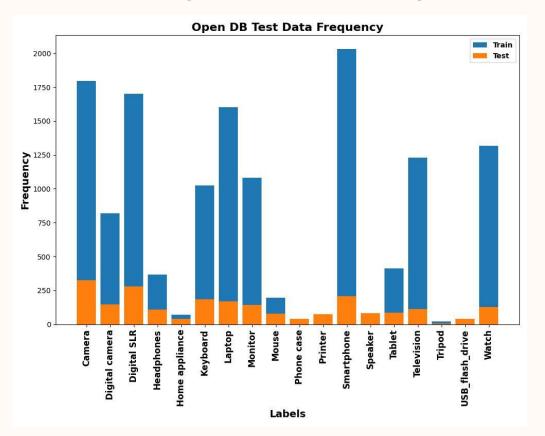


Part 3: Model Fine-tuning

- To improve the classification performance, we need to finetune the CLIP model on the select data classes
- Use of Open Images Dataset V7
- Transfer Learning
- Collected train-test data of selected classes



Open DB 7 Image Class Histogram



Num_classes = 16 Train Size = 13682 Test Size = 2088

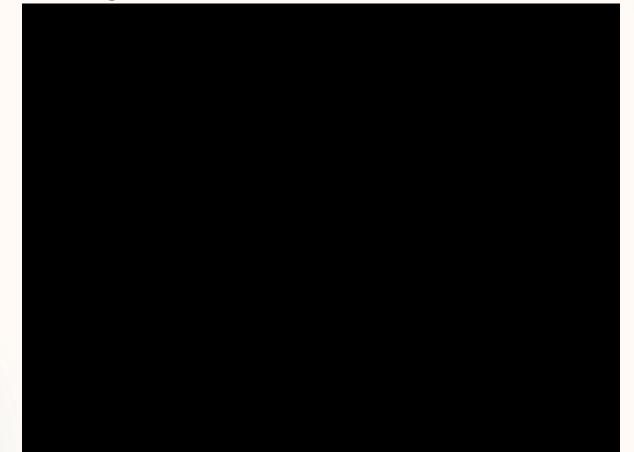
Hyper Parameter Tuning

- Model training using MLFLow
- Base Model = CLIP ViT-B/32
- CrossEntropyLoss: (text_loss + image_loss)/2
- Adam Optimizer
- Log the class_wise results for parameters:
 {epochs-training, batch size, number of frozen layers, learning rate}

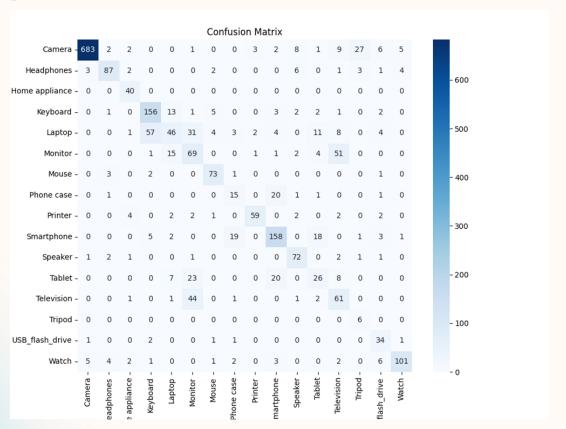
epochs-training	2-10
batch size	16, 32, 64
number of frozen layers	None, 4, 6, 8, 10
Learning rate	1e-7, 5e-6, 1e-6

Part 3: Model Fine-tuning

Model Tracking - MLFlow

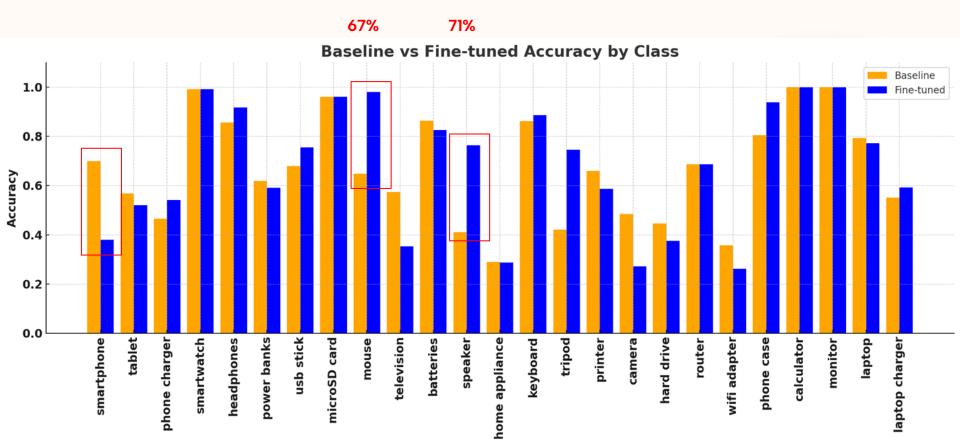


OpenDB 7 Classification Results



Overall Accuracy = 77%

Amazon Electronics Data Classification



Chatbot Observations

- Classification performance increased with Fine-tuning (4%)
- Update the fine-tuned clip model in the chatbot
- Little to no improvements in query results
- Results reduced on classes such as Smartphones

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Discussion - Challenges

- The Image-Text pair is not a correct sample for CLIP Fine-tuning
 - A photo of {class label} X
- CLIP model might perform better in knowledge retrieval if trained on Amazon Electronics
 Dataset
 - o The Amazon database has marketing-style images, while OpenDB is more real-life
- Fine-tuned with both losses (Image and Text)
- For downstream applications such as classification, fine-tuning is more relevant

Demo

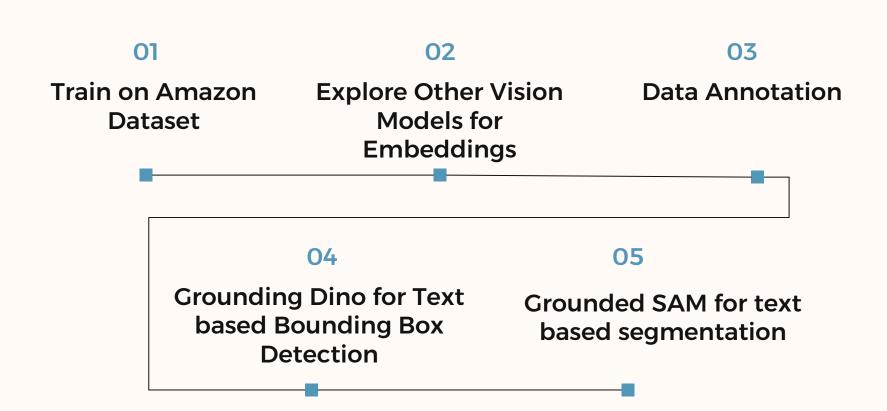
Live walkthrough of the recommendation system

- **Scenario 1:** Text query → recommended products
- **Scenario 2:** Image query → recommended products
- **Visualize:** Show retrieved similar items and why they match



http://127.0.0.1:7860/

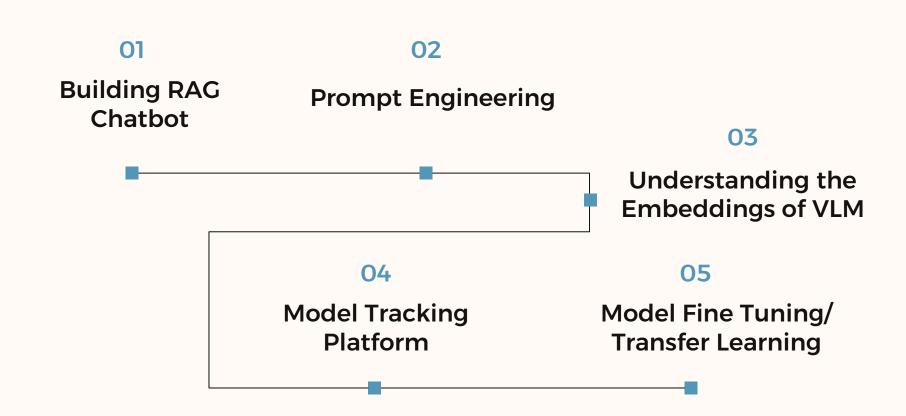
Future Work



Tools Used

- Python
- Pandas
- OpenAl CLIP
- Sentence Transformer, Huggingface
- GPT4o
- Pytorch
- Gradio
- Open Images Dataset V7
- MLFLow
- SkLearn, Seaborn

Contribution



Any questions?

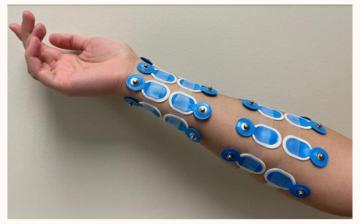
Thank you!

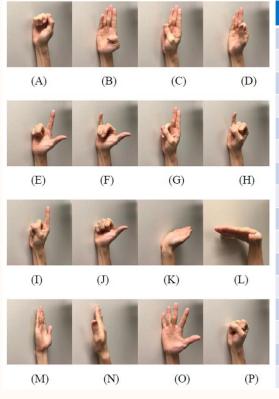
Master's Research





PhD Research





List of Hand Gestures (Codes)

- A) lateral prehension (LP)
- B) thumb adduction (TA)
- C) thumb and little finger opposition (TLFO)
- D) thumb and index finger opposition (TIFO)
- E) thumb and little finger extension (TLFE)
- F) thumb and index finger extension (TIFE)
- G) index and middle finger extension (IMFE)
- H) little finger extension (LFE)
- I) index finger extension (IFE),
- J) thumb extension (TE)
- K) wrist flexion (WF)
- L) wrist extension (WE)
- M) forearm supination (FS)
- N) forearm pronation (FP)
- O) hand open (HO)
- P) hand close (HC)

EMG-BASED BIOMETRICS

Authentication & Identification

Contrastive Language-Image Pre-training

```
# Forward pass
logits_per_image, logits_per_text = model(images, texts)

# Compute loss
ground_truth = torch.arange(len(images),dtype=torch.long,device=device)
total_loss = (loss_img(logits_per_image,ground_truth) + l
oss_txt(logits_per_text,ground_truth))/2
```