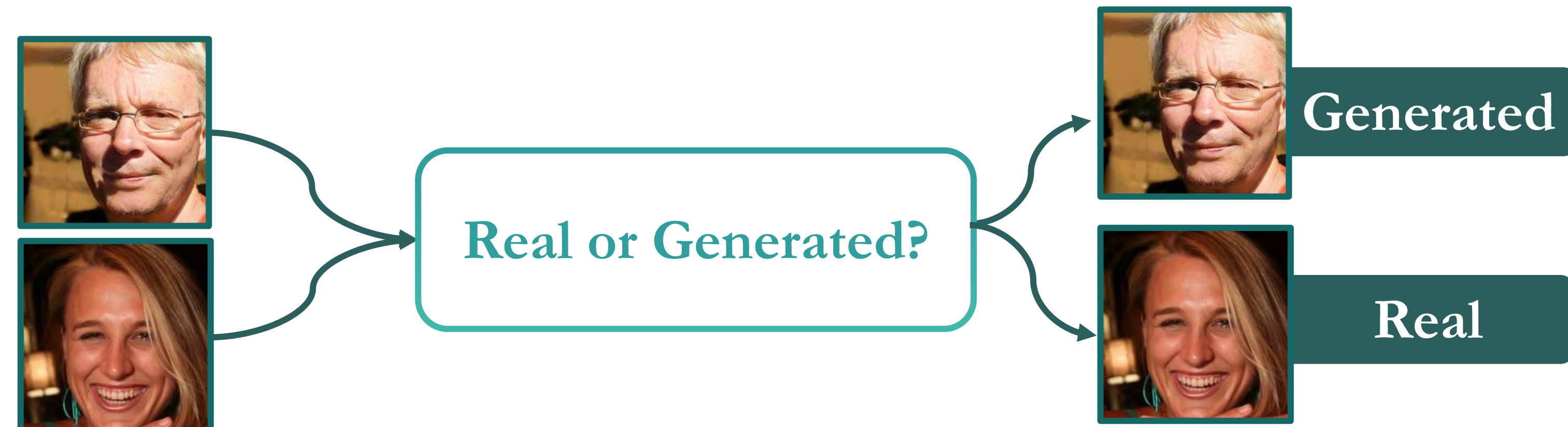


## Introduction



### Task:

detecting synthetic images by identifying unique artifacts in generated/manipulated images

### Differentiation:

Real images lack this artifact, making detection possible

### Applications:

- Fraud Prevention
- Content Moderation
- Art Forgery Detection
- Media Integrity Verification

## Challenges

### Lack of a comprehensive dataset

- Diversity of Generators (GAN-Diffusion, Fully-Partially manipulating)
- Diversity of Object Categories (Humans, Animals, Vehicles, Places, etc.)
- Reflects Real-World Scenarios (Social Media: Compression, Downsampling)

### Lack of Generalizable & Robust Solution

- Detect images from Unseen Generators (Generalization)
- Detect images in presence of Real-World Impairments (Robustness)

## Contribution

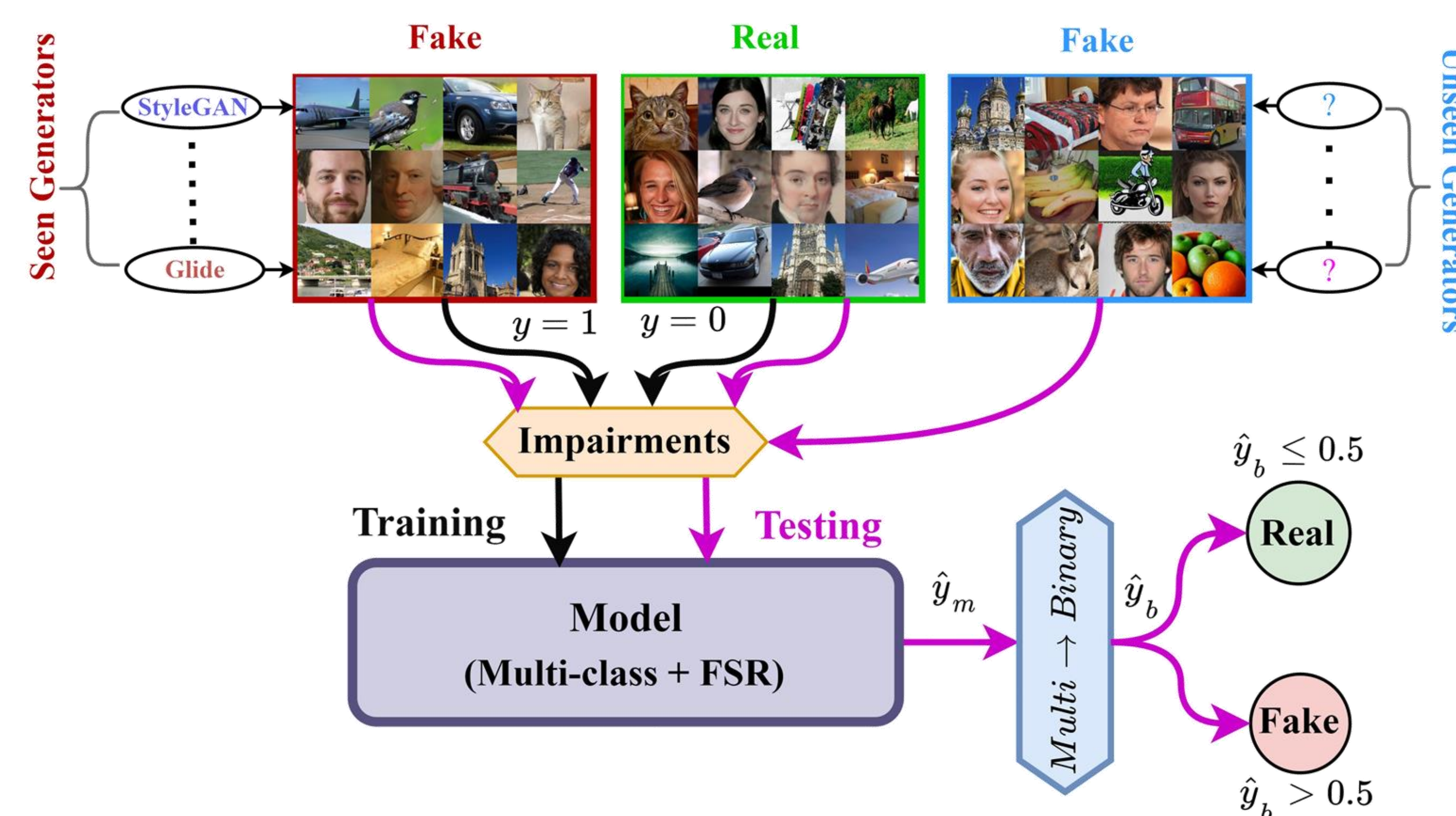
1. Proposed ArtiFact dataset with **~2.5 Million images**,
  - a) Diverse Generators
  - b) Diverse Object Categories
  - c) Reflects Real-World Scenarios
2. Proposed Generalizable & Robust Solution,
  - a) Multi-class scheme with an extra class to detect Unseen Generators
  - b) Filter Stride Reduction (FSR) strategy to tackle Impairments



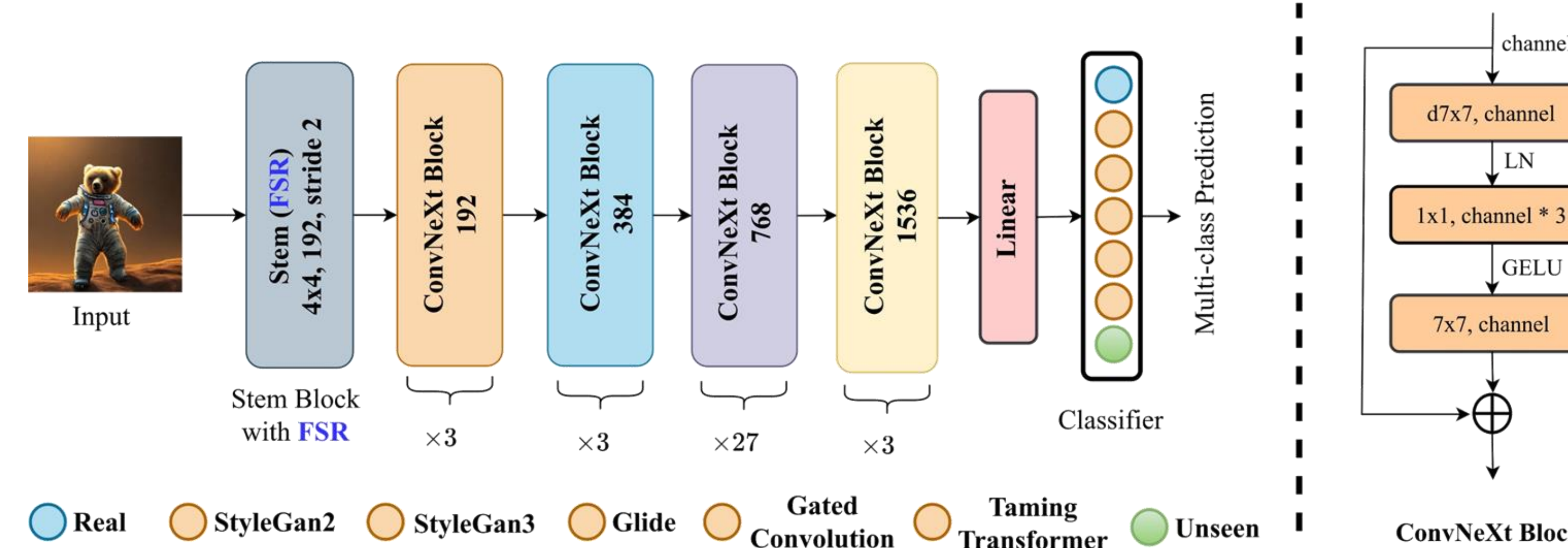
## Real World Impairments



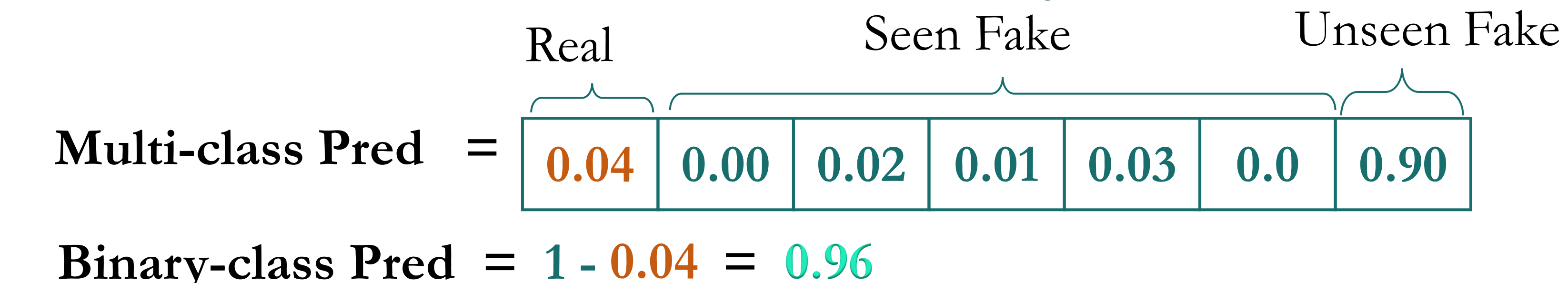
## Solution Overview



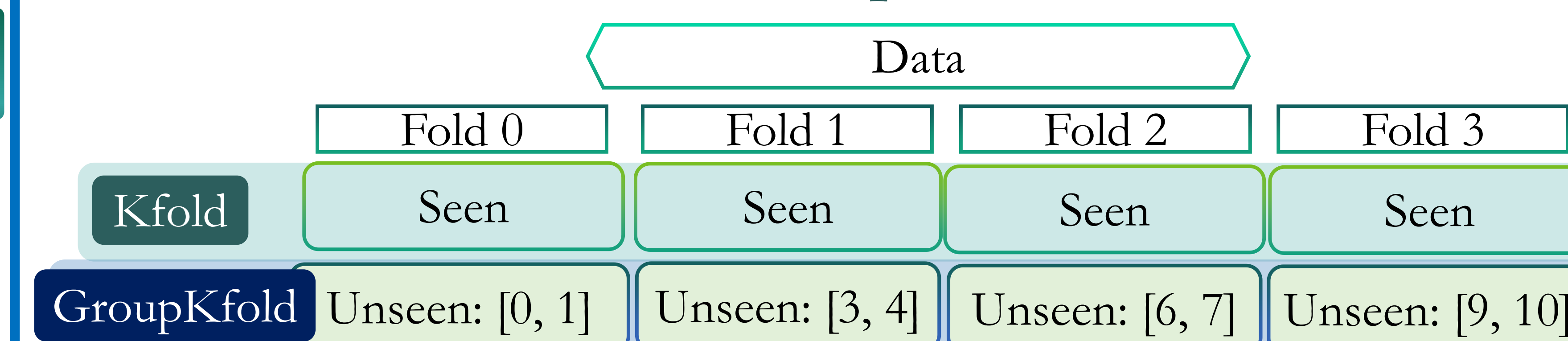
## Extra Class for Unseen Cases



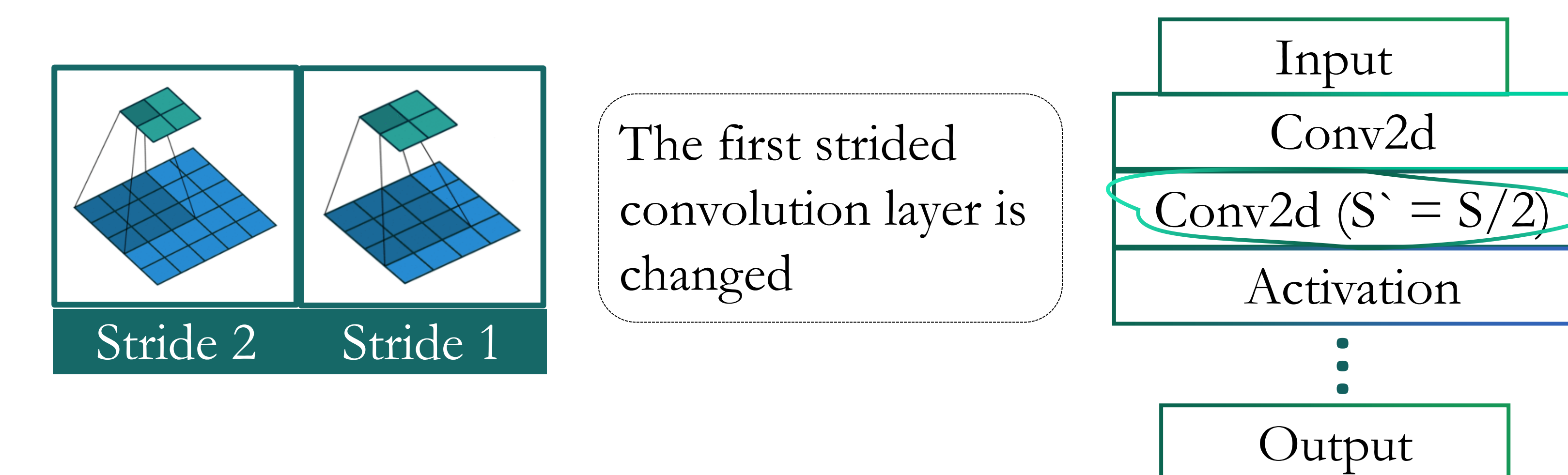
## Multi-class to Binary Class



## CV Split



## Filter Stride Reduction (FSR)



## Results

### Ablation Studies

Method	Accuracy
Binary-class	78.21
Binary-class + FSR	81.30
Multi-class	83.12
Multi-class + UF class	84.98
Multi-class + FSR	85.56
<b>Multi-class + FSR + UF class</b>	<b>87.62</b>

### VIP Cup 2022

Team Names	Test 1	Test 2	Test 3
Sherlock	87.70	77.52	73.45
FAU Erlangen-Nürnberg	87.14	81.74	75.52
<b>Megatron (Ours)</b>	<b>96.04</b>	<b>83.00</b>	<b>90.60</b>

### Comparison

Method	Accuracy
Joel et al. [3]	63.19
Francesco et al. [6]	79.28
Wang et al. [11]	79.95
Graganiello et al. [12]	81.63
<b>Multi-class + FSR + UF class (ours)</b>	<b>87.62</b>

Scan this QR Code for details

