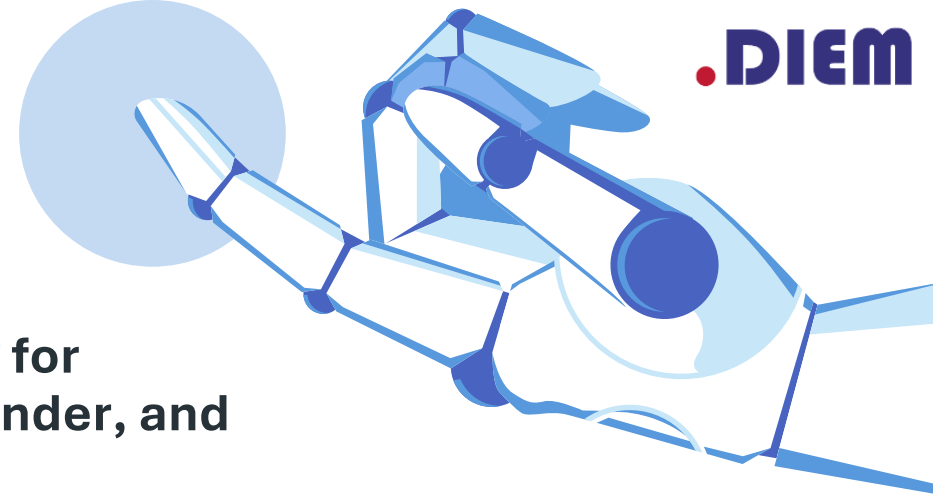


# Adapting Vision Language Models via parameter-efficient fine-tuning for Multitask Classification of Age, Gender, and Emotion


Relatori:
*Prof. Mario Vento*
*Prof. Antonio Greco*

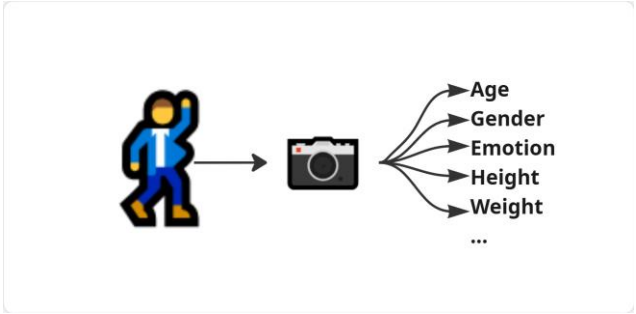
Canditato: *Antonio Sessa*
Matricola: *0622702311*

# Index

# Soft Biometric Recogntion, What and Why?

## Definition:

**Soft biometrics are non-unique human attributes that can be indirectly collected from images.** Unlike traditional biometrics such as fingerprints or iris patterns, soft biometric traits do not uniquely identify an individual but provide rich contextual information




## Applications:

**Social Robotics:** a robot estimates a user is a child and automatically switches to a simpler speech and more playful voice

**Marketing & Commerce:** A digital sign detects a shopper's likely age and gender to show a targeted ad, like for a video game or a new perfume

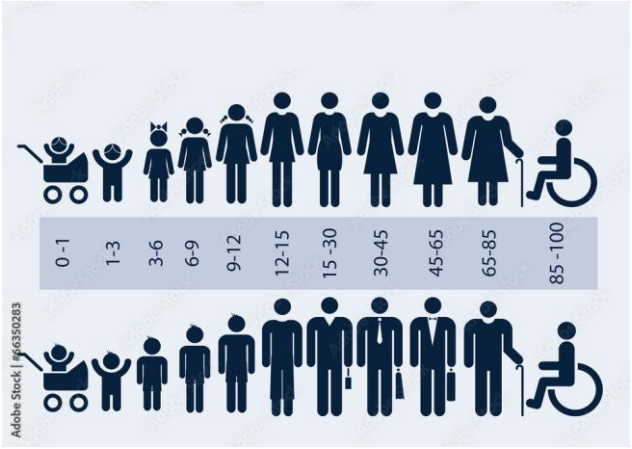
**Security & Access:** A website uses facial age estimation to automatically block a user who appears underage from accessing mature content

**Healthcare & Wellness:** A wellness app monitors a user's vocal tone or facial expression through their phone to detect signs of stress or fatigue

# Challenges of our chosen domain

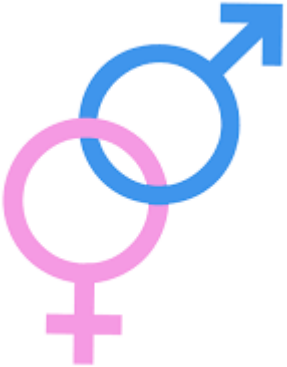
. Sadness, Surprise, Happiness, Disgust, Angry, Fear

. **Small dataset, class imbalances, low annotator agreements**




. 0-2,3-9,10-19,20-29,30-39,40-49,50-59,60-69,70+

. **High class intra variance, class imbalances**

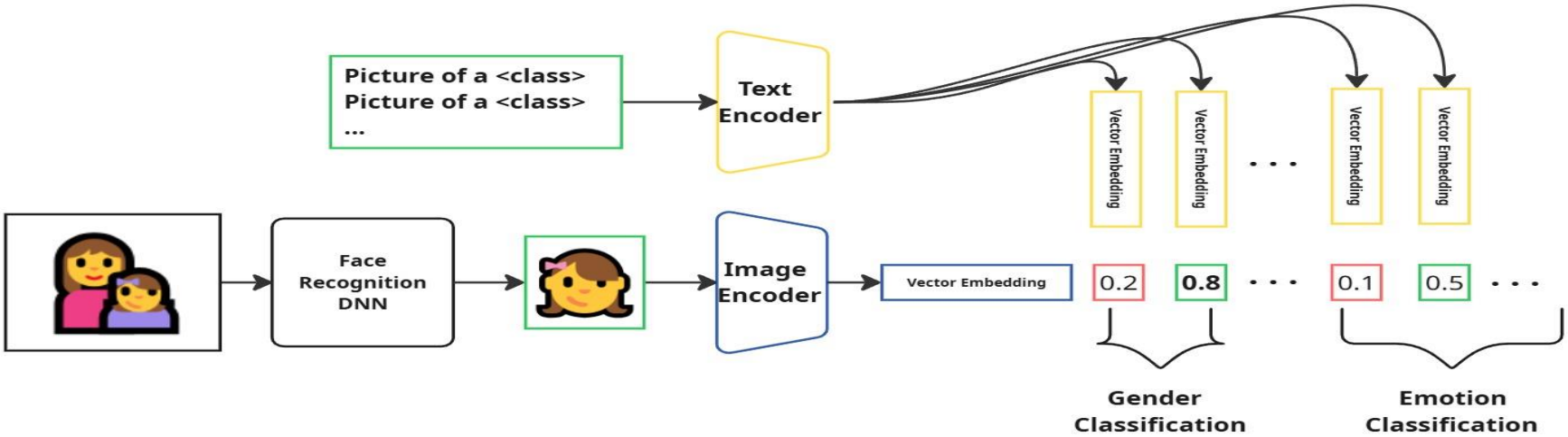


. Male and Female

. **Different age-groups and ethnicities**

# Our Approach, Vision Language Models

Vision language model (VLM) are large neural networks, trained on billion of image-text pairs, that can be use in a **zero-shot manner**.
We can create a soft-biometric recognition system using a VLM (like the Perception Encoders).



# First, unsatisfactory results:

| UTK-Age | UTK-Gender | FairFace-Age | FairFace-Gender | RAF-DB | VGG-Age | VGG-Gender |
|---|---|---|---|---|---|---|
| 48.62% | 96.63% | 46.11% | 97.60% | 66.57% | 42.01% | 95.78% |

Table 4.1: Baseline zero-shot accuracy results across testing datasets for age, gender, and emotion recognition tasks.

| Age* | Gender | Emotion | Global |
|---|---|---|---|
| 47.36% | 96.67% | 66.57% | 69.61% |

*Average calculation excludes the VggFace2 dataset as its age-labels data are synthetically obtained.

Table 4.2: Mean baseline accuracy for age, gender, and emotion recognition tasks.

| Component | Parameters |
|---|---|
| Text Encoder | 353,986,561 |
| Visual Encoder | 318,212,106 |
| **Total Parameters** | **671,137,793** |
| **GFLOPs** | **699.76** |

Table 4.3: Number of parameters used by the zero-shot baseline during inference

## Some observations:

**Zero-shot via hard-prompting,** leads to unsatisfactory results:

. Poor **accuracy** in age and emotion recognitions

. **High inference time** (~700 Gflops)

. **High memory foot-print** ( ~670 milion parameters)

Since visual understanding stems from the vision encoder, we can omit the text encoder and use the image encoder as a foundation vision model, doing so we **halve the inference time and memory footprint**.

# Datasets used to adapt the pre-trained ViT:

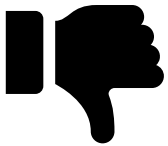
## Training Datasets:

- **FairFace,** ~97k samples age and gender labelled
- **Lagenda,** ~67k samples age and gender labelled
- **RAF-DB,** ~17k samples emotion and gender labelled
- **CelebaHQ,** ~17k samples gender labelled

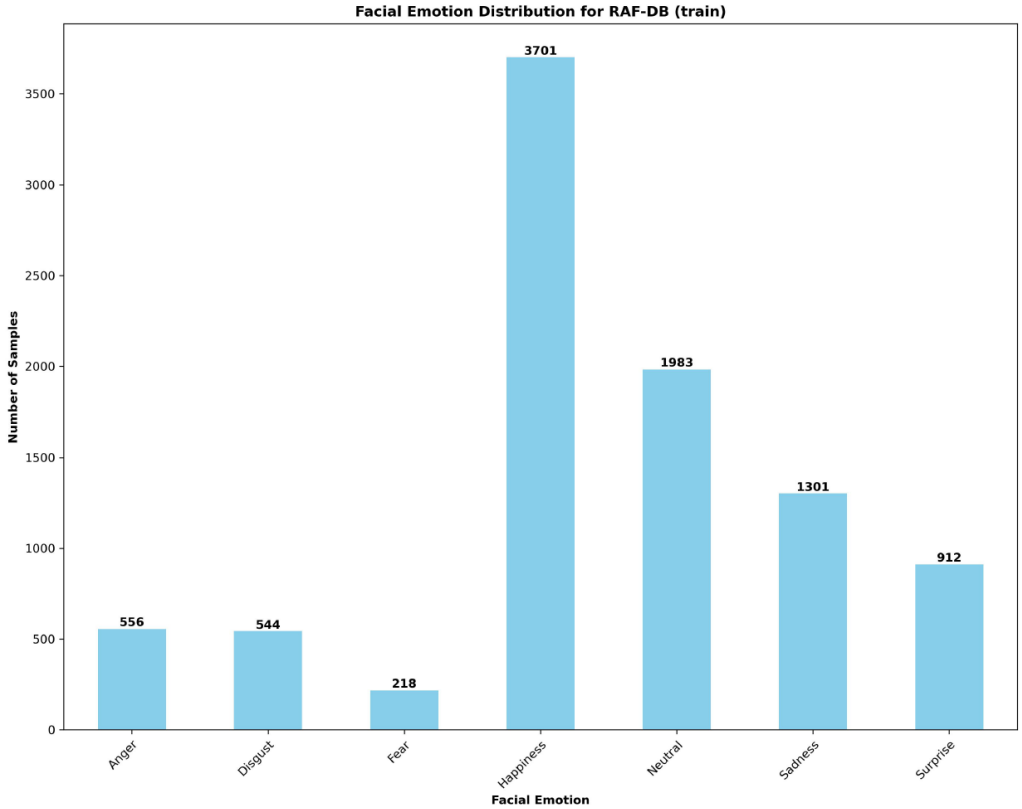
## Testing Datasets:

- **FairFace (test-split)**
- **RAF-DB (test-split)**
- **VggFace2,** ~170k samples (synthethic) age and gender labelled
- **UTKFace,** ~24k samples age and gender labelled

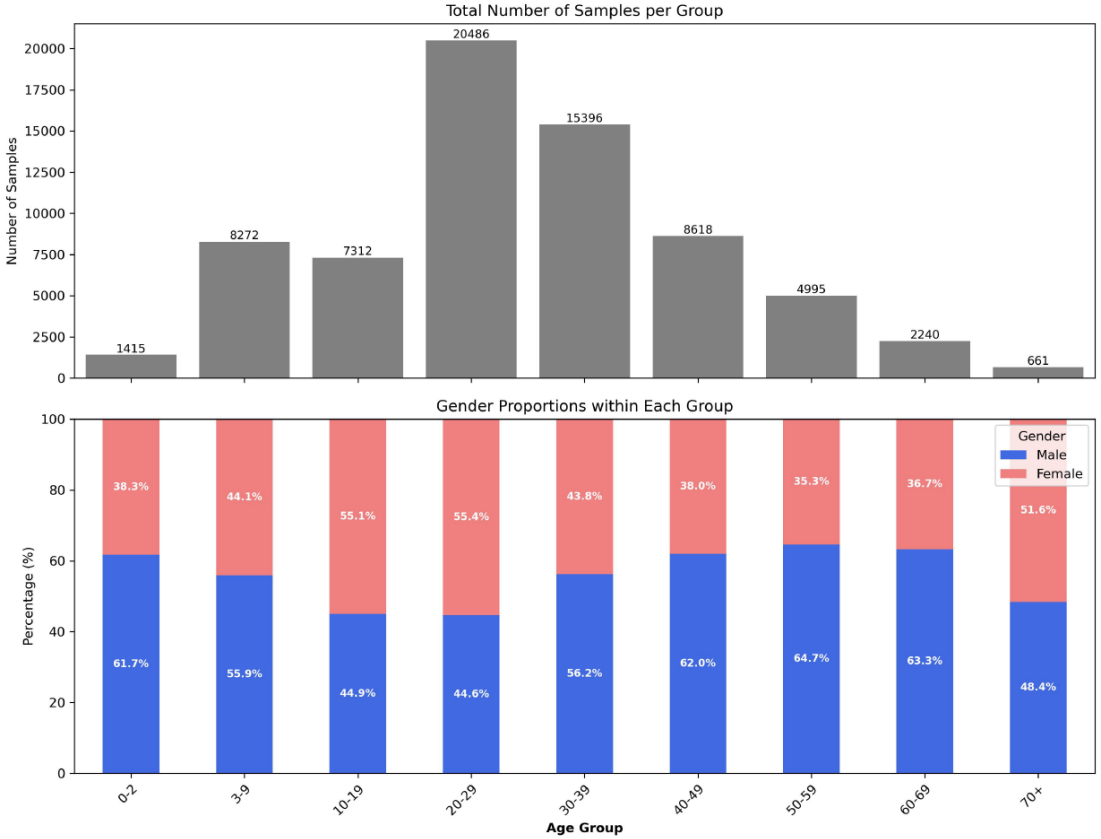
. Low amount of celebrity data in training set
. Diverse ethinicities rappresented
. High annotator agreements for the labels
. Cross-dataset generalization with UTKFace and VggFace2



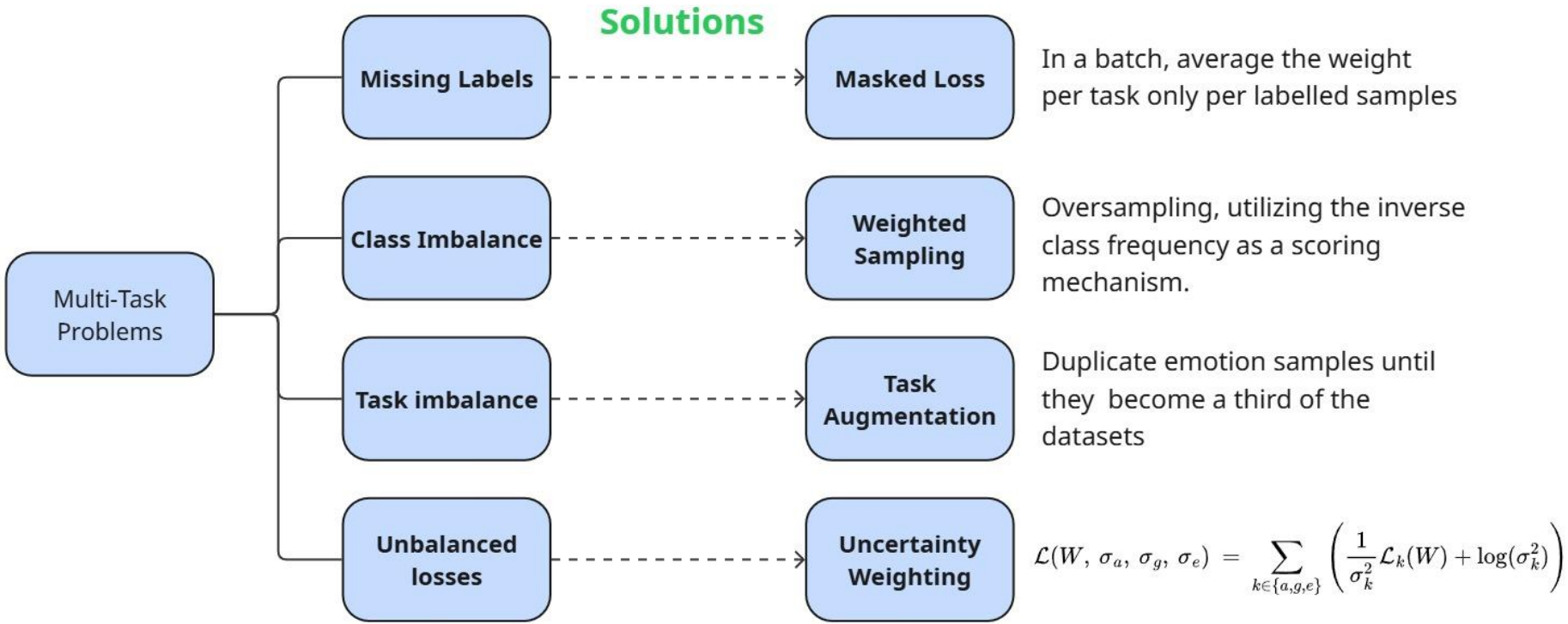
. **Intra task-class imbalance** for age and emotion
. **Task imbalance**, emotion heavily under-rapresented (5% of total)
. **Missing labels**, no samples is labelled for all tasks

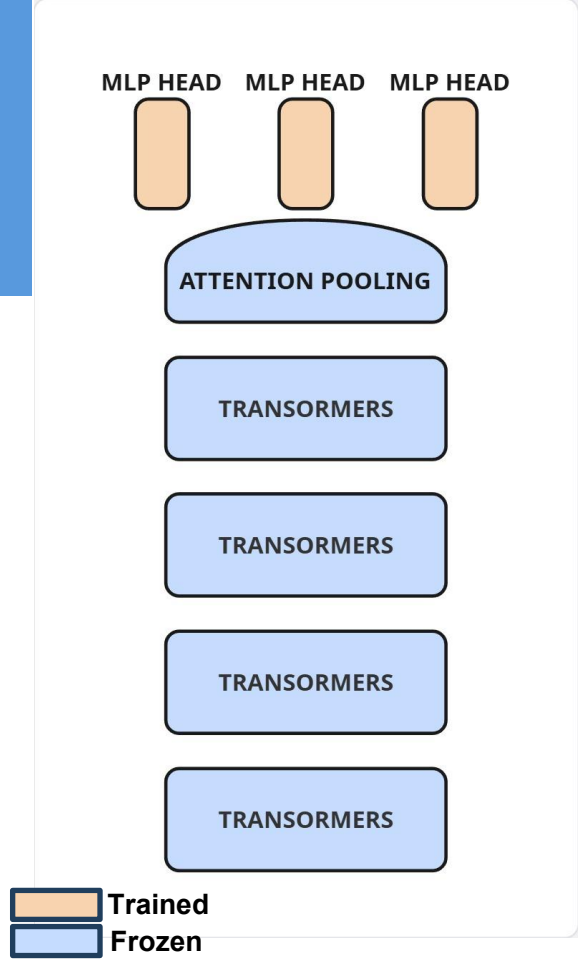

Facial Emotion Distribution for RAF-DB (train)
Number of Samples
Facial Emotion
0
500
1000
1500
2000
2500
3000
3500
556
544
218
3701
1983
1301
912
Anger
Disgust
Fear
Happiness
Neutral
Sadness
Surprise

# Distribution for FairFace (train)



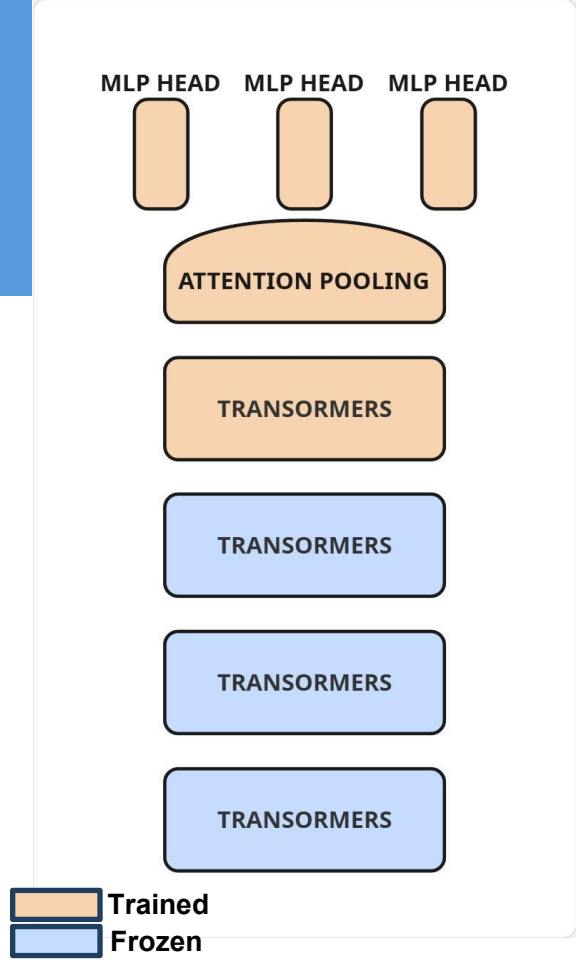
# Multi-task learning, problems and solutions






**Linear Probing:** attaching a MLP classifier per task to the output of the model, to harness the out-of-the box features of the vision transformers. As there can be no benefit to train the classification head simultaneously, as there is no parameter sharing, they are **trained sequentially** on fully labelled datasets split.

**Training: 0.33% of parameters**




**Partial fine-tune:** unfreezing the attention pooling layer and last four transformers block of the ViT, using a differential LR strategy (using 1/10 of the LR for transformers blocks)

**Training: 20.13% of parameters**

# Can we go deeper? Not really...

. **Hardware limitations:** our available hardware does not allow a full fine-tune of the model, even with mixed precision training and gradient checkpointing. It may be possible by a drastic reduction of the batch sizes, but then we incour on the problem of noisy gradients, accentued by the multi-task setting.

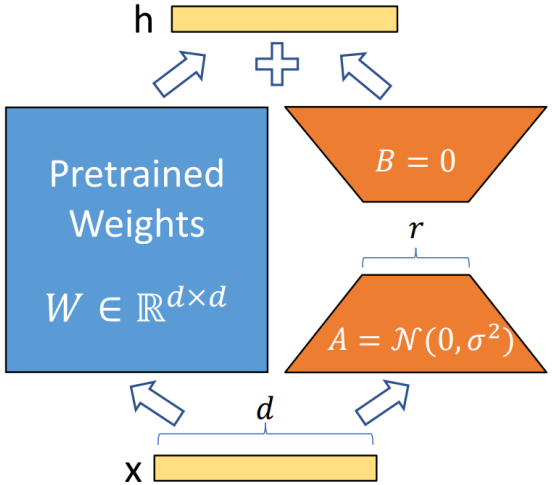
# Do we want to go deeper? Yes but...

. **Increase capacity + relatively small dataset:** when we increase the model capacity by unfreezing more transformers block, if we do not also increase the size of the dataset we may likely encounter **overfitting.**

. **Risk of catastrophic forgetting:** updating the entire network risks catastrophic forgetting, where task-specific gradients could destroy the powerful, generalized knowledge acquired during the initial 5.4 billion pair pre-training.

# Parameter Efficient Fine-tune with Low Rank Adaptation

**Main Idea:** the weight updates for large pre-trained model can be effectively represented in a low-dimensional subspace.



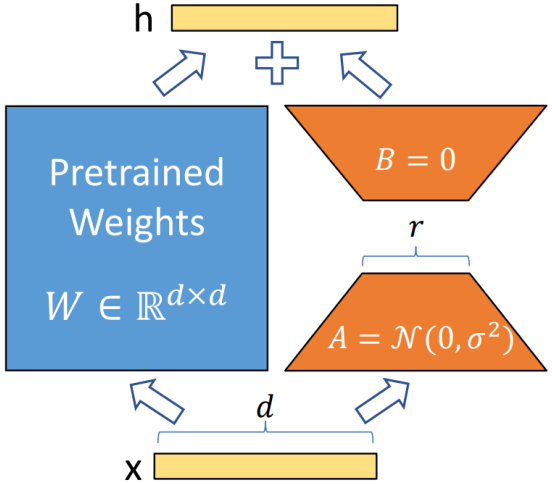

$$h = Wx + BAx$$

**Benefits of LoRA:**

- Small checkpoints
- No added inference latency and memory footprint
- Lower VRAM consumption due to parameter-efficient updates
- Prevents «catastrophic forgetting» by limiting weight update in a low-dimensional space

# Enhancements for LoRA: **LoRA+** & DoRA

**LoRA+,** improved performance and faster fine-tuning.



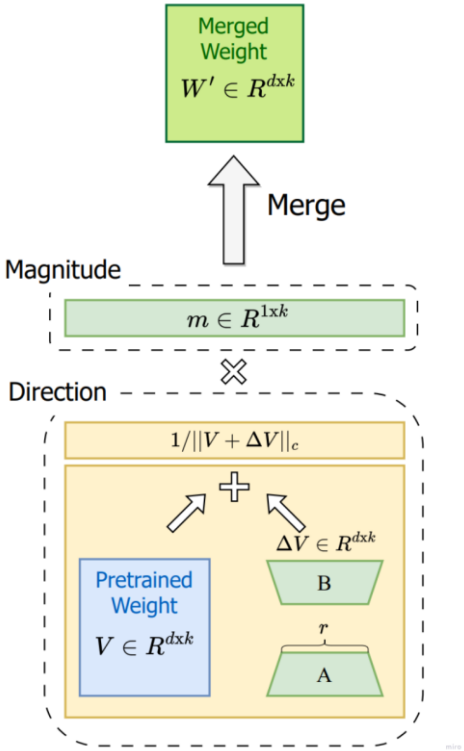

Training update for A and B matrices with LoRA+:

$$B^t = B^{t-1} - \lambda \eta G_B$$

$$A^t = A^{t-1} - \eta G_A$$

In our implementation, we set $\lambda = 6$

# Enhancements for LoRA: LoRA+ & **DoRA**

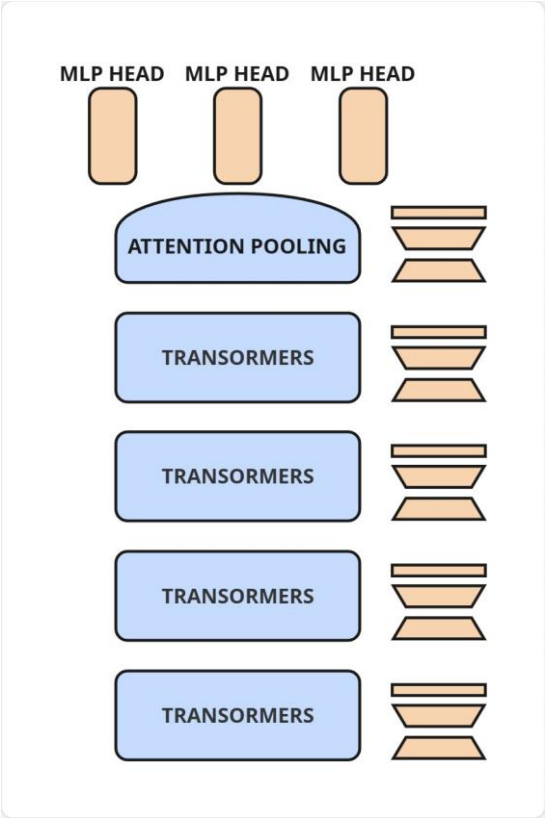



**Main Idea:** enhance the weight update by seperately training the direction and magnitude of the update.

$$h = x\left(m \cdot \frac{W + BA}{\|W + BA\|_C}\right)$$

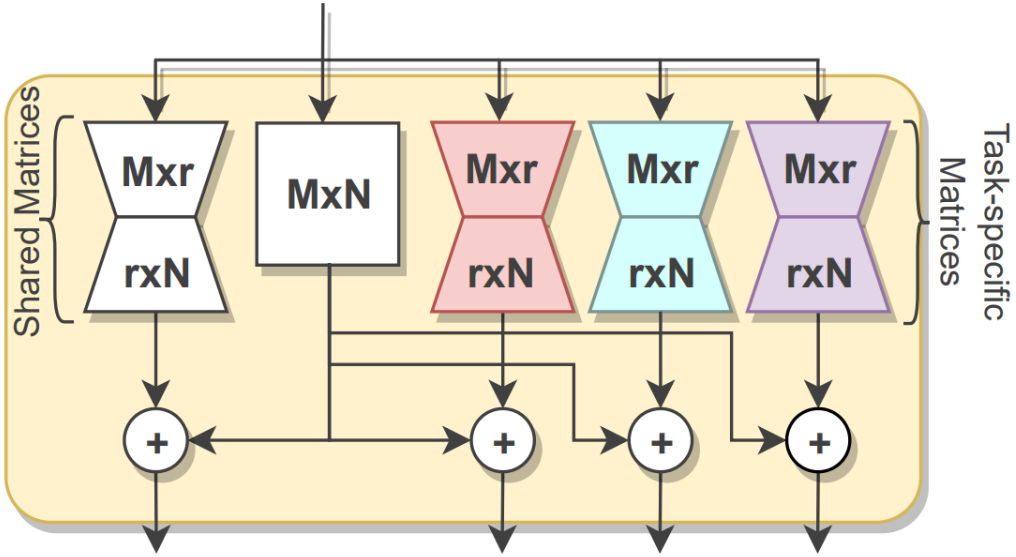
**Benefits of DoRA:**

- Same benefits of LoRA
- Increased learning capacity




**DoRA & LoRA+ :** adding DoRA adapters with rank=64 to each linear layer of the Vision Transformer and using a learning rate x6 to train the B matrices of the adapters.
**Training: 8.47% of parameters (less than half of FT4)**

# PEFT & Multi-task: MTLoRA



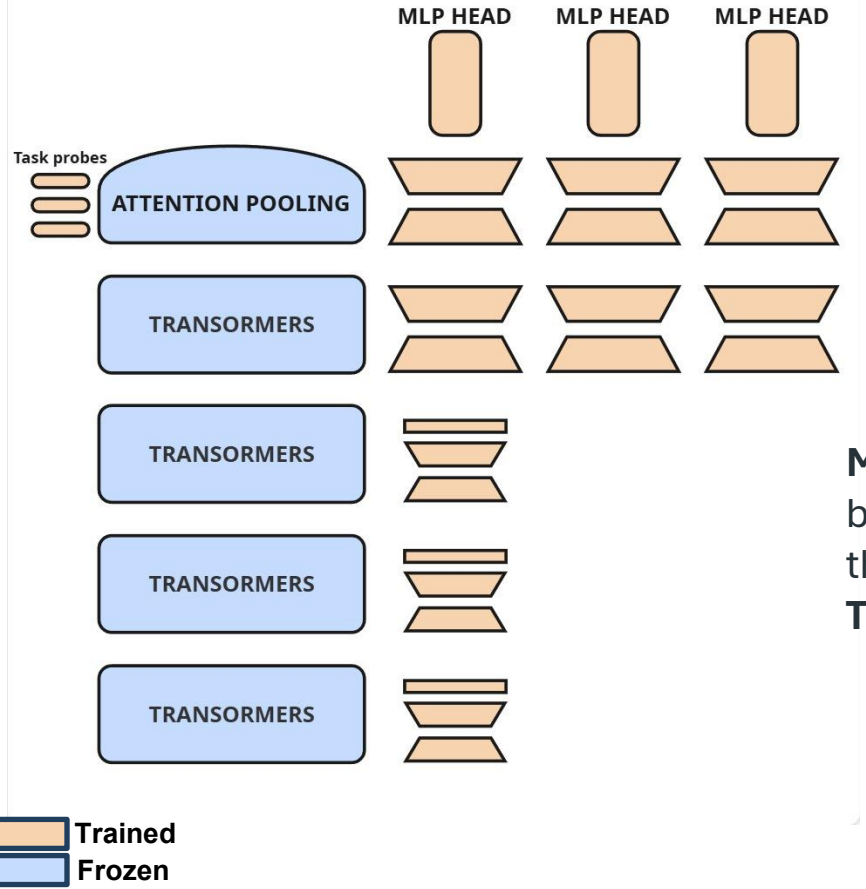

**Main Idea:** disentangle the parameter space trough **Task-Specific LoRA matrices**

**Benefit:**

- Train specialized parameters for a task, and use them to create **task-specifics feature-maps**

**Deficit:**

- The task specific LoRA matrices cannot be merged, small increase in memory footprint and inference latency




**MTLoRA:** TS-LoRA (r=64) applied to last transformer block and attention pooling layers. TA-DoRA using the same setup describe earlier.
**Training: 10.38% of parameters**

# Multi-task model results

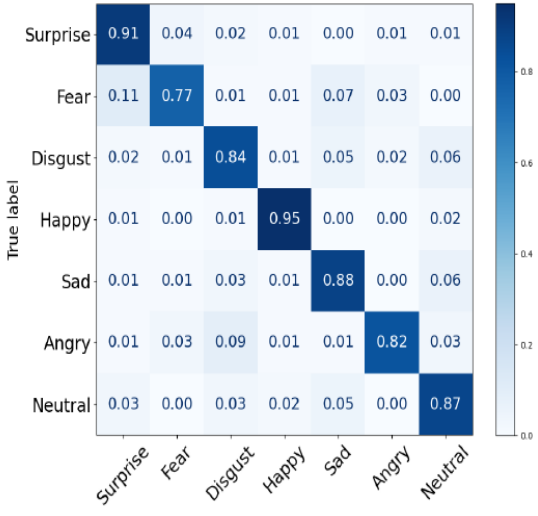
| Model | FairFace (Age) | FairFace (Gender) | RAF-DB (Emotion) | UTKFace (Age) | UTKFace (Gender) | VggFace2 (Age) | VggFace2 (Gender) |
|---|---|---|---|---|---|---|---|
| Baseline | 46.11% | 97.60% | 66.57% | 48.43% | 96.63% | 42.01% | 95.78% |
| LP | 61.00% | 97.70% | 84.82% | 61.56% | **97.00%** | 57.75% | 97.82% |
| FT_4 | 63.45% | **97.71%** | 88.42% | 62.54% | 96.68% | 61.68% | 97.81% |
| LoRA | 63.73% | 97.57% | **91.21%** | 63.34% | 96.90% | 61.69% | **98.00%** |
| MTLoRA | **64.11%** | 97.62% | 90.06% | **63.96%** | 96.93% | **63.80%** | 97.93% |

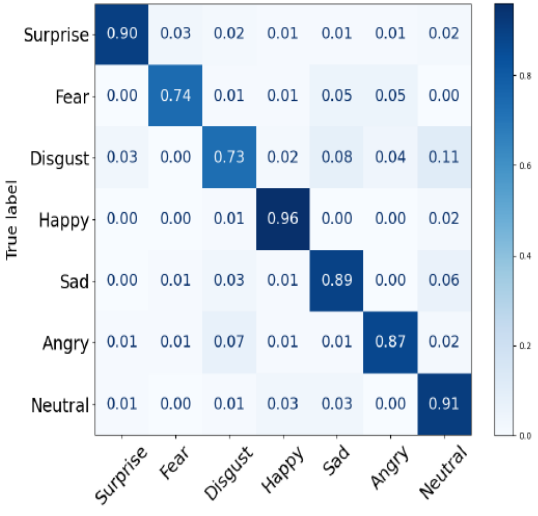
# Efficiency Comparison

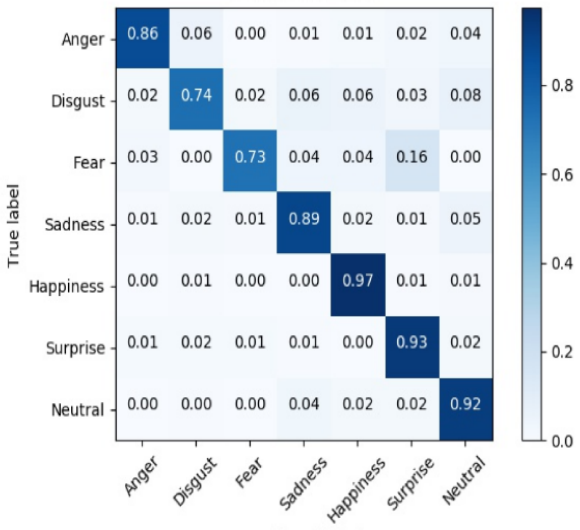
| Model | GLOPS | PARAMS | AVG. ACC |
|---|---|---|---|
| Baseline | 700 | 671 M | 69.61% |
| LoRA | 352 (-50%) | 320 M (-52%) | 84.07% (+20%) |
| MTLoRA | 368 (-47%) | 329 M (-50%) | 83.89% (+20%) |

# Comparison with the state of the art

| Model | FairFace (Age) | FairFace (Gender) | RAF-DB (Emotion) |
|---|---|---|---|
| MIVOLO | 62.28% | 97.50% | - |
| CLIP-ViT-L/14 | 63.45% | 97.10% | - |
| ResEmoteNet | - | - | **94.76%** |
| ApViT | - | - | 92.21% |
| Baseline | 46.11% | 97.60% | 66.57% |
| LoRA | 63.73% | 97.57% | 91.21% |
| MTLoRA | **64.11%** | **97.62%** | 90.06% |



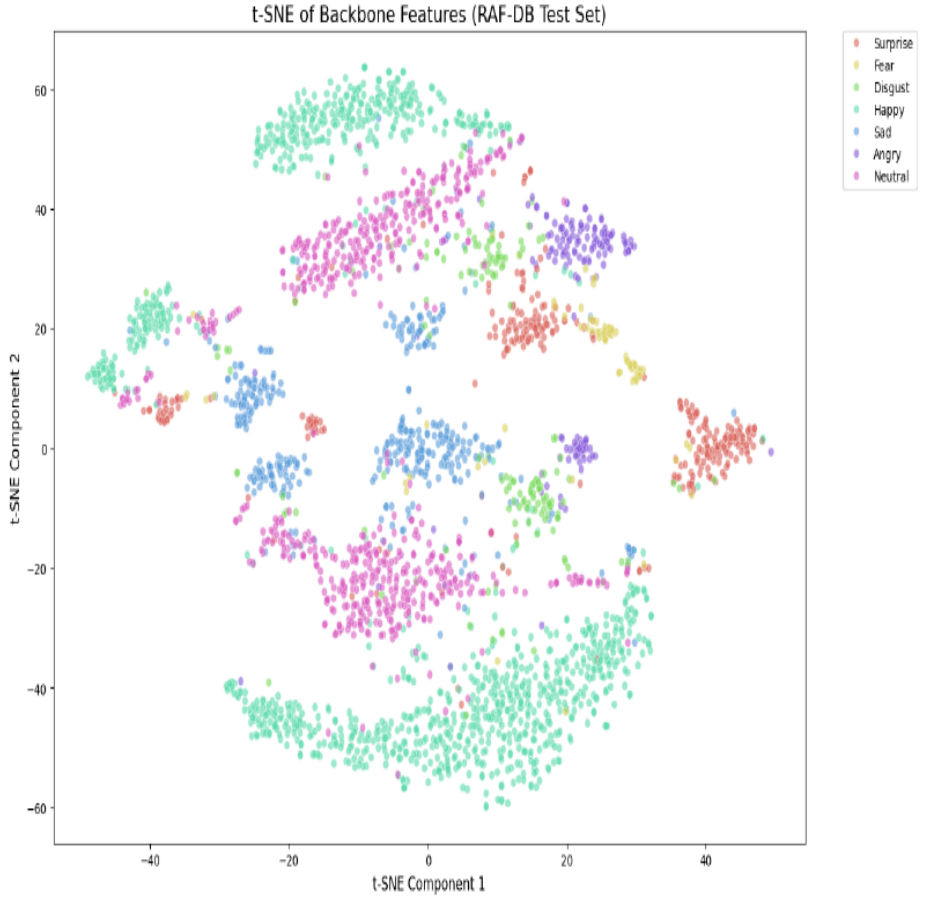




(a) MTLoRA confusion matrix on RAF-DB, balanced accuracy of 86.17 (Acc. 90.06)

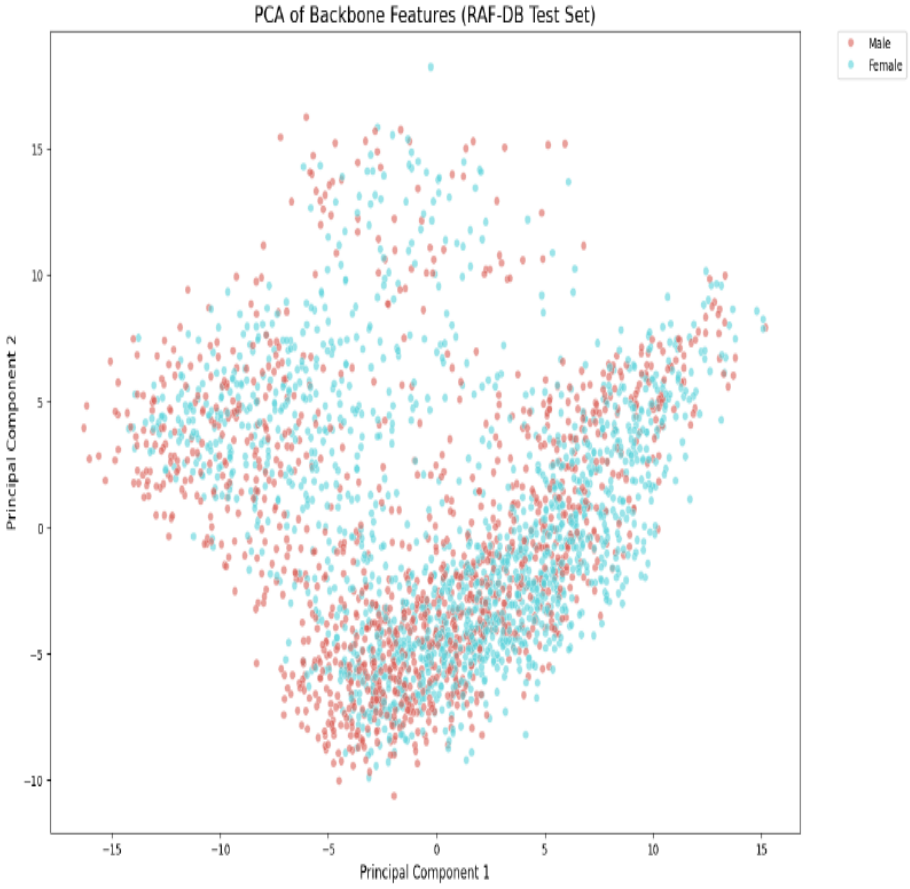
(b) LoRA confusion matrix on RAF-DB, balanced accuracy of 85.90 (Acc. 91.21)

(c) APViT confusion matrix on RAF-DB, balanced accuracy of 86.36 (Acc. 92.21)

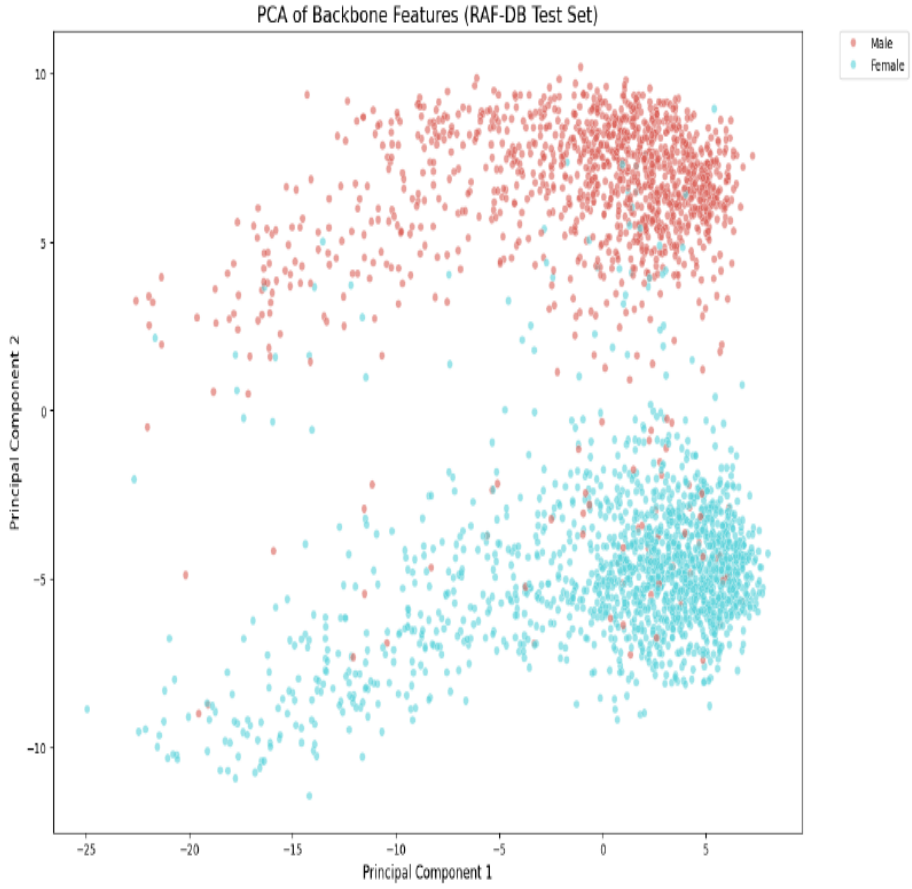

(a) t-SNE Emotion (Untrained)



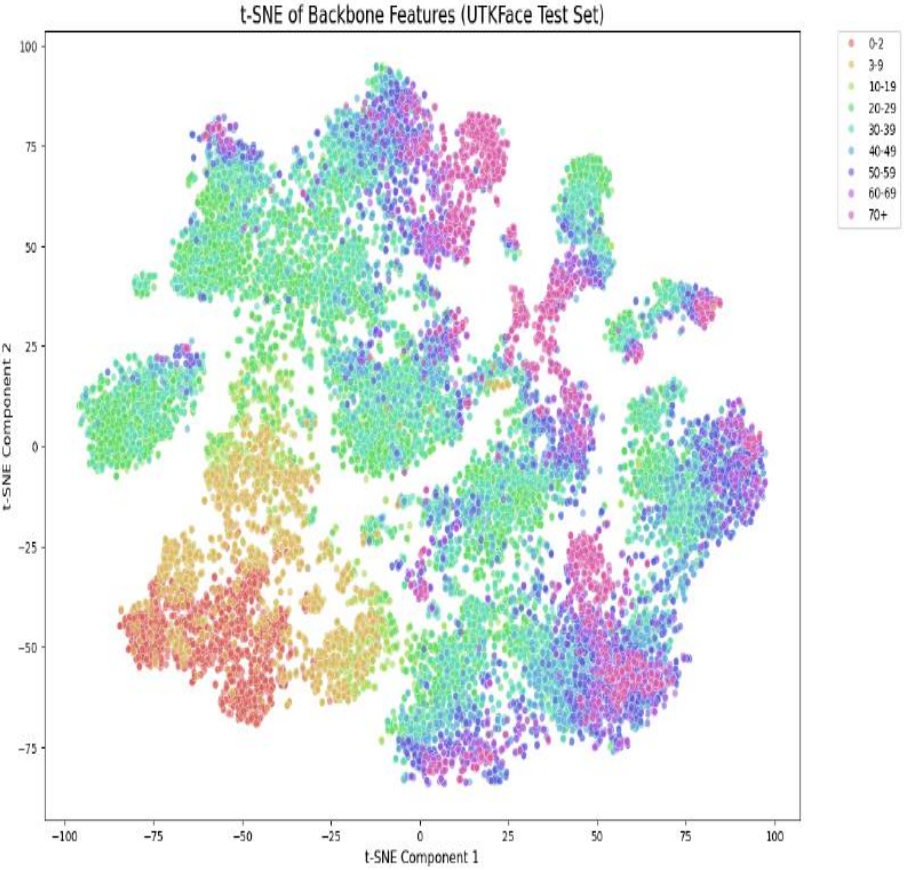

(b) t-SNE Emotion (Trained)



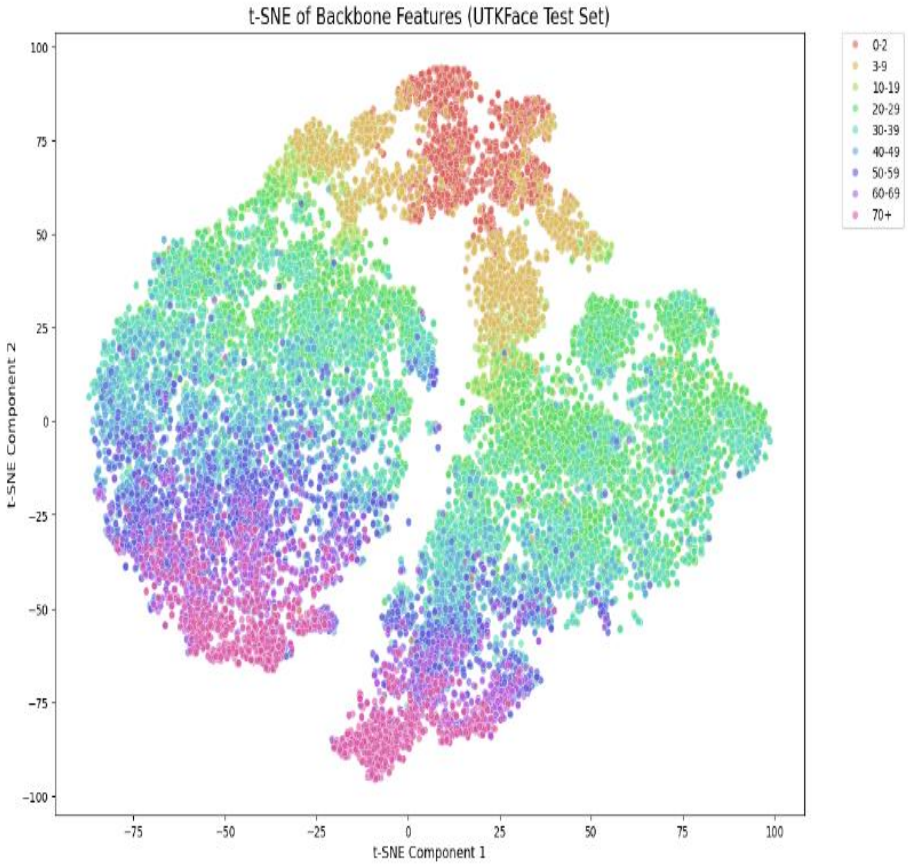

(g) PCA Gender (Untrained)




(h) PCA Gender (Trained)




(a) t-SNE Age (Untrained)




(b) t-SNE Age (Trained)

# Dimostratore

**/login tesi2025**