# 1. YOLO

## **Dataset Description:**

#### 1. Source: Combination of 2 datasets:

- Dataset A: Provided by the project team; ~100 images were manually annotated using bounding boxes and gender labels (male / female).
- Dataset B: Imported from Roboflow; pre-annotated with bounding boxes and gender classes.

#### 2. Annotation Format:

- YOLOv11-compatible .txt files for each image.
- Each line in a label file:
  - o <class\_id> <x\_center> <y\_center> <width> <height>

#### 3. Object Classes:

- $0 \rightarrow Male$
- $1 \rightarrow \text{Female}$

### 4. Image Resolution:

Varied across datasets; resized to 640×640 during training with padding where necessary.

#### 5. Dataset Statistics:

**Train:** 1872

Validate: 225

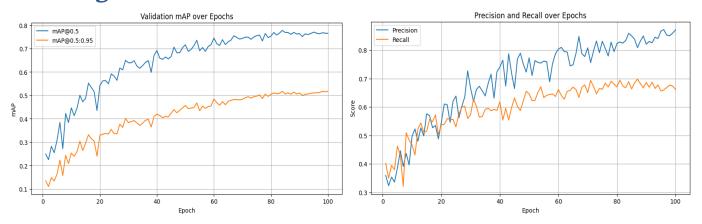
## **Model Training Details:**

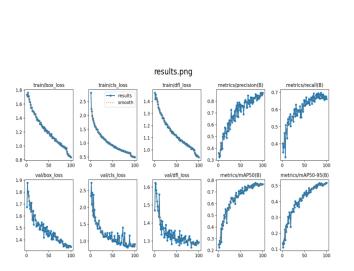
- **Model Used:** YOLOv11n (YOLO version 11 nano)
  Chosen for its light weight and fast inference while maintaining good performance on small datasets.
- Training Framework: PyTorch using Ultralytics YOLOv11
- Training Location: Kaggle Notebook
- Epochs: 100
- Image size: 640×640
- Batch size: 16
- **Device:** GPU (Tesla T4, 16 GB VRAM)

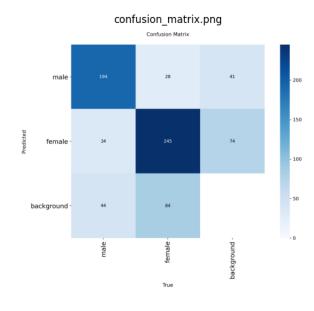
## **Training Performance Summary:**

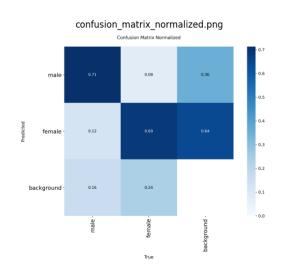
Class	Precision	Recall	mAP@0.5	mAP@0.5:0.95
All	0.857	0.689	0.778	0.518
Male	0.856	0.717	0.800	0.548
Female	0.858	0.661	0.755	0.487

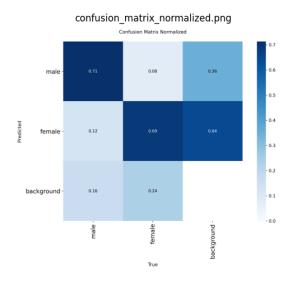
# **Training Results:**

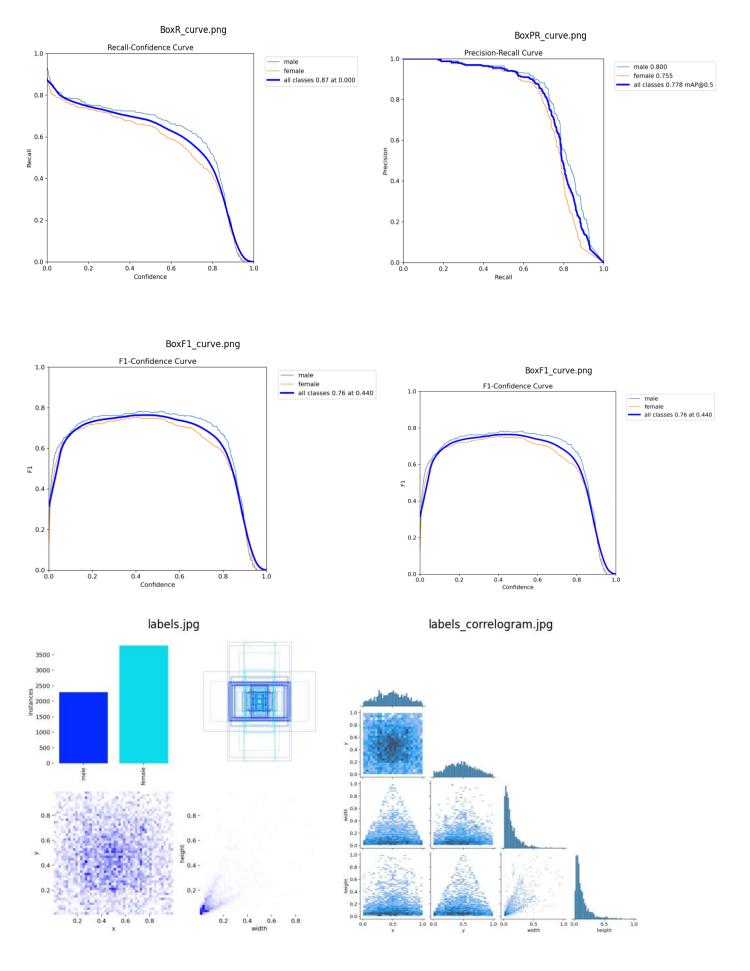






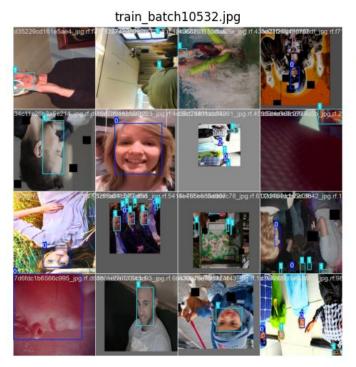














# 2. Classifier

## **Model Architecture:**

Base Backbone: EfficientNet\_V2\_S, pre-trained on ImageNet1K (IMAGENET1K\_V1 weights).

- Custom Classifier Head:
- Dropout(0.5)
- Linear( $1280 \rightarrow 512$ )
- ReLU
- Dropout(0.3)
- Linear (512  $\rightarrow$  16) (final output layer for 16 celebrity classes)

This structure balances transfer learning benefits with custom fine-tuning capacity for the specific celebrity face task.

## **Dataset Details:**

#### 1. Data Format:

- Data downloaded from Kaggle competition page.
- Images and labels loaded from .npy files (faces\_cropped.npy, labels\_cropped.npy)
- Images are already cropped face regions of shape (224, 224, 3), RGB.

### 2. Label Remapping:

Labels with value -1 (used for unknowns) were reassigned to class index 15 to maintain label consistency within 0–15.

## **Data Augmentations:**

Data augmentation was applied using Albumentations to enhance generalization and robustness:

- HorizontalFlip (p=0.5)
- Rotate (limit=30°, p=0.5)
- HueSaturationValue (hue  $\pm 20$ , sat  $\pm 30$ , val  $\pm 20$ , p=0.7)
- RandomBrightnessContrast (brightness  $\pm 0.3$ , contrast  $\pm 0.3$ , p=0.7)
- CoarseDropout: 1–2 holes, each 10–20% of image area (black mask)
- Normalization: mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]
- Conversion to tensor with ToTensorV2()

## **Training Strategy:**

### ➤ Phase 1: Train Classifier Head Only

- Freeze all layers except the classifier head.
- Optimizer: AdamW(1r=1e-3, weight\_decay=1e-4)
- Epochs: 100
- Loss Function: CrossEntropyLoss with MixUp
- Accuracy was monitored on a hold-out validation set (20%).

### ➤ Phase 2: Fine-Tune Last Feature Blocks + Head

- Only unfreeze the last 5 blocks of EfficientNet and the classifier.
- Optimizer: AdamW(lr=1e-4, weight\_decay=1e-5)
- Epochs: 50
- Same loss and sampling strategy used.

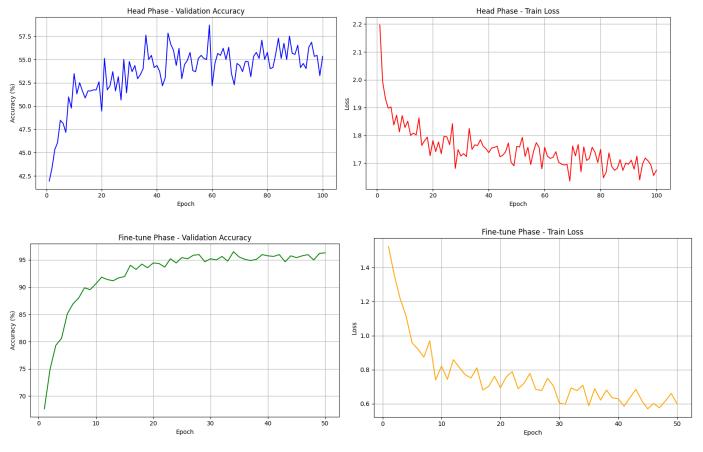
## ➤ MixUp Regularization

- MixUp was applied during training
- Hyperparameter: alpha=0.4 (Beta distribution)
- Loss computed as:

$$lam * CE(preds, y_a) + (1 - lam) * CE(preds, y_b)$$

# **Training Results:**

- Training ran for a total of 150 epochs across two phases.
- Model consistently achieved strong validation accuracy (>99%).
- This model was later used to classify cropped YOLO predictions during evaluation and visualization.



Classification	Report:																				
	precision	support	Confusion Matrix																		
0	4 0000	0.0760	0.0000	42	0 -	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	1.0000	0.9762	0.9880	42		0	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1.0000	1.0000	1.0000	42		U	42	0	U	U	U	U	U	U	U	U	U	U	U	U	U
2	1.0000	1.0000	1.0000	35	- 2	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1.0000	1.0000	1.0000	47	m -	0	0	0	47	0	0	0	0	0	0	0	0	0	0	0	0
4	1.0000	1.0000	1.0000	34		-															
5	1.0000	1.0000	1.0000	35	4 -	0	0	0	0	34	0	0	0	0	0	0	0	0	0	0	0
6	1.0000	1.0000	1.0000	38	۰ کا	0	0	0	0	0	35	0	0	0	0	0	0	0	0	0	0
7	1.0000	0.9667	0.9831	30		_		_	_					_		_			_		
8	1.0000	1.0000	1.0000	32	9 -	0	0	0	0	0	0	38	0	0	0	0	0	0	0	0	0
9	0.9744	1.0000	0.9870	38	n	0	0	0	0	0	0	0	29	0	0	0	0	0	0	0	1
10	0.9714	1.0000	0.9855	34	True	0	0	0	0	0	0	0	0	32	0	0	0	0	0	0	0
11	1.0000	1.0000	1.0000	28	. ∞ -	U	U	U	U	U	U	U	U	32	U	U	U	U	U	U	U
12	1.0000	1.0000	1.0000	35	ი -	0	0	0	0	0	0	0	0	0	38	0	0	0	0	0	0
13	1.0000	0.9762	0.9880	42	0 -	0	0	0	0	0	0	0	0	0	0	34	0	0	0	0	0
14	1.0000	0.9667	0.9831	30	-		-	-			-		-	-	-		-		-	-	
15	0.9894	0.9947	0.9920	376	# -	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0
					- 12	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0
accuracy			0.9935	918																	
macro avg	0.9960	0.9925	0.9942	918	13	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	1
weighted avg	0.9935	0.9935	0.9935	918	4 -	0	0	0	0	0	0	0	0	0	0	0	0	0	0	29	1
weighten avg	0.5555	0.5555	0.3333	310		0	0		0	0	0	0		0		1	0	0		0	374
Top 1 Assumasi	. 00 25%				15	0	0	0	U	0	0	0	0	0	1	_	,	0	0	0	3/4
Top-1 Accuracy						Ö	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Top-3 Accuracy	: 100.00%												Predi	cted							

## **Conclusion:**

This project involved two integrated models: a YOLOv11n object detector for gender detection and an **EfficientNet-based classifier** for celebrity recognition.

- 1. The **YOLOv11n model**, trained on a custom gender-labeled dataset (~2,000 images), achieved solid detection performance with:
  - Precision: 85.7%
  - Recall: 68.9%
  - mAP@0.5: 77.8%
  - mAP@0.5:0.95: 51.8%

These metrics indicate reliable detection, particularly for the male class, with lightweight architecture optimized for fast inference on small datasets.

2. The **EfficientNet\_V2\_S** classifier, fine-tuned in two stages using MixUp regularization and strong augmentations, reached >99% validation accuracy. It effectively learned to classify 16 celebrity identities from cropped facial images, even handling unknowns by remapping them to a dedicated class.

Together, these models form a robust pipeline for gender and identity recognition with efficient computation, high accuracy, and resilience to data variation—well-suited for real-world deployment or downstream analysis.

# Validation:

