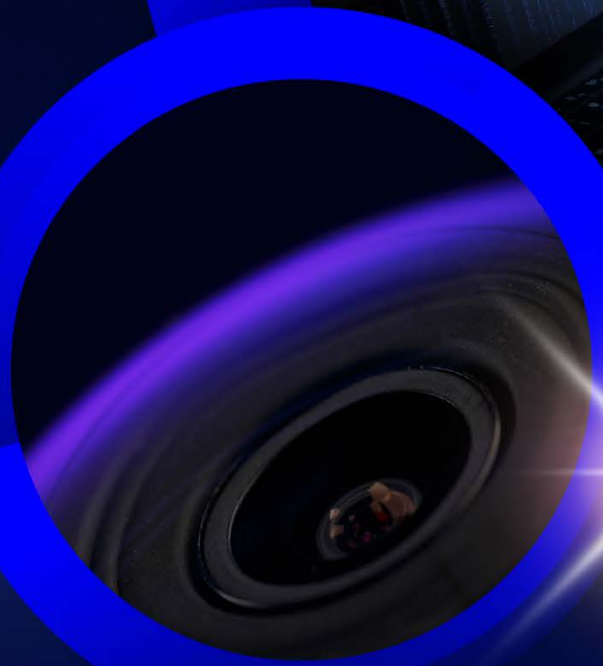
CNN – A CLOSER ANALYSIS OF THE EFFICIENTNET MODEL

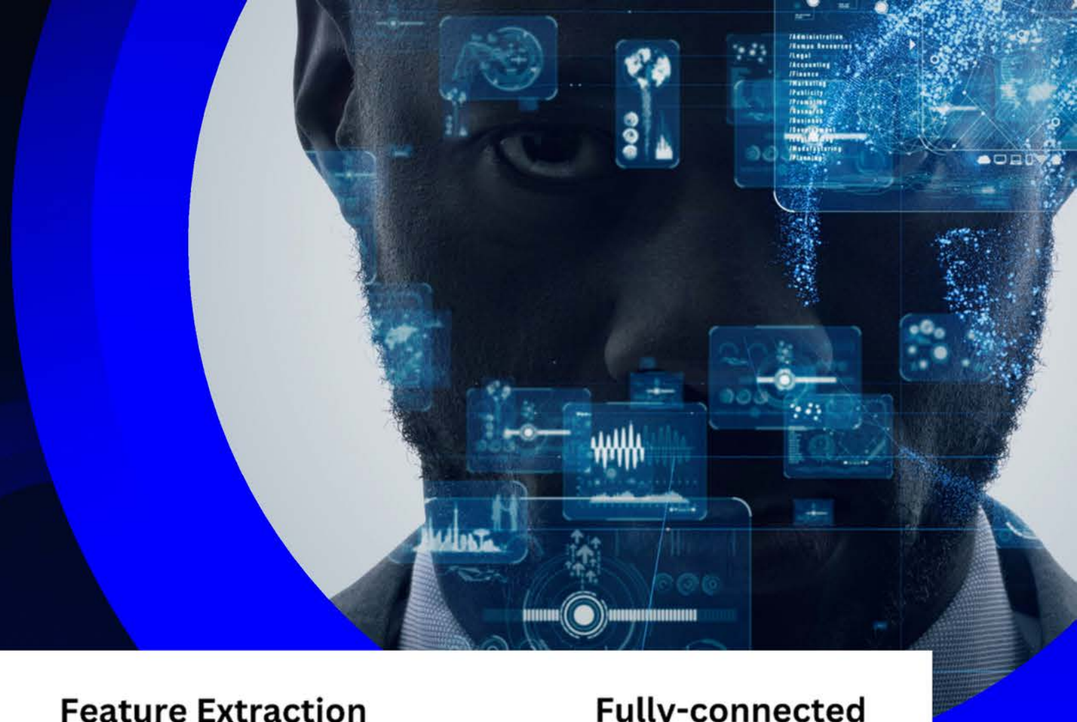
IMAGE: OBJECT CLASSIFICATION

KHIN CHAW | KHIN HPONE

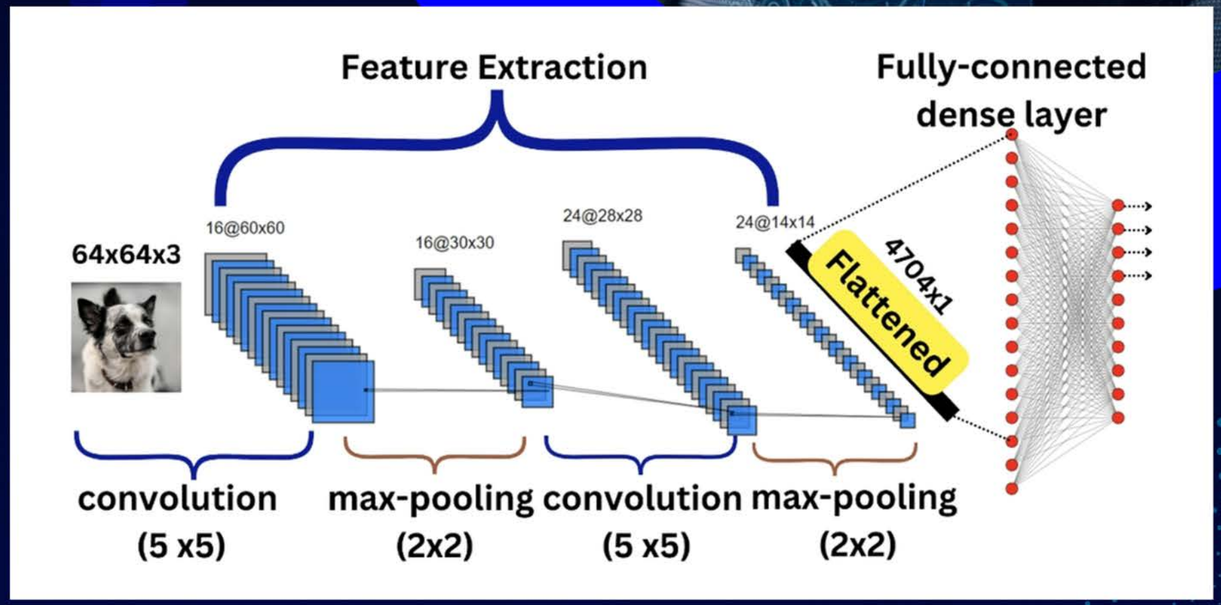


INTRODUCTION

What is a Convolutional Neural Network (CNN)?



- A deep learning model specifically designed for processing grid-like data such as images.
- CNNs automatically learn spatial hierarchies of features, making them ideal for tasks like image classification, object detection, and segmentation.



Example of CNN

WHAT IS EFFICIENTNET?

- EfficientNet is a family of convolutional neural networks developed by Google AI (Tan & Le, 2019).
- It introduces a novel compound scaling method that simultaneously scales:
  - Depth (number of layers)
  - Width (number of channels)
  - Input resolution
- Aimed at achieving high accuracy with low computational cost.
- The EfficientNet family includes models from B0 to B7, where:
  - B0 is the baseline network,
  - B1–B7 progressively scale up in size and performance.

- https://www.geeksforgeeks.org/computer-vision/efficientnet-architecture/

WHY EFFICIENTNET IS EFFICIENT

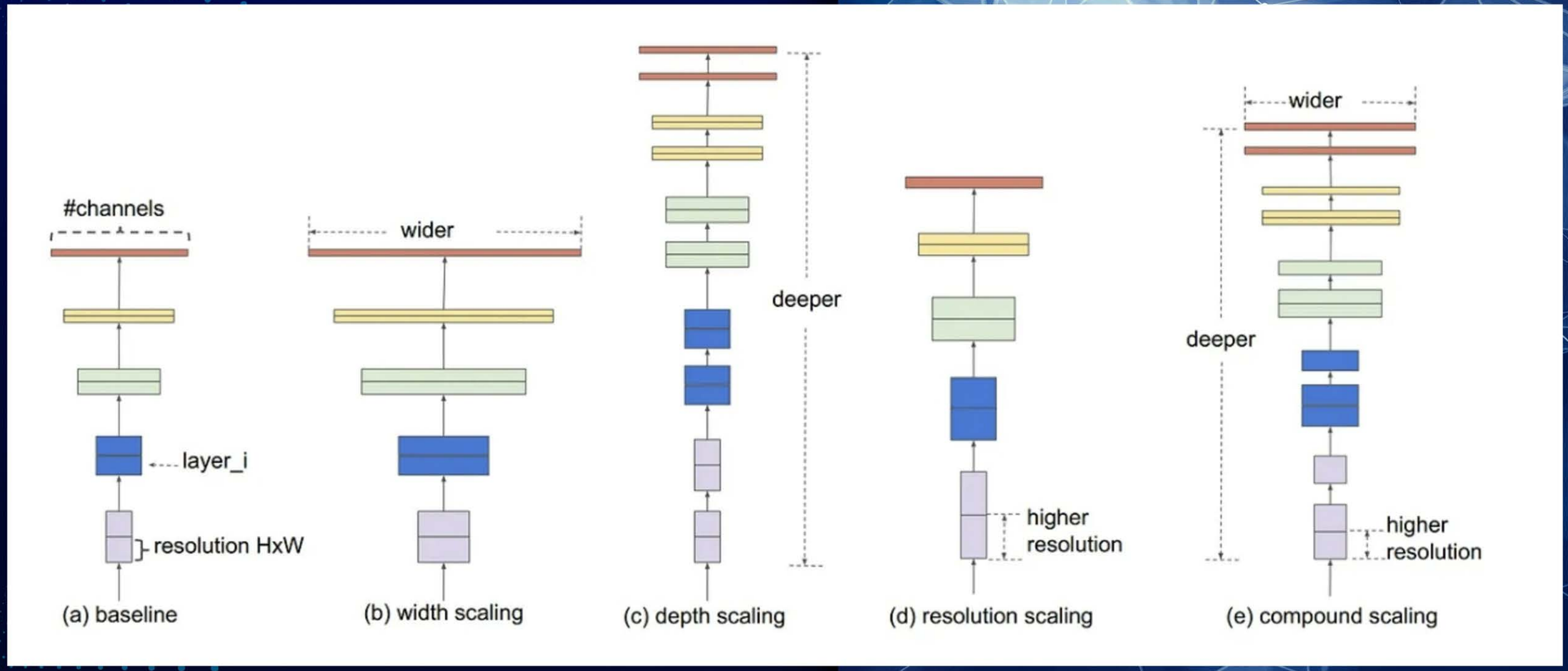
- Uses MBConv (Mobile Inverted Bottleneck Convolution) with:
- Depthwise separable convolution
- Squeeze-and-Excitation (SE) blocks
- Swish activation (instead of ReLU)
- Compound scaling formula:

$$\text{depth} = \alpha^{\phi},\ \text{width} = \beta^{\phi},\ \text{resolution} = \gamma^{\phi},\ \text{s.t. } \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$$

$$\textit{Width} \times \textit{Depth}^2 \times \textit{Resolution}^2 \approx \textit{Constant}$$

EfficientNet-B0 is the baseline; B1–B7 are scaled up versions

EFFICIENTNET



MODEL SCALING REF:Mingxing Tan and Quoc V. Le. Efficientnet: Rethinking model scaling for convolutional neural networks. In Proceedings of the 36th International Conference on Machine Learning, ICML, pages 6105–6114., 2019.

EfficientNet-B0 Layer Structure

Stage	Operator	#Channels	#Layers	Resolution	Stride
1	Conv3x3	32	1	224×224	2
2	MBConv1, 3x3	16	1	112×112	1
3	MBConv6, 3x3	24	2	112×112	2
4	MBConv6, 5x5	40	2	56×56	2
5	MBConv6, 3x3	80	3	28×28	2
6	MBConv6, 5x5	112	3	14×14	1
7	MBConv6, 5x5	192	4	14×14	2
8	MBConv6, 3x3	320	1	7×7	1
9	Conv1x1 + Pool	1280	1	7×7	-

- ALL CONVOLUTIONAL LAYERS ARE FOLLOWED BY:
  - BATCH NORMALIZATION
  - SWISH ACTIVATION (BETTER THAN RELU)
- MBCONV INCLUDES SE BLOCK (RECALIBRATION OF CHANNELS

EFFICIENTNET Layer Components

- Input Layer
  - Typically uses 224×224×3 RGB images
  - Applied normalization and standard resizing
- Stem Layer
  - 3×3 Conv, stride 2, output shape ↓ from 224×224 to 112×112
  - Uses swish activation function (f(x) = x * sigmoid(x))
- MBConv Blocks (Mobile Inverted Bottleneck Convolution)
  - Each block includes:
    - 1×1 Pointwise conv (expansion)
    - 3×3 or 5×5 Depthwise conv
    - 1×1 Pointwise conv (projection)
    - Squeeze-and-Excitation (SE) block (channel-wise recalibration)
  - Replaces traditional convolutions blocks for better efficiency
- Final Layers
  - 1×1 Conv → Global Average Pooling → Dropout → Fully Connected Layer (e.g., 1000-class for ImageNet)

Compound Scaling

EfficientNet scales:

- **Width (w)** → # of channels
- **Depth (d)** → # of layers
- **Resolution (r)** → input image size

  Using a **compound coefficient φ**, it balances all three:

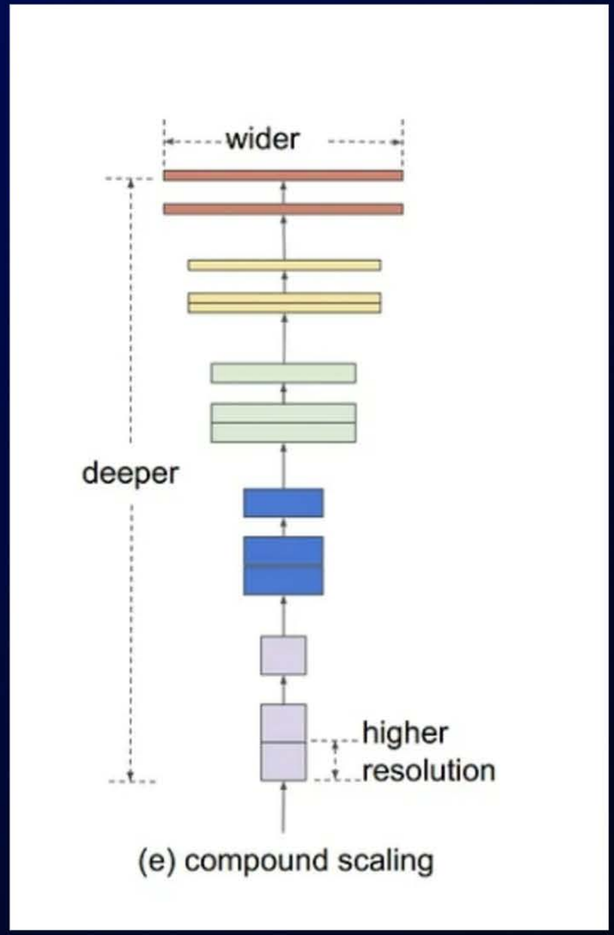
$$\text{depth} = \alpha^{\phi}, \quad \text{width} = \beta^{\phi}, \quad \text{resolution} = \gamma^{\phi}$$

Subject to constraint:

$$\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2, \quad \alpha, \beta, \gamma > 1$$

Compound Scaling in Action

- Width scaling: Adds more channels per layers
- Depth scaling: Adds more layers
- Resolution scaling: Increases input image size
- Compound scaling is more balanced and effective than scaling one factor alone.

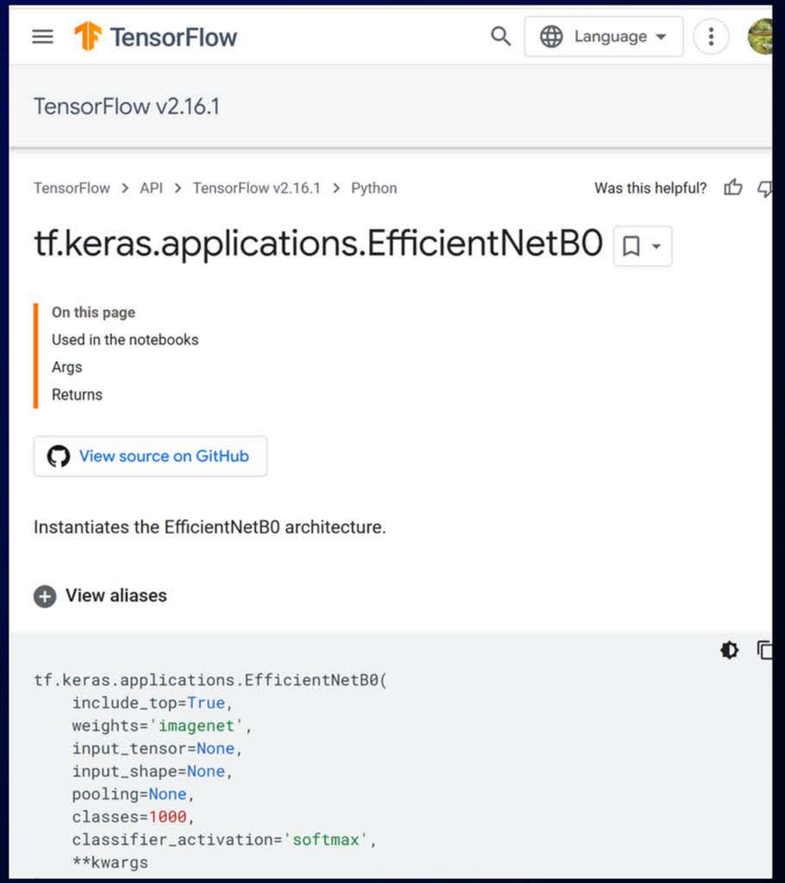


“https://www.tensorflow.org/api_docs/python/tf/keras/applications/EfficientNetB0

Kernel Sizes & Configurations

Block Type	Kernel Size	Stride	Expansion Ratio	Repeats
MBConv1	3×3	1	1	1
MBConv6	3×3 or 5×5	2	6	varies

- Varies across EfficientNet-B0 to B7.
- Each version (B0 to B7) increases model capacity by scaling depth, width, and resolution using compound scaling
- Depth-wise separable convolutions reduce FLOPs (Floating Point Operations), reduces model size & parameters, maintains high accuracy.



"https://www.tensorflow.org/api_docs/python/tf/keras/applications/EfficientNetB0

LIMITATIONS

- Higher inference time on CPU-only environments
- Difficult to customize compared to plain CNNs due to compound scaling
- SE blocks and Swish activation are computationally expensive, especially on edge/mobile devices

Use Cases & Applications

- Best suited for high-accuracy tasks where sufficient resources are available
- Applied in: medical imaging (e.g., tumor detection), retail product detection, mobile apps (EffNet-Lite)

Project Overview

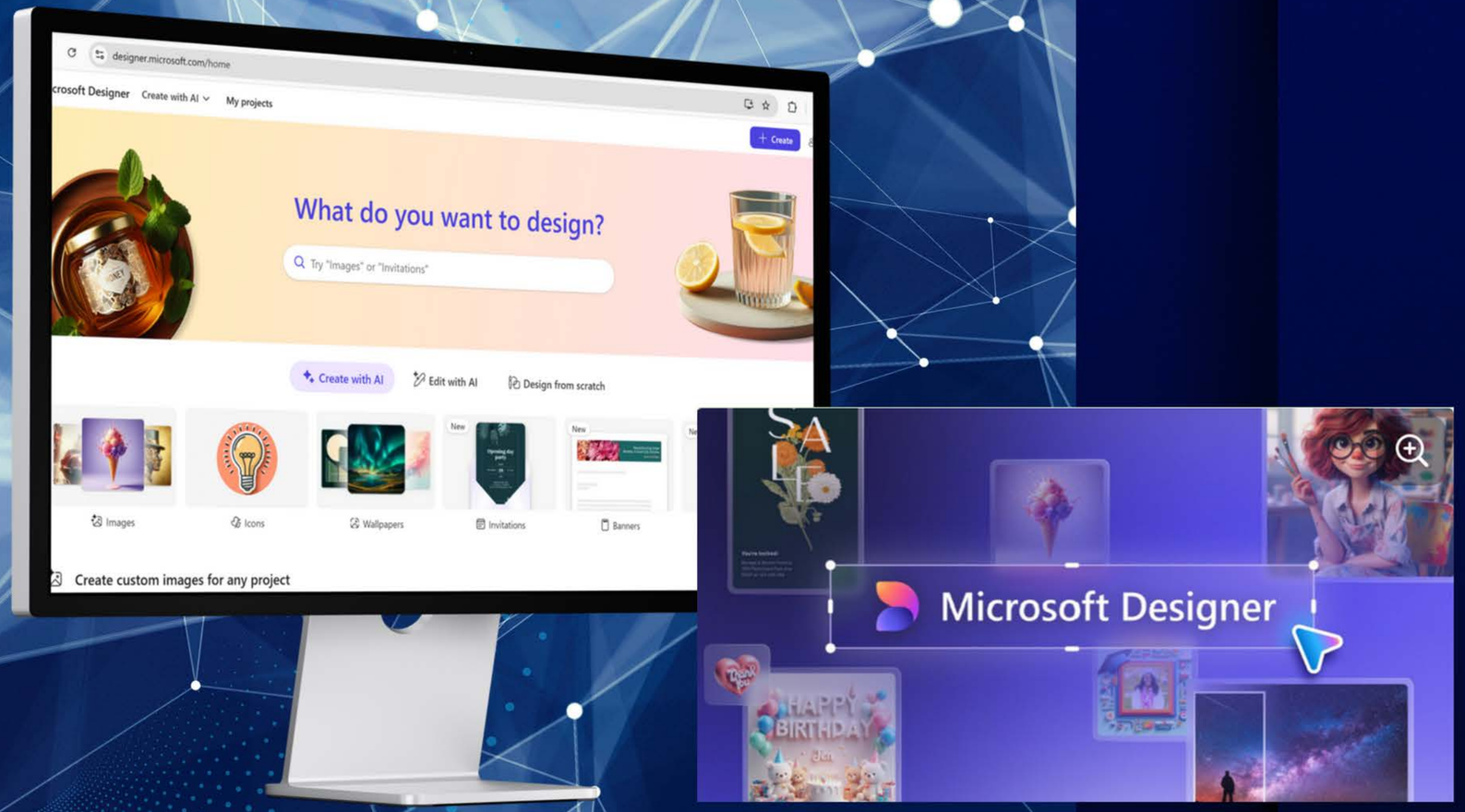
Comparative Study of CNN Architectures for Image Classification : Focusing on EfficientNet

- explored the performance of five popular Convolutional Neural Network (CNN) architectures using Python and Keras.
- The models used are: ResNet50, VGG16, InceptionV3, ConvNeXt-Tiny, and EfficientNetB7.
- used a dataset of 40 images (20 real and 20 synthetic) to test the EfficientNet model.

GOAL

TO COMPARE EACH MODEL'S PERFORMANCE IN TERMS OF PREDICTION ACCURACY, INFERENCE SPEED, AND PRACTICAL USABILITY.

MICROSOFT IMAGE GENERATOR



DATASET

- The dataset contains:
- 20 real images collected from the internet
- 20 synthetic images generated by Microsoft's AI image generator
- Real images vary in size; synthetic images are fixed at 1024 × 1024 pixels.
- All images were preprocessed and resized to fit model's input shape .

Microsoft. Microsoft image creator. "https://designer.microsoft.com/image-creator", 2025.

DATASET-REAL AND SYNTHETIC















DATASET–REAL AND SYNTHETIC









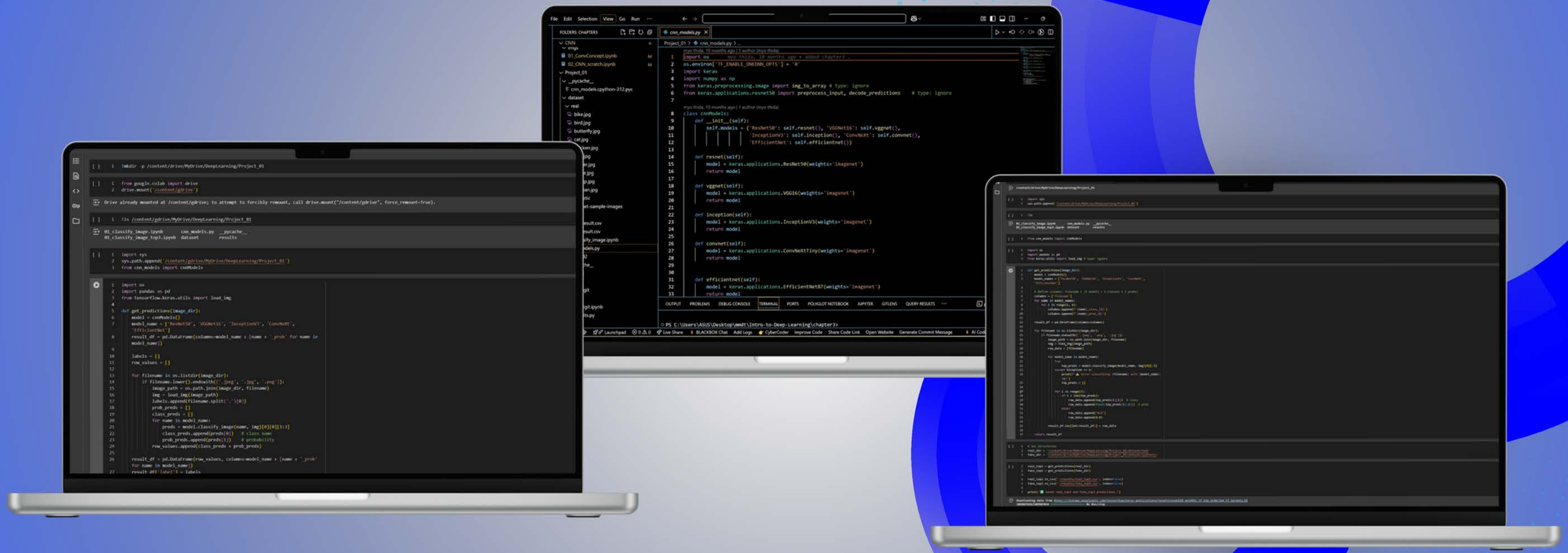






DATASET–REAL AND SYNTHETIC

EXPERIMENT



- All models were pre-trained on the ImageNet dataset using Keras.

- time.perf_counter() was used to calculate per-image inference time.
- Predictions were decoded using decode_predictions() to get top-3 results.

IMAGE CLASSIFICATION

```
6
7  for model in ['ResNet50', 'VGGNet16', 'InceptionV3', 'ConvNeXt', 'EfficientNet']
   :
8      table_df[model] = df.apply(lambda row: format_top1(row[model], row[f"{model}
       _prob"]), axis=1)
9
10 table_df.head()
```

	filename	ResNet50	VGGNet16	InceptionV3	ConvNeXt	EfficientNet
0	cow	muzzle (0.39)	miniature_pinscher (0.08)	hammer (0.99)	hen (0.07)	chainlink_fence (0.12)
1	toy	ballpoint (0.22)	pencil_box (0.25)	pitcher (0.58)	tennis_ball (0.39)	saltshaker (0.07)
2	flower	pot (0.26)	sulphur_butterfly (0.19)	flatworm (0.67)	hummingbird (0.39)	reel (0.11)
3	dog	Persian_cat (0.83)	Persian_cat (0.67)	web_site (1.00)	Persian_cat (0.59)	Arctic_fox (0.44)
4	bird	African_grey (0.95)	quail (0.48)	web_site (0.99)	African_grey (0.86)	window_screen (0.50)

```
1  import pandas as pd
2
3  df = pd.read_csv('/content/gdrive/MyDrive/DeepLearning/Project_01/results/
   fake_result.csv')
4  df.head()  # or df[['label', 'ResNet50', 'ResNet50_prob', ...]]
```

	ResNet50	VGGNet16	InceptionV3	ConvNeXt	EfficientNet	ResNet50_prob	VGGNet16_prob	InceptionV3_p
0	Pembroke	sunglasses	stopwatch	fountain	sunglass	0.415618	0.422213	0.999
1	hen	cock	clog	hen	hen	0.539845	0.519462	0.999
2	car_mirror	mountain_tent	clog	bullet_train	bullet_train	0.556300	0.316349	0.916
3	hamper	Persian_cat	flatworm	tabby	tiger_cat	0.361622	0.572489	0.999
4	candle	candle	stole	bakery	stove	0.674406	0.387122	0.996

```
1  import pandas as pd
2
3  df = pd.read_csv('/content/gdrive/MyDrive/DeepLearning/Project_01/results/
   real_result.csv')
4  df.head()  # or df[['label', 'ResNet50', 'ResNet50_prob', ...]]
```

	ResNet50	VGGNet16	InceptionV3	ConvNeXt	EfficientNet	ResNet50_prob	VGGNet16_prob	Incep
0	muzzle	miniature_pinscher	hammer	hen	chainlink_fence	0.387831	0.080818	
1	ballpoint	pencil_box	pitcher	tennis_ball	saltshaker	0.219144	0.247788	
2	pot	sulphur_butterfly	flatworm	hummingbird	reel	0.256225	0.187836	
3	Persian_cat	Persian_cat	web_site	Persian_cat	Arctic_fox	0.832892	0.668904	
4	African_grey	quail	web_site	African_grey	window_screen	0.945016	0.481908	

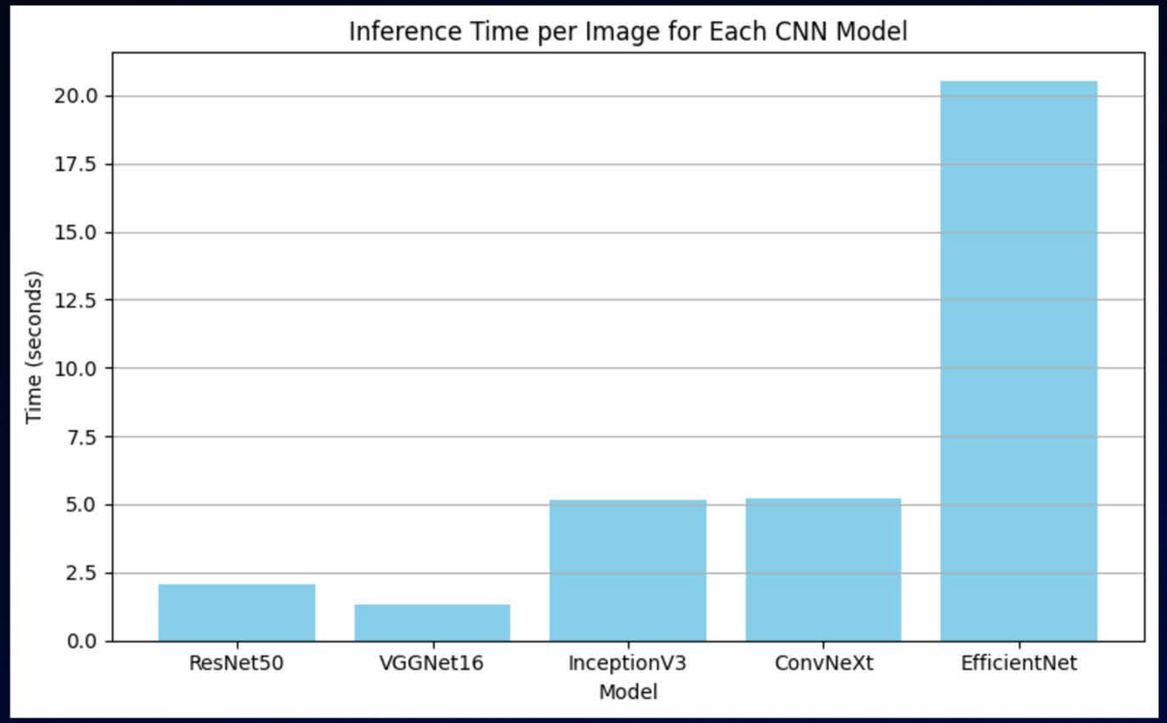
IMAGE CLASSIFICATION: REAL

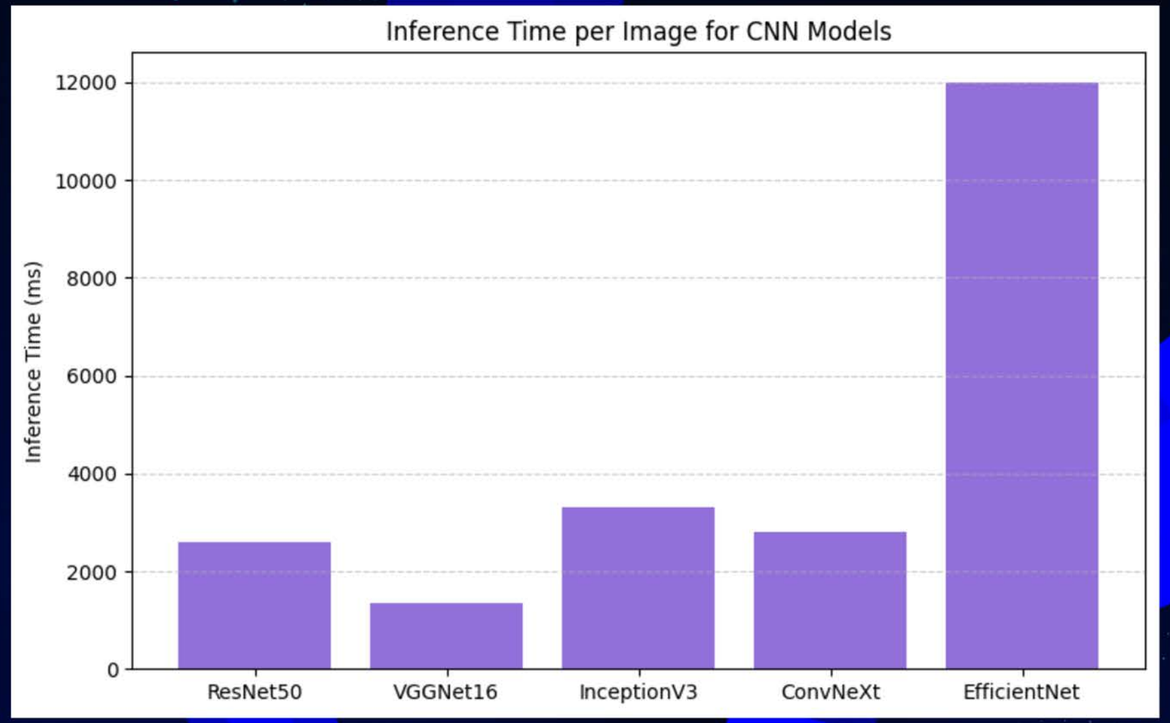
A	B	C	D	E	F	G	H	I	J	K
ResNet50	VGGNet16	InceptionV3	ConvNeXt	EfficientNet	ResNet50_prob	VGGNet16_prob	InceptionV3_pro	ConvNeXt_prob	EfficientNet_prob	label
muzzle	miniature_pinsch	hammer	hen	chainlink_fence	0.3878315	0.08081827	0.99297863	0.07476012	0.11729001	cow
ballpoint	pencil_box	pitcher	tennis_ball	saltshaker	0.21914423	0.2477882	0.58344233	0.38547233	0.07368472	toy
pot	sulphur_butterfly	flatworm	hummingbird	reel	0.256225	0.18783566	0.6741588	0.3888667	0.10678629	flower
Persian_cat	Persian_cat	web_site	Persian_cat	Arctic_fox	0.8328918	0.66890377	1	0.59154844	0.43703032	dog
African_grey	quail	web_site	African_grey	window_screen	0.94501597	0.4819076	0.9906729	0.85805225	0.5037069	bird
plate	plate	pitcher	wok	strainer	0.67530185	0.65339124	0.99392855	0.3796683	0.77589095	cake
passenger_car	bullet_train	sock	bullet_train	cab	0.90250206	0.9173202	0.81538737	0.45826787	0.2625382	train
canoe	canoe	hammer	canoe	canoe	0.3432207	0.4159075	0.99999905	0.2534945	0.69345	boat
chimpanzee	chimpanzee	ashcan	chimpanzee	chimpanzee	0.99999964	0.9903126	1	0.863563	0.80125403	monkey
diaper	diaper	web_site	diaper	diaper	0.92203164	0.81497616	0.9955249	0.40672663	0.60209274	baby
tiger	tiger	pitcher	tiger	tiger_cat	0.86475635	0.84903365	0.9999975	0.7405015	0.5470659	tiger
Granny_Smith	pomegranate	web_site	Granny_Smith	Granny_Smith	0.29145214	0.5377776	0.9841814	0.92453253	0.24539247	apple
rubber_eraser	rubber_eraser	clog	rubber_eraser	rubber_eraser	0.85895944	0.6875064	0.9994199	0.8447058	0.23501019	pencil
canoe	lakeside	web_site	lakeside	alp	0.6804078	0.4947493	0.9955877	0.4838826	0.12623677	lake
dining_table	dining_table	stopwatch	dining_table	window_screen	0.92214185	0.73553246	0.9999585	0.9642549	0.22803657	dining_table
school_bus	passenger_car	binoculars	passenger_car	limousine	0.9107605	0.3958574	0.47202057	0.78599834	0.07698787	school_bus
shopping_baske	shopping_baske	pitcher	shopping_baske	shopping_baske	0.999997	0.9999981	0.5271109	0.90707844	0.7847785	plastic_basket
hen	hen	flatworm	hen	window_screen	0.91908205	0.8252454	1	0.91907793	0.09330011	hen
water_bottle	water_bottle	flatworm	cocktail_shaker	water_bottle	0.99084634	0.9098153	0.9999862	0.6170162	0.7646816	water_bottle
tabby	tabby	web_site	Egyptian_cat	tabby	0.5086882	0.41537073	1	0.224414	0.533094	cat

IMAGE CLASSIFICATION: FAKE

A	B	C	D	E	F	G	H	I	J	K
ResNet50	VGGNet16	InceptionV3	ConvNeXt	EfficientNet	ResNet50_prob	VGGNet16_prob	InceptionV3_pro	ConvNeXt_prob	EfficientNet_prob	label
Pembroke	sunglasses	stopwatch	fountain	sunglass	0.41561753	0.42221278	0.99936837	0.27203736	0.07401339	cow
hen	cock	clog	hen	hen	0.5398454	0.5194624	0.99939394	0.7929004	0.07392945	hen
car_mirror	mountain_tent	clog	bullet_train	bullet_train	0.55630046	0.3163486	0.91653734	0.54976016	0.72447175	train
hamper	Persian_cat	flatworm	tabby	tiger_cat	0.3616216	0.572489	0.9999889	0.23659141	0.46088853	cat
candle	candle	stole	bakery	stove	0.6744064	0.38712204	0.99627614	0.25372165	0.10477709	cake
toyshop	toyshop	clog	toyshop	teddy	0.99368423	0.93309903	0.9999989	0.8793247	0.4359823	toy
tiger	fountain	flatworm	tiger	tiger_cat	0.5448647	0.13387209	0.9999994	0.85821325	0.27814662	tiger
school_bus	school_bus	flatworm	school_bus	church	0.9273219	0.9992399	0.9999975	0.8030589	0.6982585	school_bus
water_bottle	water_bottle	stopwatch	water_bottle	water_bottle	0.59653836	0.26066345	0.9985195	0.91486984	0.8406696	water_bottle
yawl	yawl	stopwatch	yawl	catamaran	0.7840371	0.34552598	0.9967843	0.77020305	0.2344706	boat
indigo_bunting	hummingbird	flatworm	indigo_bunting	jay	0.37666985	0.25452876	0.99821943	0.4781175	0.56312877	bird
pinwheel	umbrella	clog	umbrella	matchstick	0.9226753	0.7096159	1	0.34280324	0.70447534	pencil
comic_book	mask	flatworm	comic_book	comic_book	0.6911051	0.45315897	0.8420374	0.25946134	0.14329687	monkey
shopping_baske	shopping_baske	flatworm	shopping_baske	shopping_baske	0.9543658	0.47739467	0.83421165	0.6977798	0.6070933	plastic_basket
boathouse	volcano	web_site	mashed_potato	web_site	0.5870327	0.28246665	1	0.62775177	0.030386461	lake
bee	daisy	flatworm	daisy	matchstick	0.3811552	0.3241558	0.76654124	0.25772262	0.052193206	flower
golden_retriever	golden_retriever	flatworm	golden_retriever	golden_retriever	0.97924495	0.84636927	0.9997991	0.8799979	0.5961258	dog
restaurant	restaurant	flatworm	dining_table	window_screen	0.7806092	0.8331283	0.9968098	0.6387252	0.1026649	dining_table
Granny_Smith	lipstick	web_site	Granny_Smith	strainer	0.48318785	0.21608412	1	0.87527907	0.6327593	apple
maraca	candle	flatworm	wig	pill_bottle	0.442965	0.801257	0.99996054	0.48872933	0.21910615	baby

Inference Time per Image

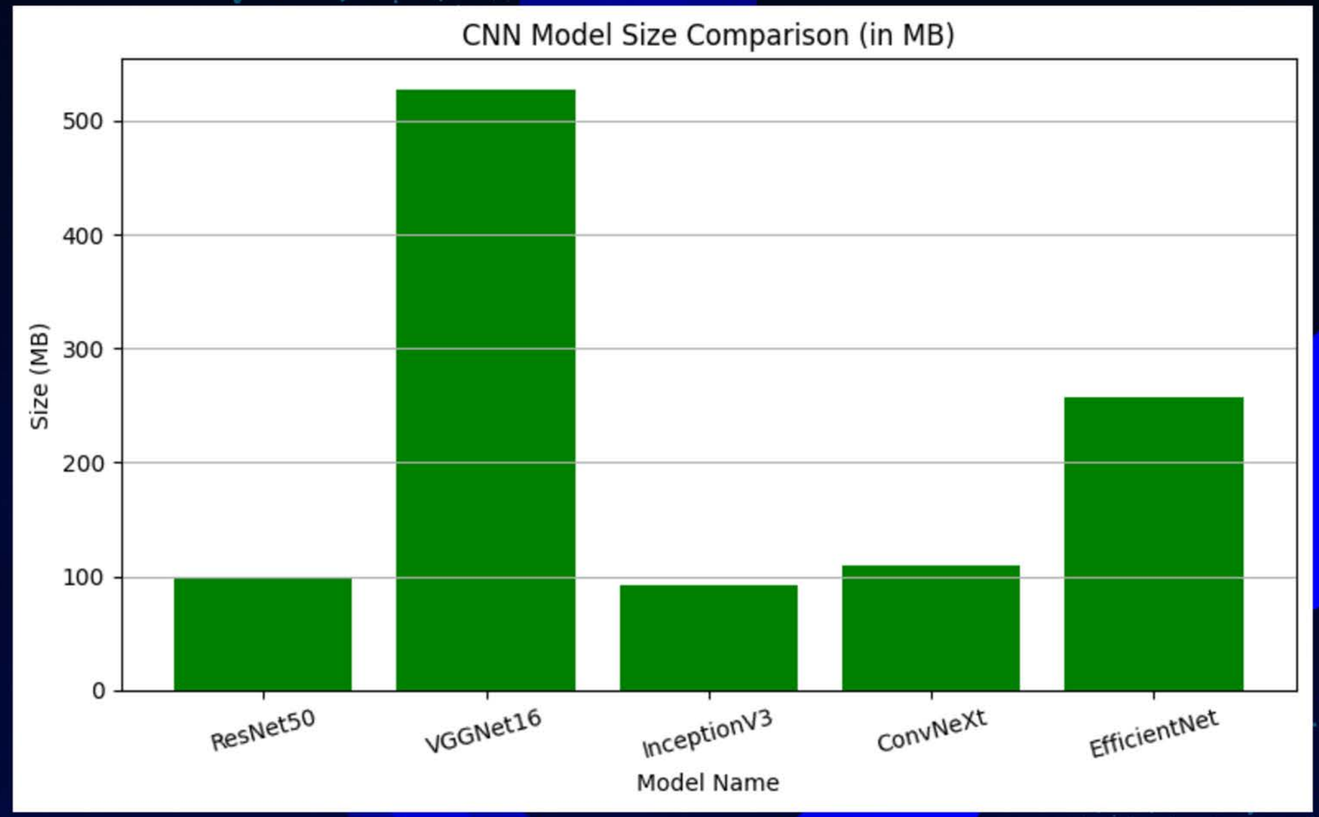




- Fastest: VGGNet16 (~1s)
- Slowest: EfficientNet (~11s)
- Observation: EfficientNet, while being accurate in some cases, had the longest inference time.

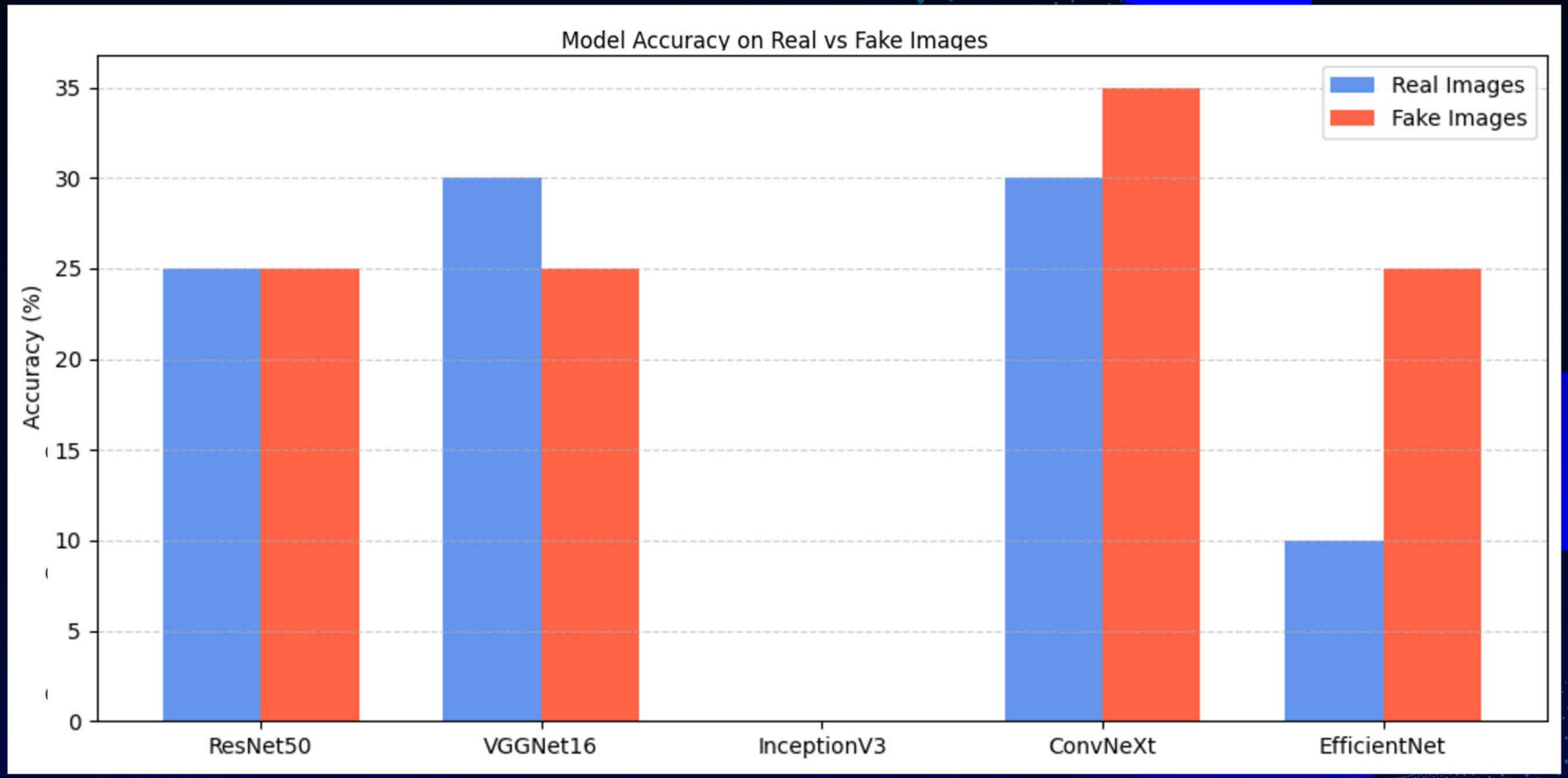
Model size and Memory footprint

Model	File Size (MB)
ResNet50	98.35
VGG16	527.87
InceptionV3	91.93
ConvNexXt-Tiny	109.53
EfficientNetB7	256.59



- Smallest: ResNet50 (~98 MB)
- Largest: VGGNet16 (~528 MB)
- Observation: VGGNet16 is over 5x the size of ResNet50 with only slightly better accuracy.

MODEL ACCURACY



- ConvTeXt-Tiny is close with good trade-off between accuracy and speed.

Results & Discussion

- Prediction Accuracy (Soft Match)
- ResNet50: Real = 25%, Fake = 25%
- VGGNet16: Real = 30%, Fake = 25%
- InceptionV3: Real = 0%, Fake = 0%
- ConvNeXt: Real = 30%, Fake = 35%
- EfficientNet: Real = 10%, Fake = 25%
- Observation: ConvNeXt showed the highest accuracy for fake images (35%) and tied with VGGNet16 on real (30%). InceptionV3 failed to recognize both.

FINDINGS

- InceptionV3 has high confidence but 0% accuracy, indicating it is confidently wrong.
- ResNet50 is the most balanced in terms of accuracy and confidence.
- ConvNeXt performs best on fake images in both accuracy and confidence.
- EfficientNet has the lowest average confidence and performs poorly.

Limitations

- Small dataset: Limited number of images used for evaluation
- No fine-tuning: All models used pre-trained ImageNet weights without custom training
- Limited evaluation metric: Only soft match accuracy and top-3 predictions were used
- No qualitative error analysis: Misclassified images not visually inspected

Future Work

- Expand dataset size and diversity for more reliable benchmarking
- Fine-tune models on a custom dataset to increase domain-specific performance
- Include more evaluation metrics: Precision, Recall, F1-score
- Test on different image types (e.g., grayscale, occluded, rotated) for robustness
- Deploy models in a simple web or mobile app for interactive testing

CONCLUSION

- Best Overall Tradeoff: ConvNeXt — highest accuracy (real: 30%, fake: 35%) and moderate inference time and size
- Best for Speed: VGGNet16 — fastest inference, but very large size
- Worst Performer: InceptionV3 — 0% accuracy despite moderate speed and size
- Insight: Model size doesn't directly correlate with accuracy or speed

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