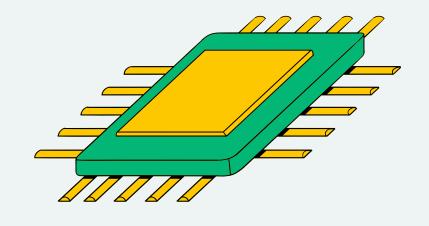
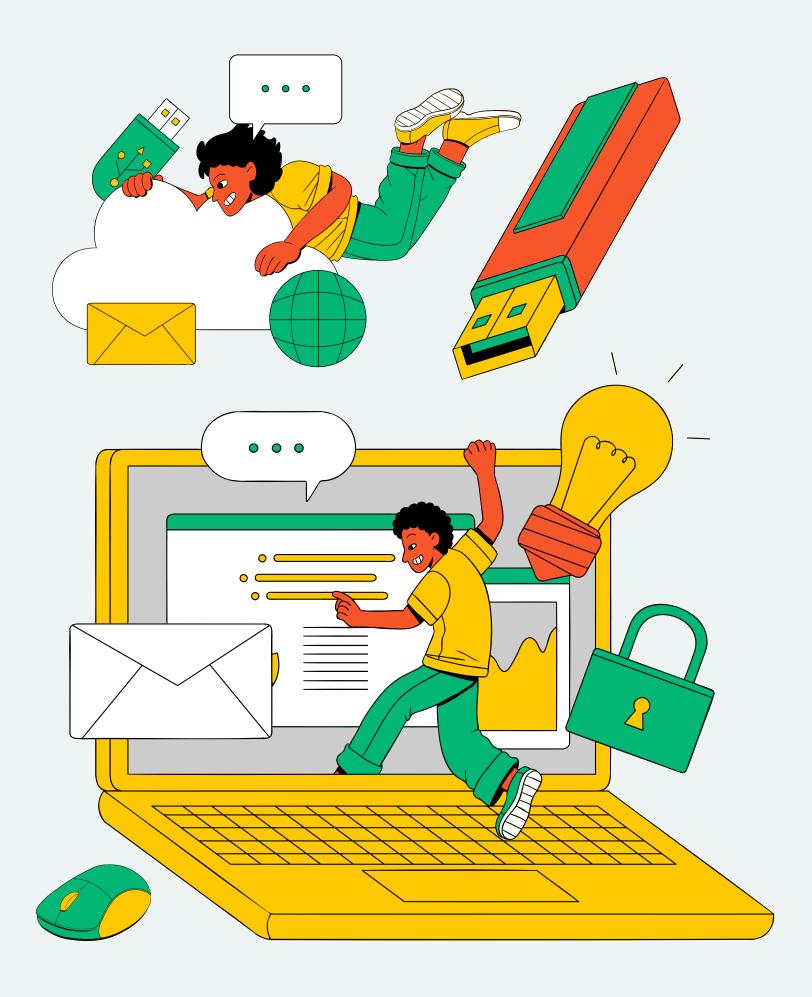


# DEEPFAKE DETECTION USING A HYBRID MODEL VGG16 AND BEIT **VISION TRANSFORMER**

PRESENTED BY:
DANIELE PANCOTTINI



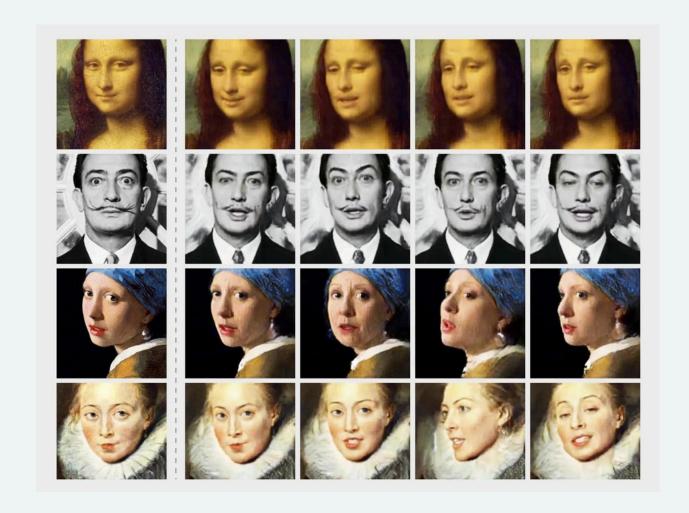


# PRESENTATION OUTLINE

- Introduction
- Related works
- Proposed model
- Datasets and metrics
- Implementation details
- Experimental results
- Conclusion and future works



# INTRODUCTION



- Deepfakes are AI-generated media that can manipulate reality, posing serious challenges to security and media integrity.
- This project introduces a hybrid deepfake detector combining VGG16 and the BEIT Vision Transformer to extract complex visual features and classify images.

## WHY A HYBRID MODEL?

 Complementary nature of CNNs and Transformers: VGG16 captures local features, while ViT captures global context (long-range relationships).

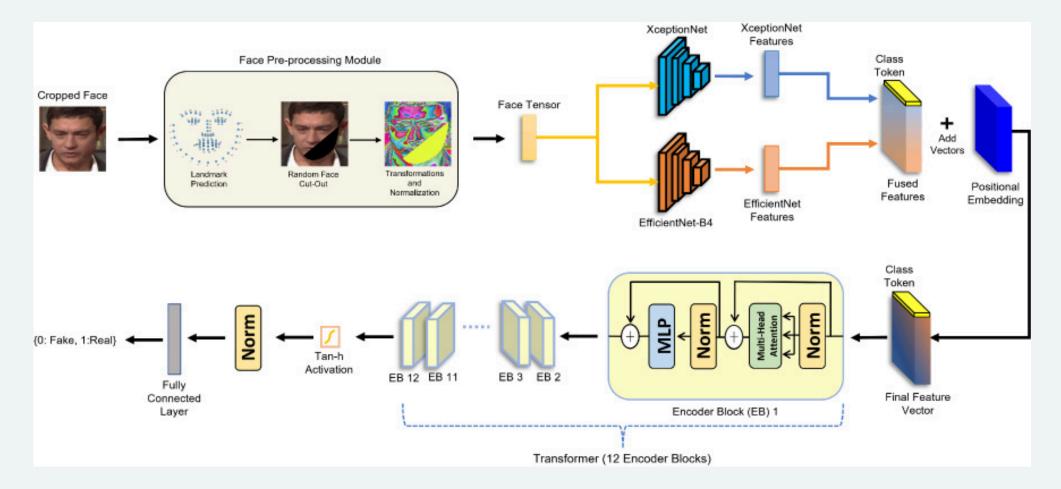
 Combining both models allows leveraging local and global features for better accuracy



## RELATED WORKS

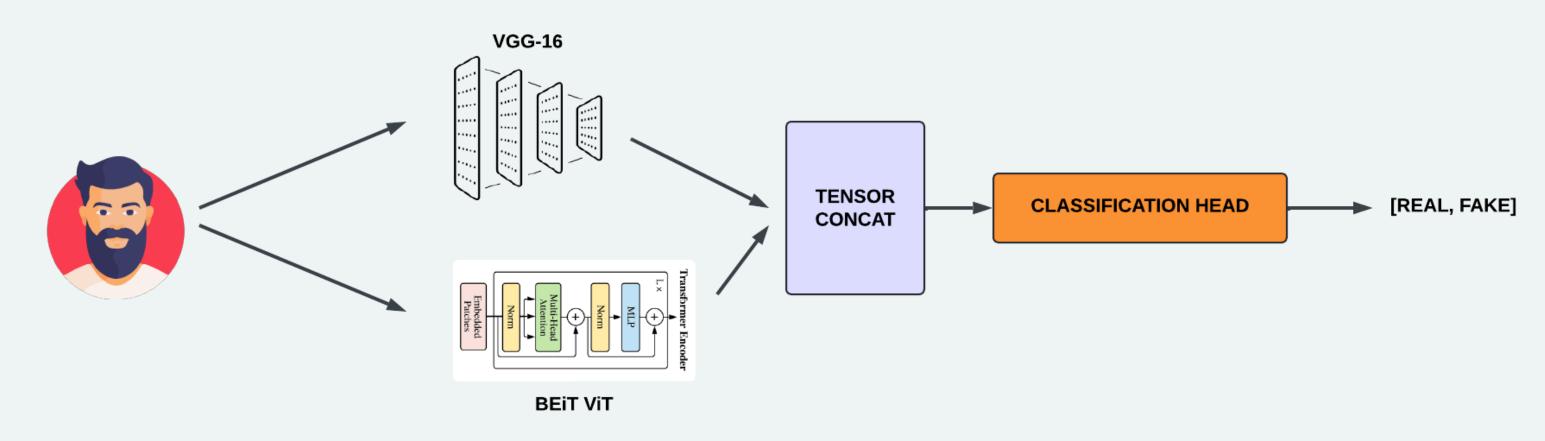
## Hybrid models combining CNN and Vision Transformers:

- Wang, Y., Huang, L., & Zhu, X. (2022). Improved Hybrid CNN-Transformer Network for Deepfake Detection
- Luo, Y., Zhang, S., & Wang, Y. (2021). Deepfake Detection with Temporal-Aware CNN and Vision Transformer





## PROPOSED MODEL



- The same image is fed into both VGG16 and BEiT models
- Features from VGG16 and BEiT are concatenated
- The concatenated features are passed through the classification head



## IMPLEMENTATION DETAILS

#### **Feature Extractors:**

Pretrained VGG16 and BEiT (ViT) are used as feature extractors, with their parameters
 frozen during training

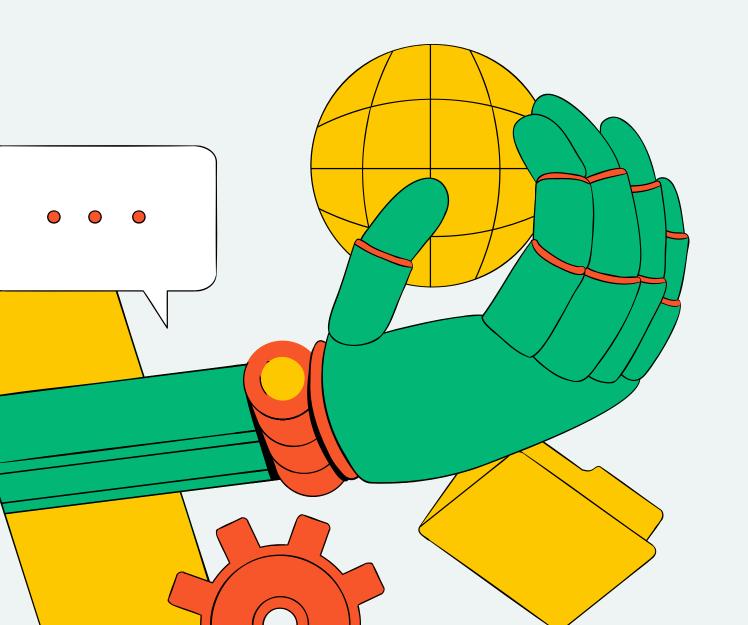
#### **Classification Head:**

- A fully connected layer (FCL) of size 1768 x 256 with ReLU activation function.
- A **fully connected layer** (FCL) of size **256** x **2**, returning **unsoftmaxed** prediction logits for use with the **CrossEntropy** loss function

## **Training:**

 Training for six epochs, with a learning rate of le-4, using the Adam optimizer and CrossEntropy loss function

# DATASETS



## **Training Dataset:**

UNICT Deepfake Detection
 Challenge Training set

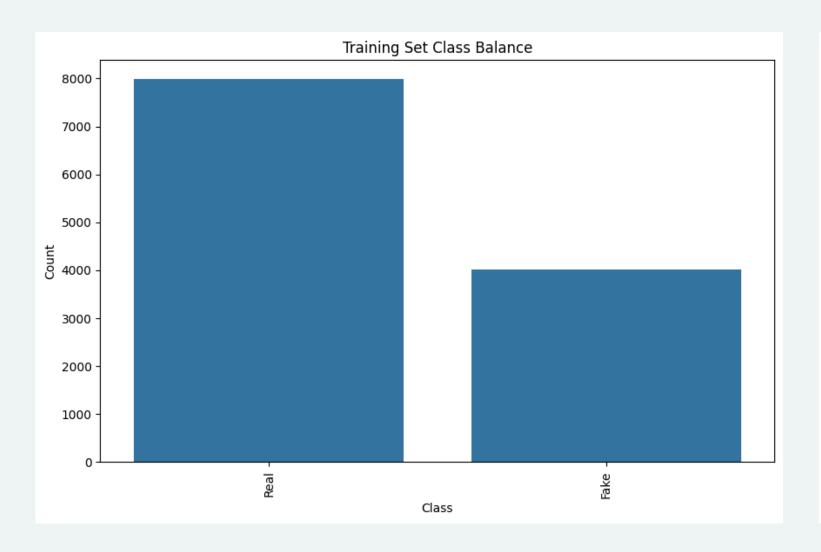
### **Evaluation Datasets:**

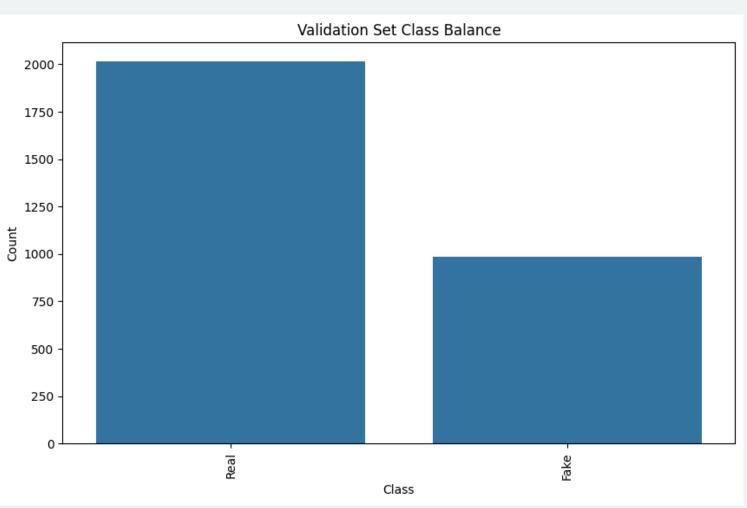
- FFHQ (Flickr-Faces-HQ) Dataset
- UNICT Deepfake Detection
   Challenge Test set

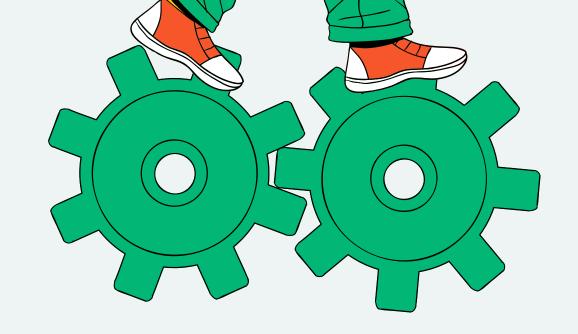


# TRAINING DATASET

- Dataset containing **15.000 images**: **10.000 real** images and **5.000 fake** images
- Random training split of 80% of the entire dataset and 20% for the validation set









## EVALUATION DATASETS

Randomly Subsampled FFHQ Dataset: Approximately
 35.000 real images

• UNICT Deepfake Detection Challenge Test Set: Approximately **7,000 images** (5,000 fake and 2,000 real).





# EVALUATION METRICS

- **Accuracy**: the ratio of correctly predicted instances (both true positives and true negatives) to the total instances.
- **Precision**: the proportion of true positive predictions out of all positive predictions made by the model.
- **Recall**: the proportion of true positive predictions out of all actual positive instances.
- **F1-score:** the harmonic mean of precision and recall, providing a balanced measure when precision and recall are uneven.



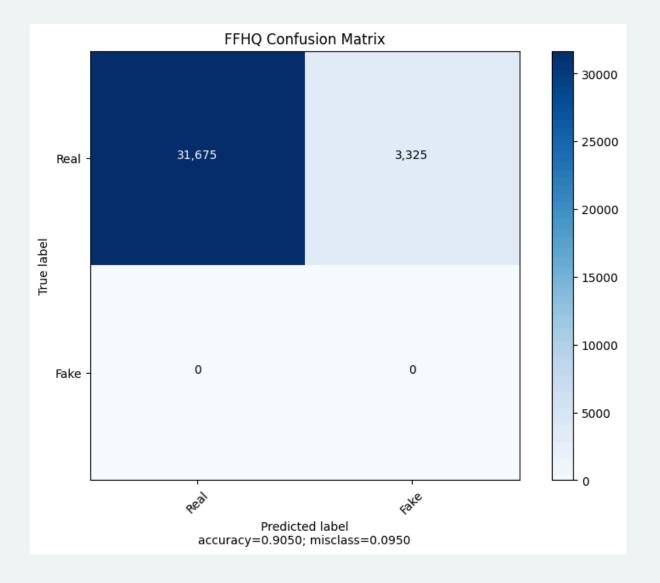


## **MODEL RESULTS**

## FFHQ Dataset

Accuracy: 90% Precision: 100%

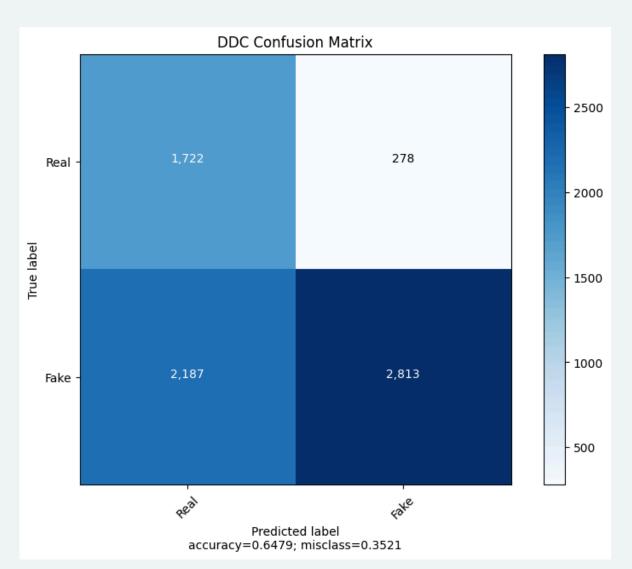
**Recall**: 90.50% **F1-score**: 95.01%



## **DDC Dataset**

**Accuracy**: 64.79% **Precision**: 77.59%

**Recall**: 64.79% **F1-score**: 66.32%





## COMPARING RESULTS

#### Ranking list of the best seven models evaluated using the DDC dataset

Ranking	Team Name	Accuracy (%)
#1	VisionLabs	93.61%
#2	DC-GAN (Amped Team)	90.05%
#3	Team Nirma	75.38%
#4	AIMH Lab	72.62%
#5	PRA Lab—Div. Biometria	63.97%
#6	Team Wolfpack	40.61%
#7	SolveKaro	36.85%

 The hybrid approach achieved an accuracy of 64.79%, resulting in a fifth-place position overall



# CONCLUSION AND FUTURE WORK

**Future works** about this project would involve performance improvements:

• **Expand Dataset**: increase the size of the training dataset beyond the current **15.000 samples** 

 Improve Data Quality: address issues with data balancing and distribution

• Longer Training Duration: extend the number of epochs beyond the current six to improve model performance.

• Optimize Classification Head: implement changes to the classification head architecture to enhance accuracy

