EfficientNet-B6 Model

EfficientNet-B6 is a high-performance convolutional neural network architecture that is part of the **EfficientNet** family, which was introduced by **Google AI** in 2019. The EfficientNet models use a novel **compound scaling** method to systematically scale up the network's depth, width, and resolution in a balanced way, leading to improved accuracy and efficiency compared to traditional CNN architectures.

EfficientNet-B6 specifically offers **state-of-the-art accuracy** while maintaining a relatively **low computational cost** compared to other large models like **ResNet** or **Inception**. It is designed for high-resolution image inputs (528x528) and has **approximately 43 million parameters**. The model is well-suited for tasks requiring fine-grained image classification and is widely used in industrial and academic applications.

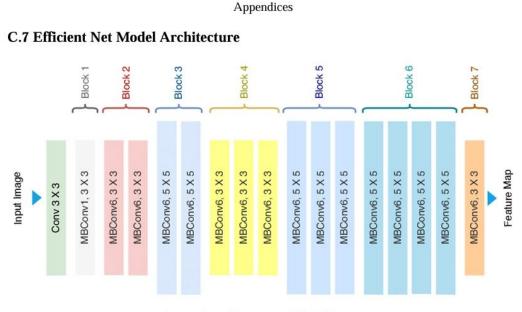


Figure 0C.7 Efficient Net Model Architecture

Task Objective:

Al Image Generation Detection:

Our system leverages advanced deep learning techniques to **accurately detect AI-generated images** (such as those produced by GANs, diffusion models, or other generative techniques) and distinguish them from authentic, human-created images. This involves:

- **Feature Extraction**: Utilizing high-capacity convolutional neural networks (e.g., **EfficientNet**, **ResNet**) to extract subtle statistical patterns and artifacts commonly found in AI-generated images.
- **Multi-domain Training**: Training on diverse datasets that include synthetic images from popular generative models like StyleGAN, StyleGAN2, EF3D and Stable Diffusion to ensure generalization across different sources.
- **Fine-grained Classification**: Implementing classifiers that can detect minute inconsistencies in textures, lighting, edges, and noise patterns that are often imperceptible to the human eye.
- **Robust Performance**: Evaluated across multiple benchmarks to ensure high precision and recall, even when images are post-processed, resized, or compressed.

Used Datasets:

Building a Diverse Face Collection

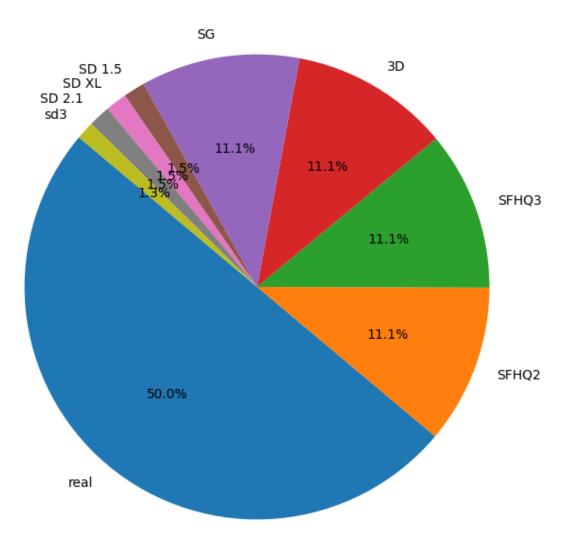


- **140k Real and Fake Faces**: Combines 70,000 real faces from the Flickr dataset with 70,000 fake faces generated by StyleGAN, resized to 256px.
- CelebA-HQ resized (256x256): Contains 30,000 high-quality celebrity faces, suitable for training and evaluating generative models.
- Synthetic Faces High Quality (SFHQ) Part 2: Includes 91,361 high-quality 1024x1024 curated face images, enhanced using StyleGAN2 techniques.
- Face Dataset Using Stable Diffusion v1.4: Comprises real faces from the Flickr dataset and fake faces generated by Stable Diffusion models, resized to 256px.
- **Stable Diffusion Face Dataset**: Al-generated human faces using Stable Diffusion 1.5, 2.1, and SDXL 1.0 checkpoints, covering resolutions of 512x512, 768x768, and 1024x1024.
- Synthetic Faces High Quality (SFHQ) Part 3: Contains 118,358 high-quality 1024x1024 face images generated by StyleGAN2, utilizing advanced truncation tricks.
- Synthetic Human Faces for 3D Reconstruction: Generated by drawing samples from the EG3D model, resulting in high-quality 512x512 synthetic face images.

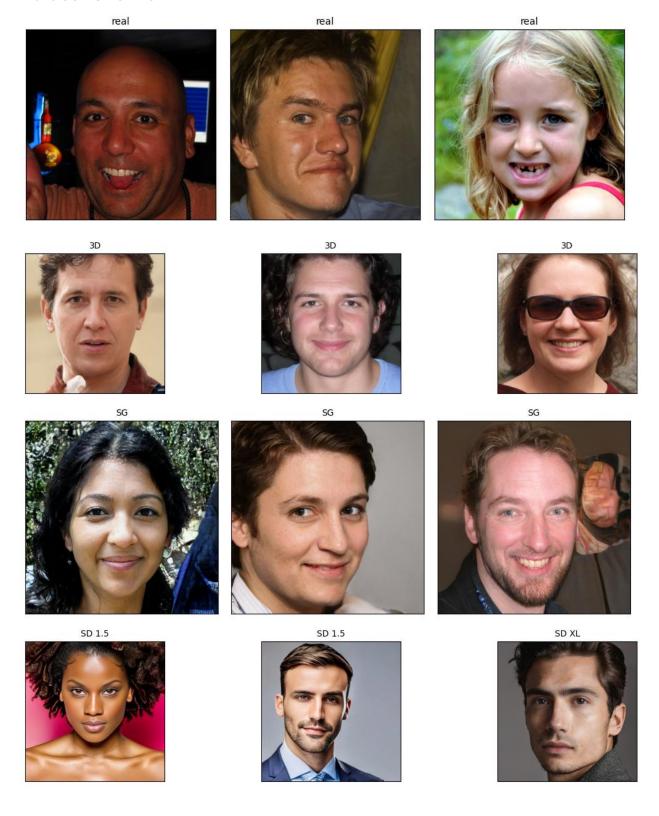
200K images 100 k Real									
100 k Real 100 k Fake									
Train		Validate		Test					
Real: 70 k	Fake: 70 k	Real: 15 k	Fake: 15 k	Real: 15 k	Fake: 15 k				
70k Flickr	3k SD V2.1	15 k CelebA	3k SDXL 1.0	15 k CelebA	2536 SD 1.4				
	3k SD V1.5	HQ	3k SG1	HQ	3116 SG1				
	16k SG1		3k EG3D		3116 EG3D				
	16k EG3d		16k S SG2		3116 S SG2				
	16k S SG2		16k S SD1.4		3116 S SD1.4				
	16k S SD1.4								
70% Data		15% Data		15% Data					

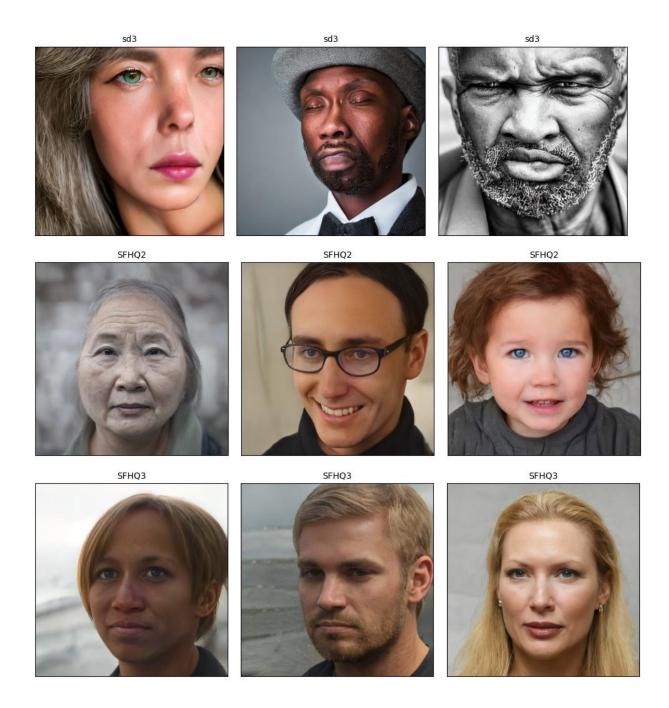


Distribution of Labels



Dataset Overview:





Model Selection:

Overview of Initial Model Candidates:

We initially evaluated several models for image detection, and we chose one based on the reported performance for our dataset characteristics.

- EfficientNet: Chosen for its balance between accuracy and computational efficiency.
- **ResNet**: Evaluated for its strong performance in image classification.
- **Xception**: Considered for its capability to detect fine-grained image features.

Evaluation Criteria:

Models were evaluated based on the following criteria

- Accuracy: Overall classification performance.
- Precision and Recall: Balance between false positives and false negatives.
- F1 Score: Combined measure of precision and recall.
- ROC-AUC: Trade-off between true positive and false positive rates.

Experimental Setup:

Each model was trained using a standardized dataset split of 70% training, 15% validation, and 15% testing, and models were trained on high-performance GPUs.

Results of Initial Models:

- **EfficientNet**: Balanced accuracy and computational efficiency, with an accuracy of 99%.
- **ResNet**: Achieved an accuracy of 99% but required more computational resources.
- Xception: Offered detailed feature extraction but was less efficient compared to EfficientNet.

Metrics	Accuracy	Precision	Recall	F1-Score
EfficientNetB2	94.3%	94.3%	94.2%	94.2%
EfficientNetB6	99.5%	99.5%	99.5%	99.5%
Xception	97%	98%	97%	98%
ResNet-50	98.2%	98.2%	98.2%	98.2%
VIT-224	96.7%	96.6%	96.7%	96.6%

Final Model Selection:

Based on the initial evaluations, the following refinements were made:

EfficientNet was selected for its optimal balance between accuracy and computational efficiency, with additional data augmentation applied to improve generalization, Preferred for its efficiency and high accuracy in distinguishing Real from Al-generated images.

Training Setup:

EfficientNet-B6 Model was trained with:

Batch Size:16

Learning rate: 5e-5

• Epochs: 2.5

Performance Metrics:

Classification Report:

Classification report:								
	precision	recall	f1-score	support				
Real	0.9978	0.9915	0.9946	15000				
Fake	0.9916	0.9978	0.9947	15000				
accuracy			0.9947	30000				
macro avg	0.9947	0.9947	0.9947	30000				
weighted avg	0.9947	0.9947	0.9947	30000				

Confusion Matrix:

