Hi People! It's us,

CV-D GEOFFREY HINTON

PROJECT 1: Face Recognition

(Gender Classification)

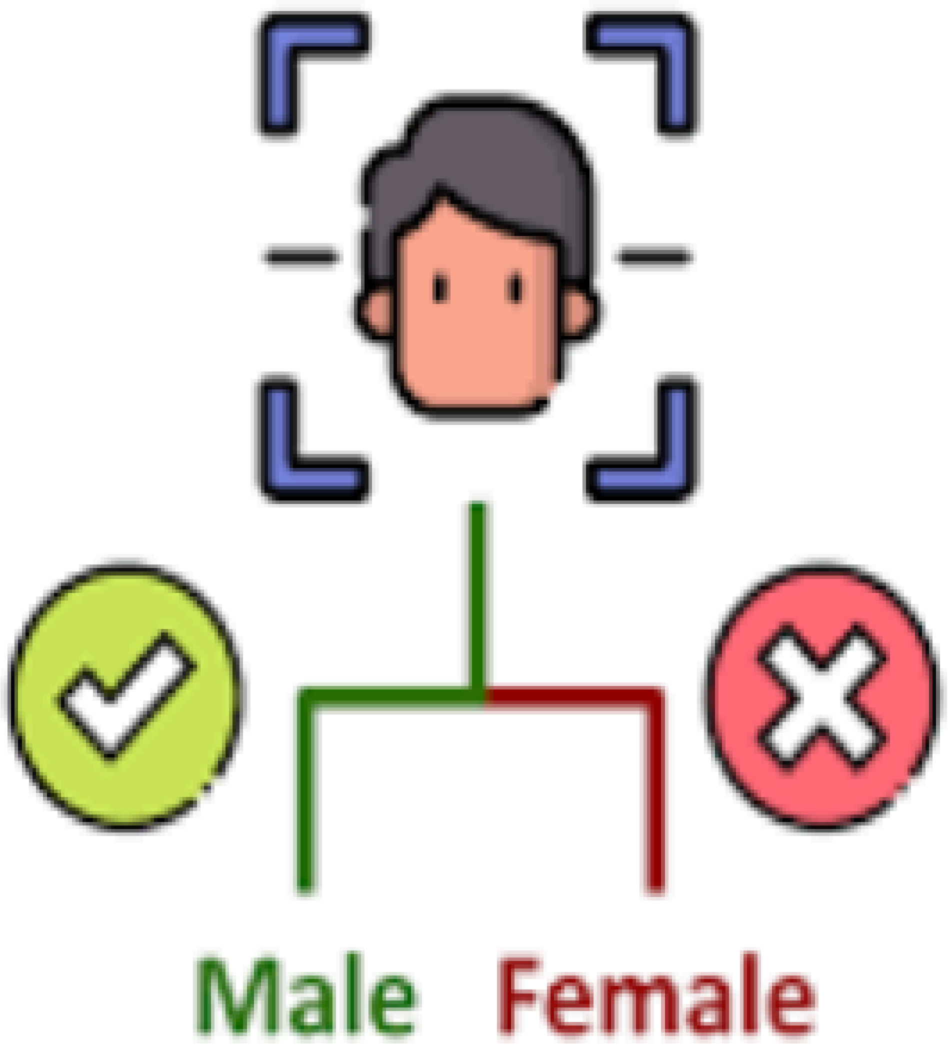
Background

Face recognition can be classified as an algorithm to identify and differentiate human faces based on an image or video. It studies unique features of the human face to make its predictions. One part of this algorithm is **gender classification**.

Gender classification is used to determine whether a subject is **male** or **female**. This feature is important, especially for automatic surveillance or monitoring systems. Examples include:

- surveillance of gender specific areas.
- count customers of each gender for sales evaluation.

This study explores the use of Artificial Intelligence, specifically 3 commonly known Convolutional Neural Networks (CNNs) for gender classification.



OBJECTIVE AND **MODEL**

Objectives

- To **obtain CNN models that can classify gender** based on images of human faces.
- To **compare** the classification performance of **3 different CNN models** (VGG, ResNet, and GoogLeNet)

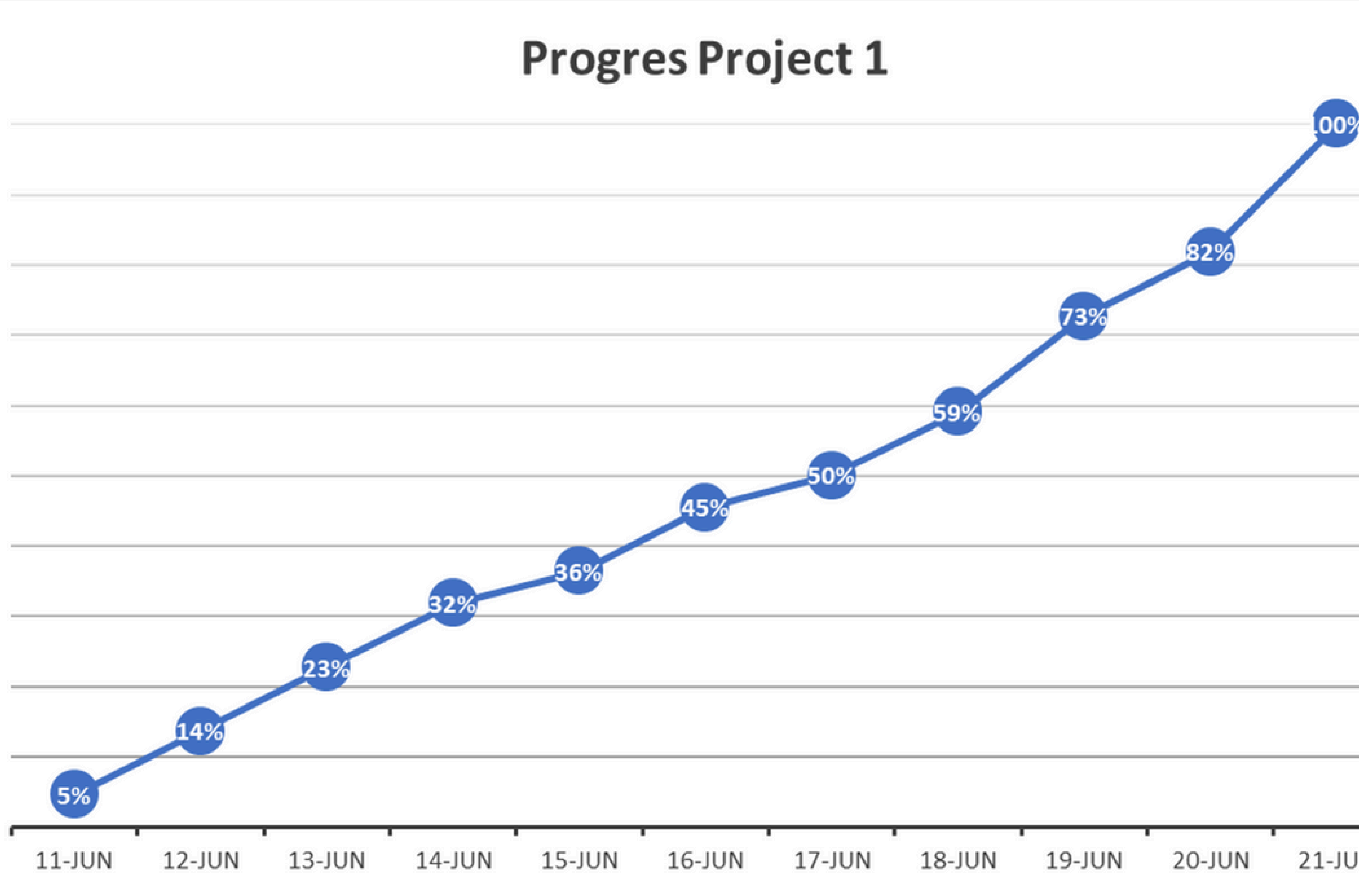
Model

Dependent variable = Gender

- Binary classification problem
- Supervised learning Method

TIMELINE

Task and Specifics	Attendees	Date													
		6/11	6/12	6/13	6/14	6/15	6/16	6/17	6/18	6/19	6/20	6/21	6/22	6/23	6/24
Project planning and scheduling															
Meeting	A, B, C, E, S														
Task and data understanding															
Translation of task	B, C														
Data preparation and preprocessing	B, C														
Meeting (member update)	B, C, S														
Coding															
Training algorithm understanding & creation	B, C, S														
Model training & algorithm evaluation 1	B, C, S														
algorithm evaluation 2	A, B, C, E, S														
Result Analysis															
Analysis, Graphing, and Validation	B, C														
Presentation															
Powerpoint creation	A, B, C, E, S														
rehearsal	A, B, C, E, S														
Others															
Evaluation and Revision	A, B, C, E, S														
Upload finished code to github	A, B, C, E, S														



Legend :

A : Alamul Yaqin
B : Shania Salsabilla (Bella)
C : Calvin Christian Chandra
E : Eureka Labdawara
S : Satrio Fatturahman

DATASET:

Used a subset of CelebFaces Attributes Dataset (CelebA) which can be accessed through:

https://drive.google.com/drive/folders/1xaVtzZSFGaRRz1FQikrBwDm4JjgK36zo

Utilizes 2 items:

- ‘Images’ folder: contains images of **5017** celebrities with a few duplicates.
- List_attribute.txt: contains mainly face attribute data of the images. Will only consider the [’**Male**’] column for this study.

PREPROCESSING

Removing Duplicate Images

```
[29]: images_list_dup = [i for i in images_list if len(i) > 11]
      images_list_dup
```

```
[29]: ['189651(1).jpg',
       '189513(1).jpg',
       '183145(1).jpg',
       '182912(1).jpg',
       '189297(1).jpg',
       '183005(1).jpg',
       '189132(1).jpg',
       '183121(1).jpg',
       '189324(1).jpg',
       '182793(1).jpg',
       '183018(1).jpg',
       '182809(1).jpg',
       '189512(1).jpg',
       '183111(1).jpg',
       '189581(1).jpg',
       '183050(1).jpg',
       '182943(1).jpg']
```

Filter Row Label with Images supplied

From 202599 rows of list_attribute, only 5000 row supplied with each respective training Image in provided Images folder.

```
remove_data = data[data['file_name'].isin(images_list) == False]
remove_data
```

[37]:

	file_name	5_o_Clock_Shadow	Arched_Eyebrows	Attractive	Bags_Under_Eyes	Bald
0	000001.jpg	-1	1	1	-1	-1
1	000002.jpg	-1	-1	-1	1	-1
2	000003.jpg	-1	-1	-1	-1	-1
3	000004.jpg	-1	-1	1	-1	-1
4	000005.jpg	-1	1	1	-1	-1
...	...	...	...	...	...	...
202594	202595.jpg	-1	-1	1	-1	-1
202595	202596.jpg	-1	-1	-1	-1	-1
202596	202597.jpg	-1	-1	-1	-1	-1
202597	202598.jpg	-1	1	1	-1	-1
202598	202599.jpg	-1	1	1	-1	-1

197599 rows × 41 columns

+ Code + Markdown

PREPROCESSING

Using ‘Male’ Column only for label

Transforming -1 value to 0 in ‘Male’ Column

	file_name	Male
0	000001.jpg	-1
1	000002.jpg	-1
2	000003.jpg	1
3	000004.jpg	-1
4	000005.jpg	-1
...	...	...
202594	202595.jpg	-1
202595	202596.jpg	1
202596	202597.jpg	1
202597	202598.jpg	-1
202598	202599.jpg	-1

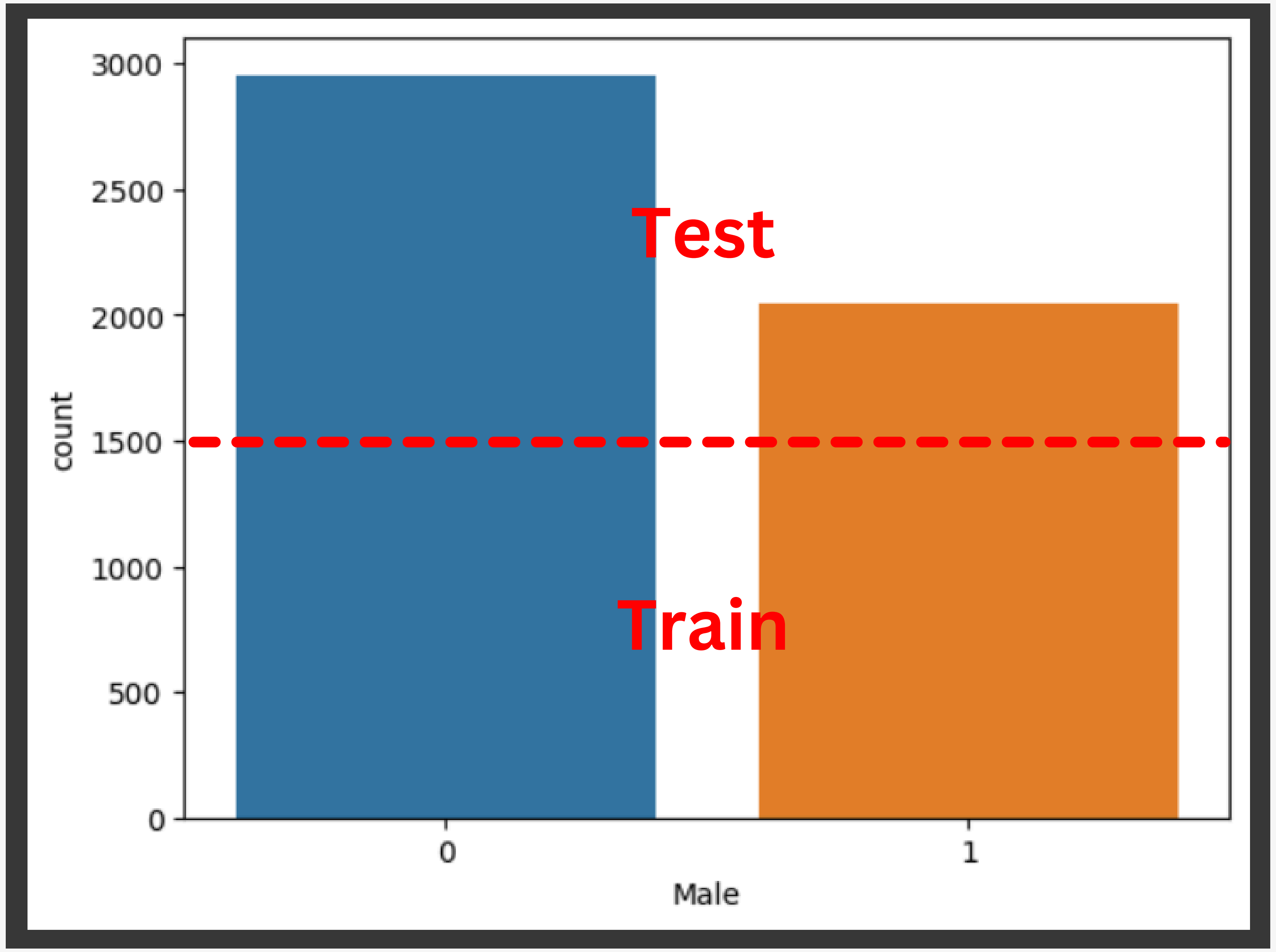
	file_name	Male
50	000051.jpg	1
51	000052.jpg	1
64	000065.jpg	1
165	000166.jpg	1
197	000198.jpg	0
...	...	...
202319	202320.jpg	0
202339	202340.jpg	0
202346	202347.jpg	0
202356	202357.jpg	0
202565	202566.jpg	1

5000 rows × 2 columns

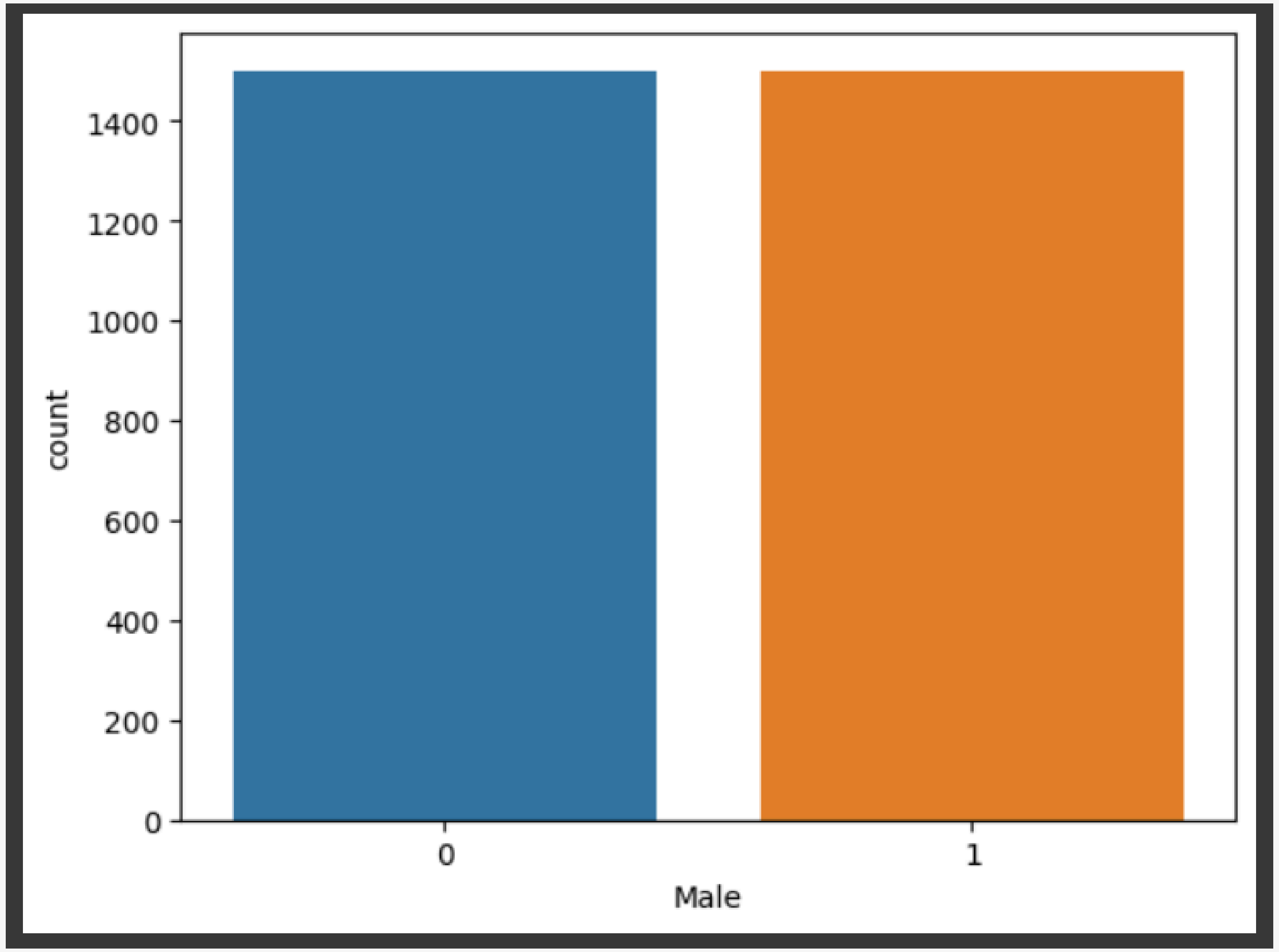
PREPROCESSING:

Imbalanced Dataset

Raw Data



Resulting Train Data

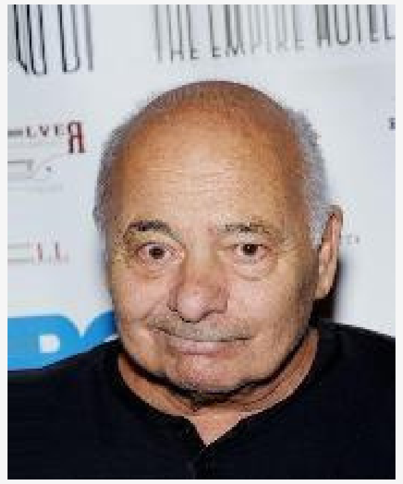


Data Augmentation

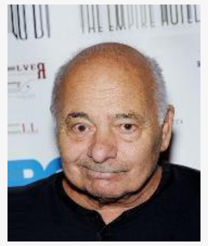
We Augment separately / differently for Train and Test Images. For Train Images we applied more steps like Random Horizontal Flip and Random Rotation to enrich our Train data.

```python
# Define the Transformations:
transforms = {
    'train': transforms.Compose([
        transforms.RandomHorizontalFlip(),
        transforms.Resize(256),
        transforms.RandomRotation(45),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'test': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
}
```

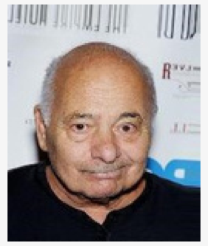
Example of Image Transformations visualized



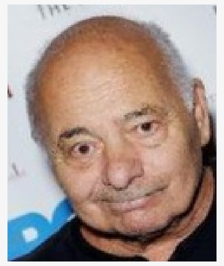
Raw



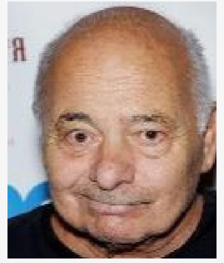
Resize



Random Horizontal Flip



Random Rotation



Center Crop

Study Setup : Constant Parameters

Parameters	Value
Epoch	25
Initial Learning Rate	0.0001
Optimizer	Adam
Image Input Dimension	224 x 224 px, except **Inception v3** = 299 x 299 px
Batch Size	32
Notebook & Accelerator	Kaggle GPU T4 x2

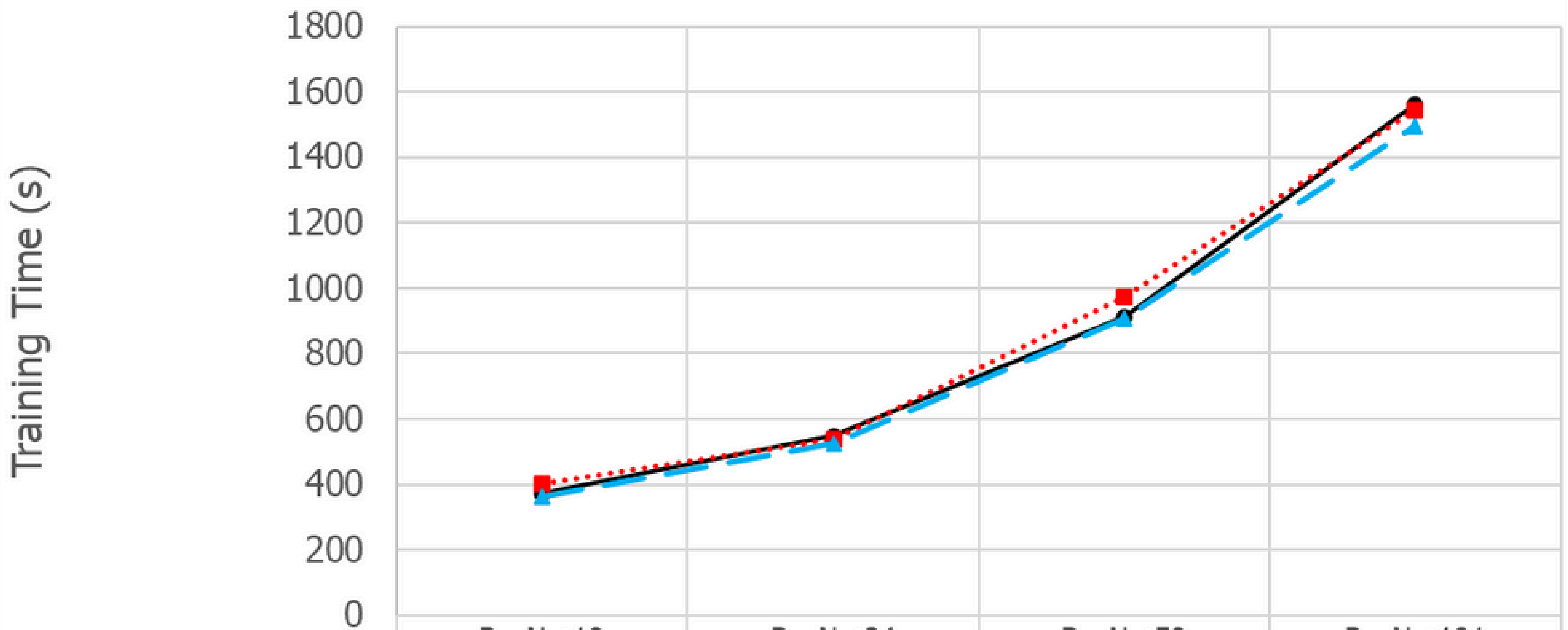
Study Setup : Varied Parameters

Models	1	2	3	4
VGG	VGG-11	VGG-13	VGG-16	VGG-19
ResNet	ResNet-18	ResNet-34	ResNet-50	ResNet-101
Inception	Inception V1	Inception V3	-	-

Variations	Initially use Pretrained weights?	Loss Criterion
1	X	BCEWithLogitsLoss
2	V	BCEWithLogitsLoss
3	X	CrossEntropyLoss

Results Training Time

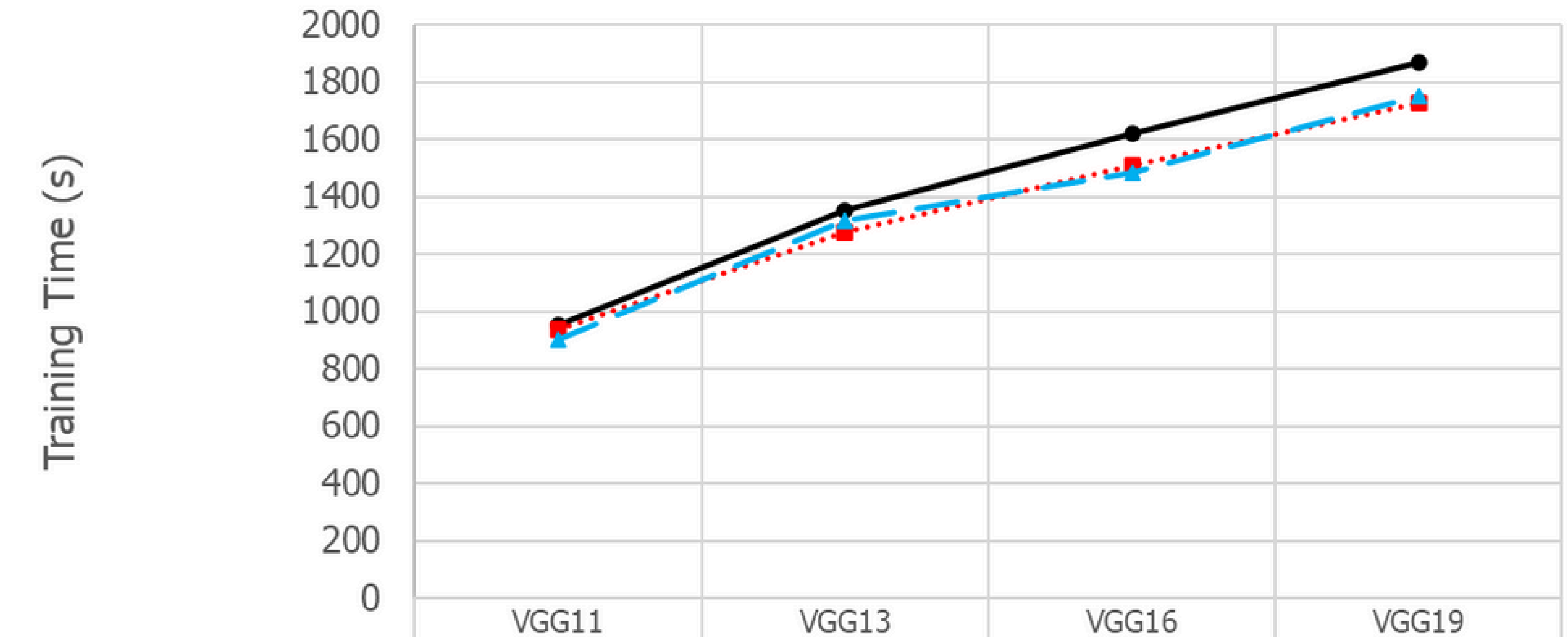
ResNet Models' Training Time



	ResNet18	ResNet34	ResNet50	ResNet101
Base	374	549	912	1562
Pretrained	403	541	972	1542
Multi Class Criterion	363	524	909	1495

Model Variation

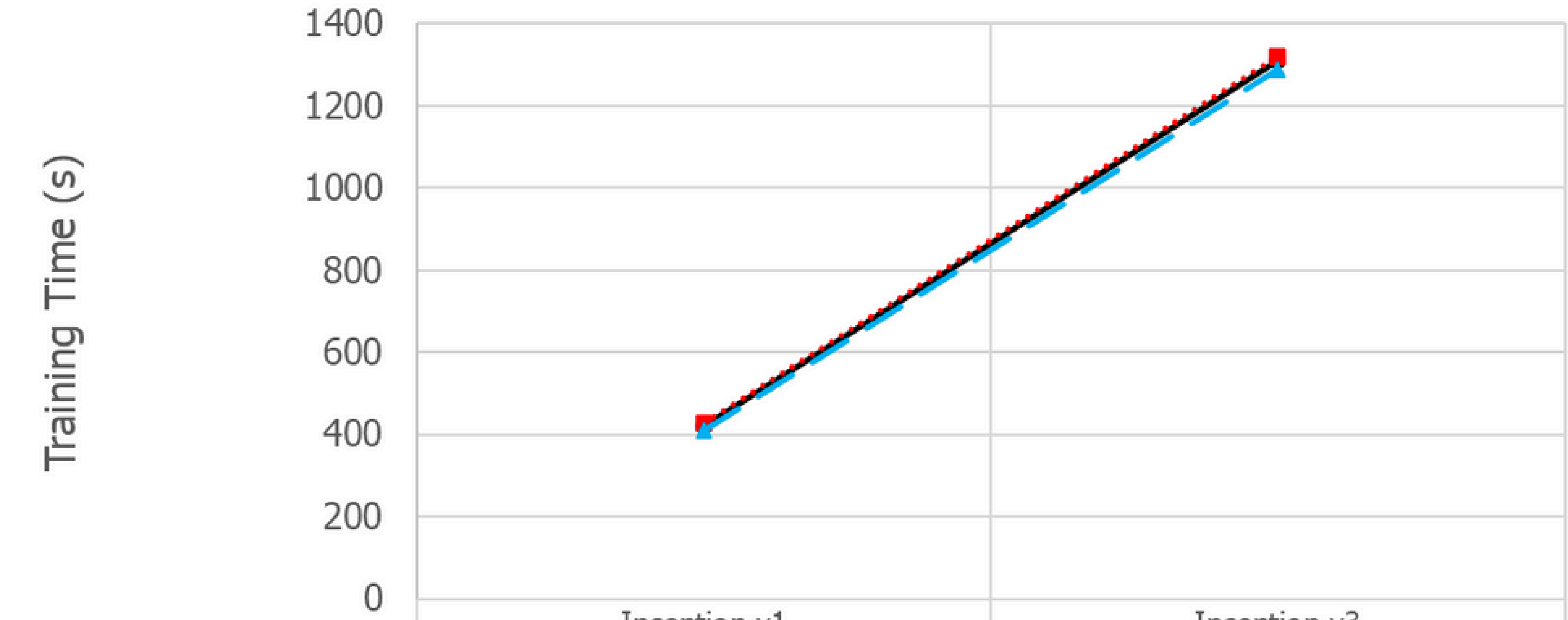
VGG Models' Training Time



	VGG11	VGG13	VGG16	VGG19
Base	951	1354	1621	1868
Pretrained	939	1276	1510	1725
Multi Class Criterion	904	1315	1485	1754

Model Variation

Inception Models' Training Time

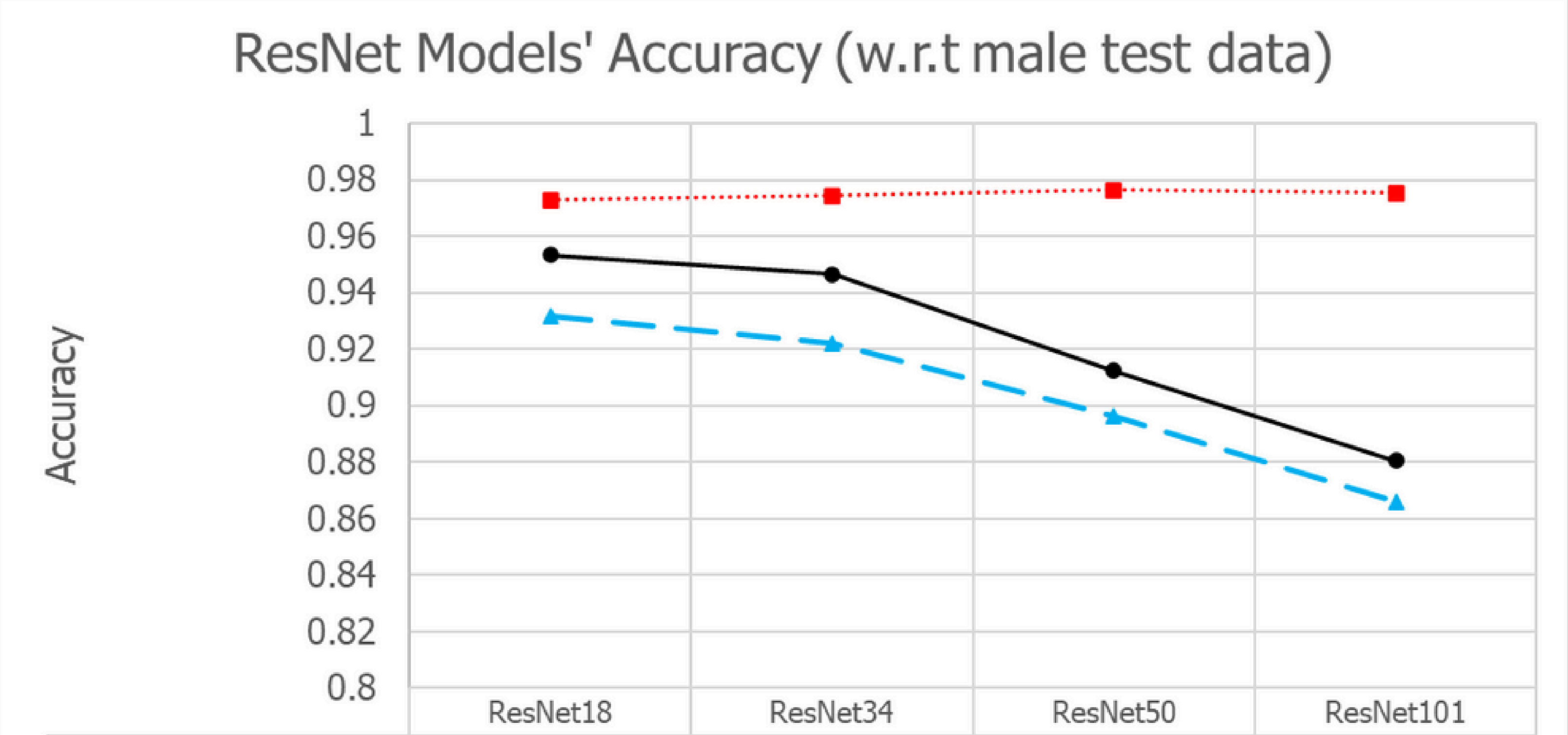


	Inception v1	Inception v3
Base	420	1308
Pretrained	427	1319
Multi Class Criterion	409	1287

Model Variation

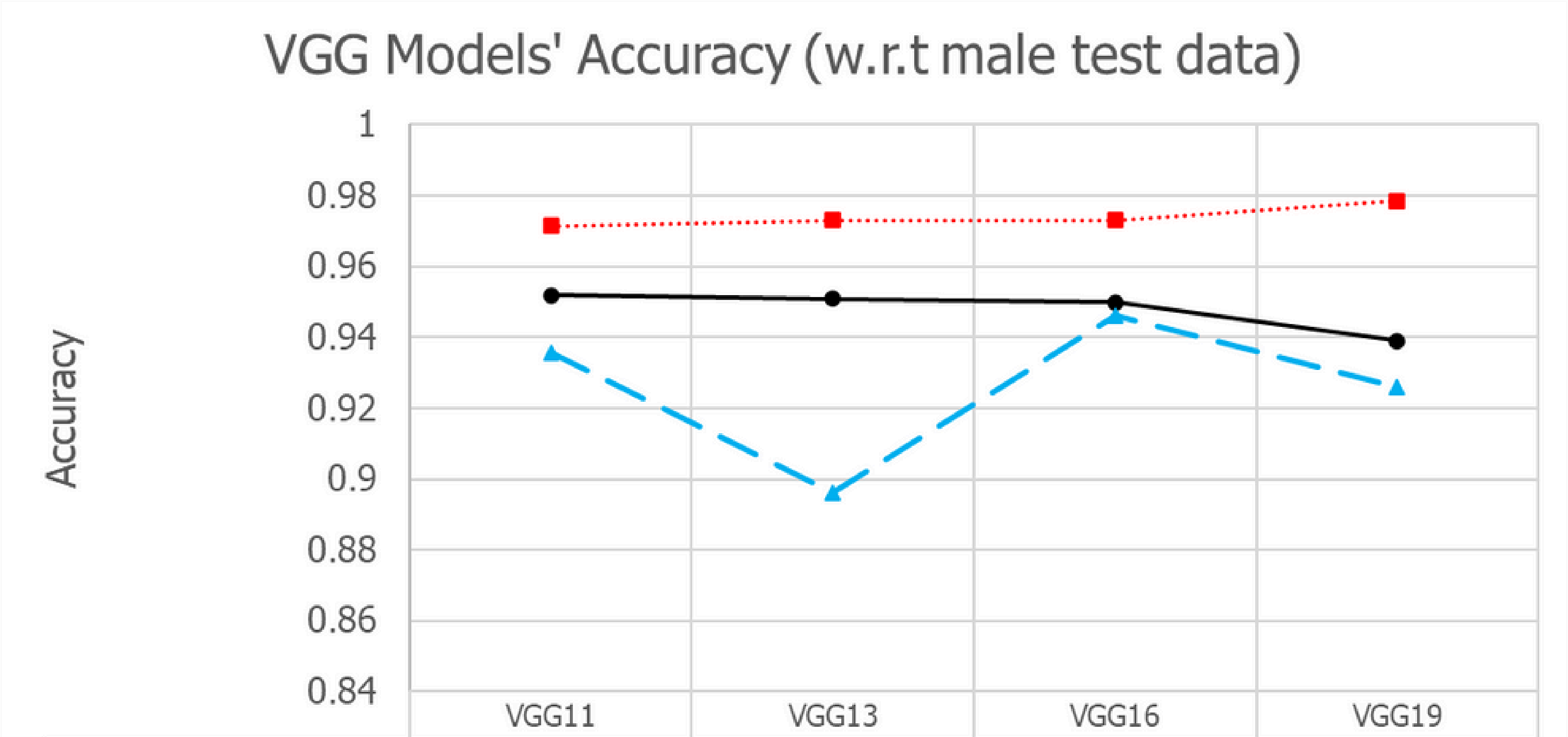
Results

Accuracy



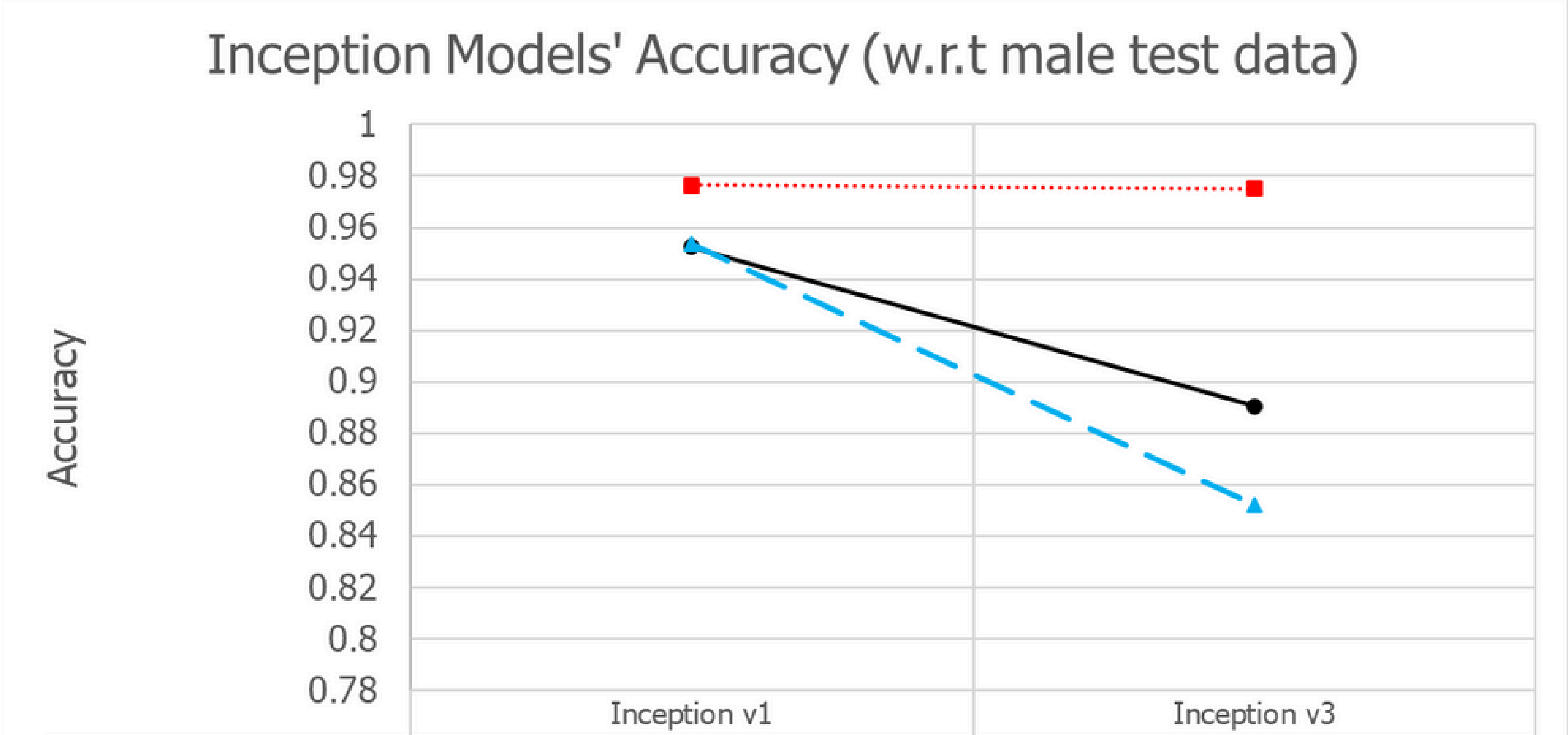
	ResNet18	ResNet34	ResNet50	ResNet101
Base	0.9535	0.9465	0.9125	0.8805
Pretrained	0.973	0.9745	0.9765	0.9755
Multi Class Criterion	0.932	0.9222	0.8965	0.866

Model Variation



	VGG11	VGG13	VGG16	VGG19
Base	0.952	0.951	0.95	0.939
Pretrained	0.9715	0.973	0.973	0.9785
Multi Class Criterion	0.9355	0.896	0.946	0.926

Model Variation

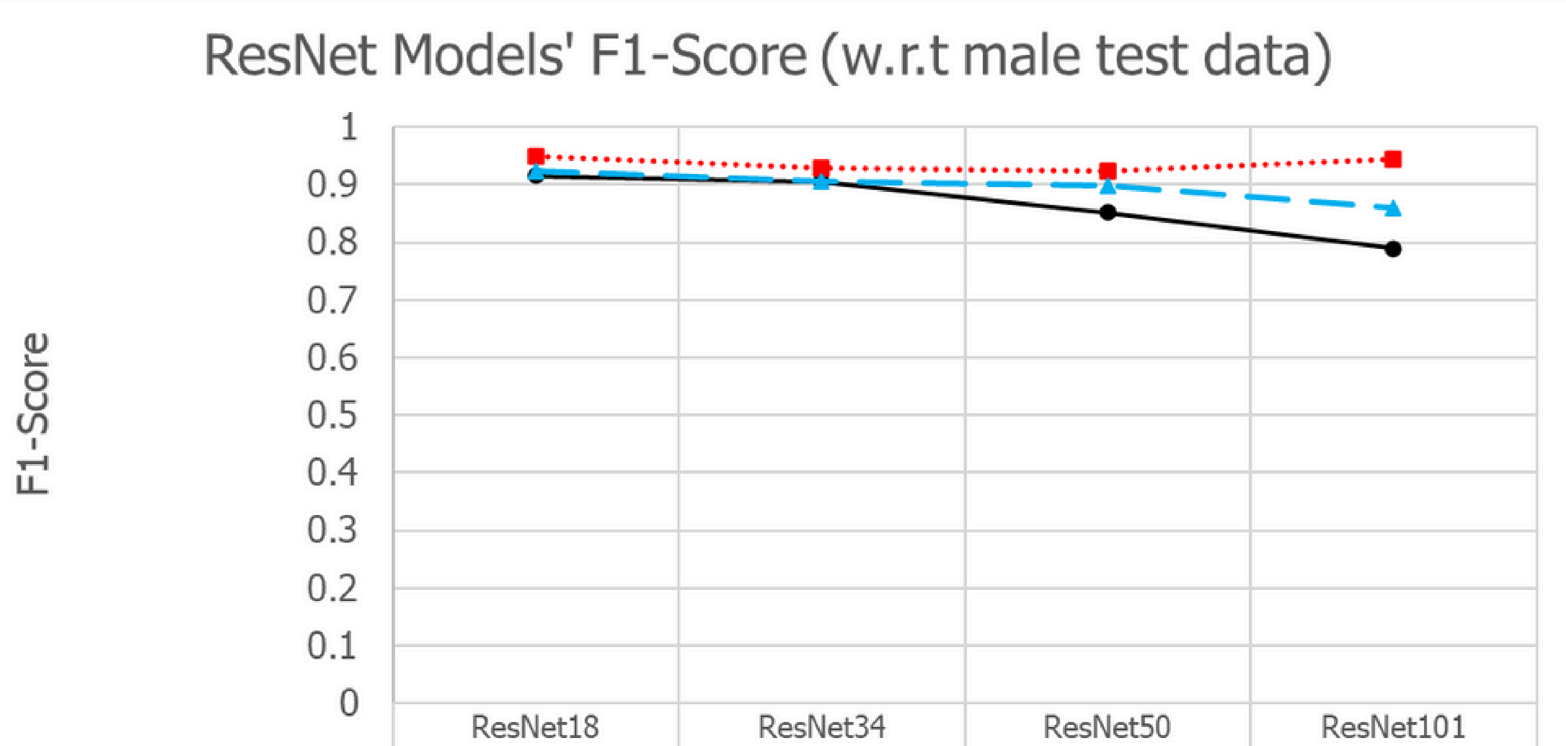


	Inception v1	Inception v3
Base	0.9525	0.8905
Pretrained	0.9765	0.975
Multi Class Criterion	0.9535	0.852

Model Variation

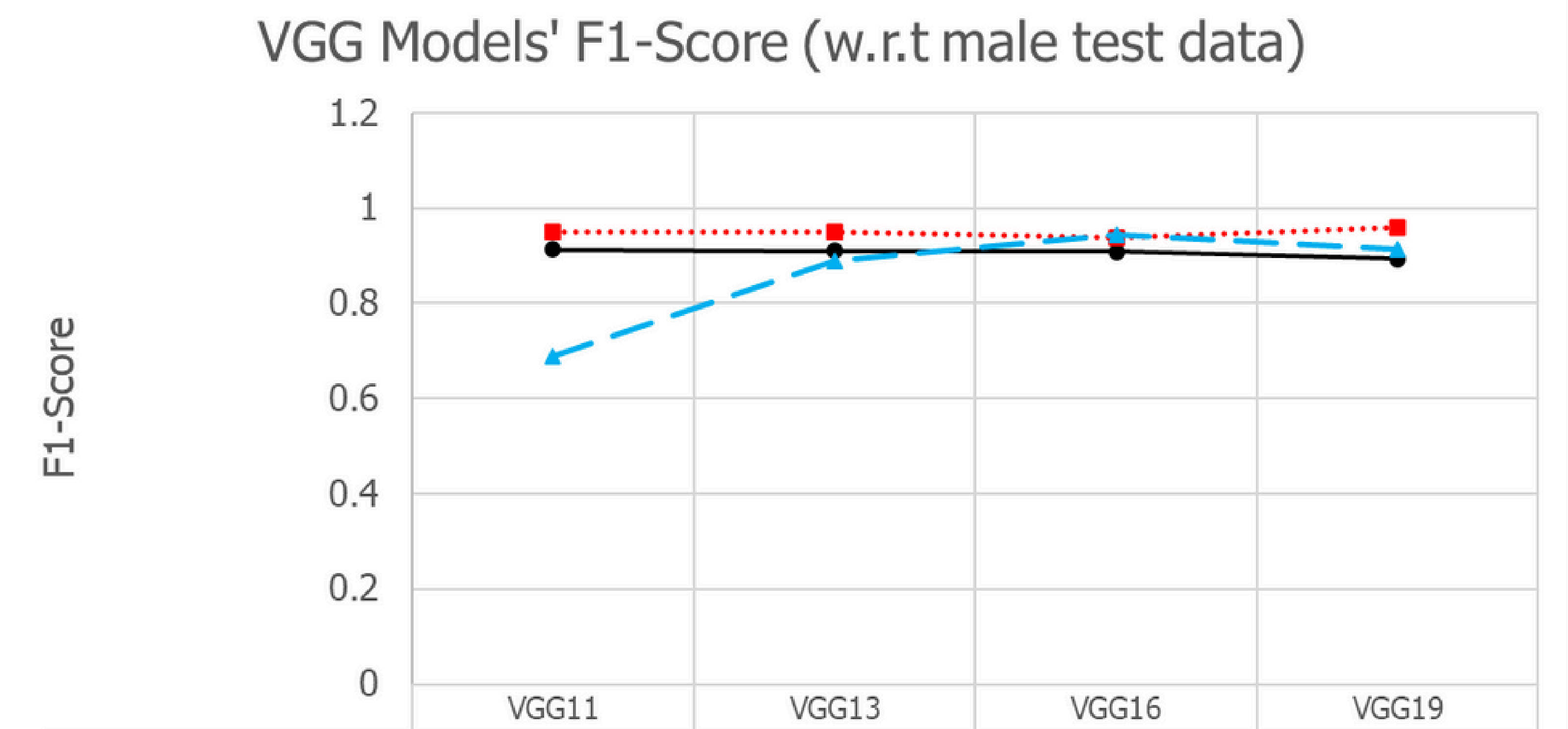
Results

F1-Score



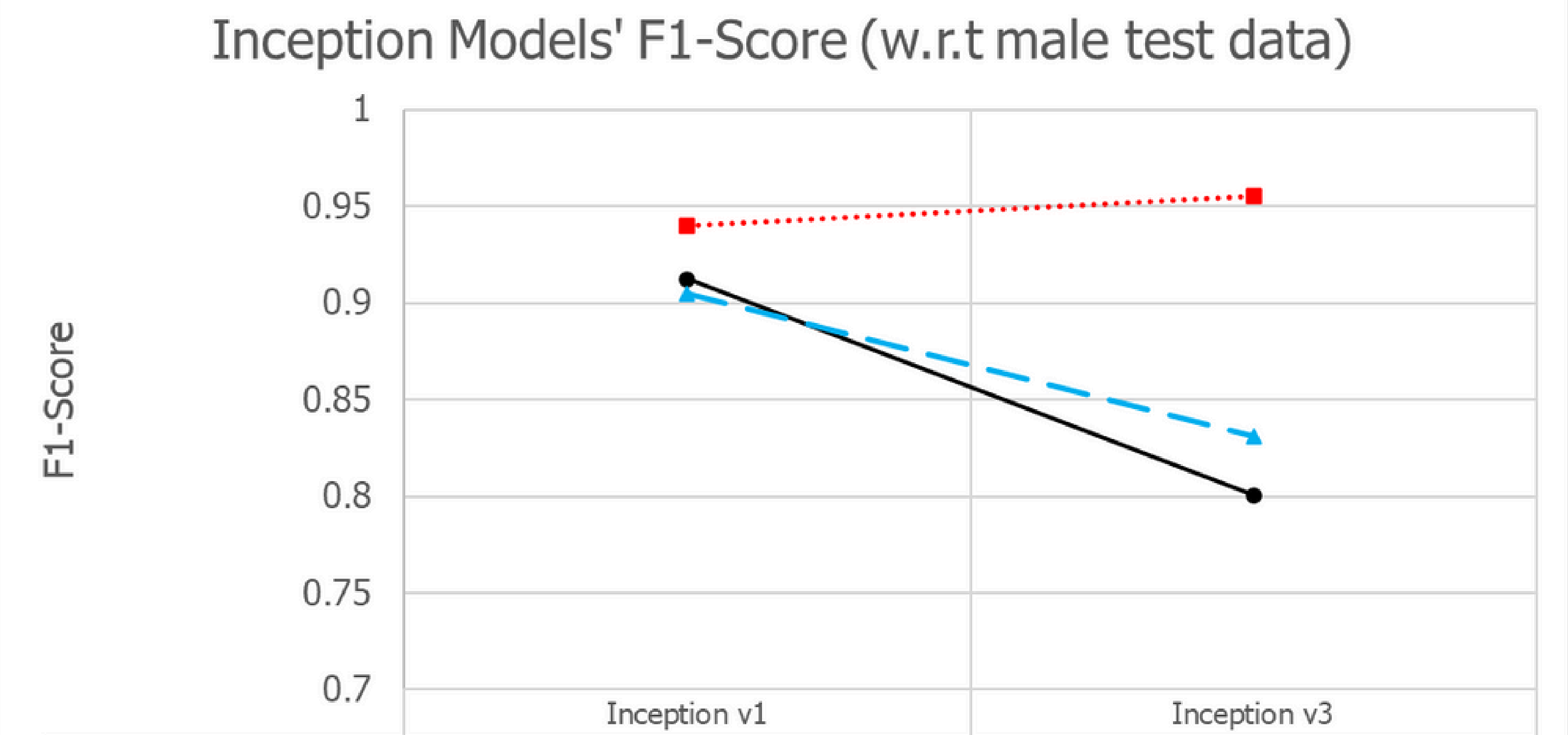
	ResNet18	ResNet34	ResNet50	ResNet101
Base	0.9157	0.9051	0.8523	0.7894
Pretrained	0.9502	0.9286	0.9251	0.9433
Multi Class Criterion	0.924	0.905	0.8996	0.8609

Model Variation



	VGG11	VGG13	VGG16	VGG19
Base	0.9134	0.9109	0.9094	0.893
Pretrained	0.9493	0.9516	0.9383	0.9611
Multi Class Criterion	0.6877	0.8897	0.9455	0.9139

Model Variation



	Inception v1	Inception v3
Base	0.9124	0.8007
Pretrained	0.9396	0.9553
Multi Class Criterion	0.9044	0.8311

Model Variation

Validation

	1	2	3	4	5
Female					
Male					

Validation Results

Highest Accuracy Pretrained Models

ResNet-50	1	2	3	4	5
Female	0	0	0	0	0
Male	0	0	1	1	1
Inference time (s/image)	0.1402539				

VGG-19	1	2	3	4	5
Female	0	0	0	0	0
Male	1	1	1	1	1
Inference time (s/image)	0.1037431				

Inception V1	1	2	3	4	5
Female	1	1	1	1	1
Male	1	1	1	1	1
Inference time (s/image)	0.0707185				

Validation Results

Highest F1-Score Pretrained Models

ResNet-18	1	2	3	4	5
Female	0	1	0	1	1
Male	1	1	1	1	1
Inference time (s/image)	0.1156472				

VGG-19	1	2	3	4	5
Female	0	0	0	0	0
Male	1	1	1	1	1
Inference time (s/image)	0.1037431				

Inception V3	1	2	3	4	5
Female	1	1	1	0	0
Male	1	0	0	1	1
Inference time (s/image)	0.1355324				

Validation Results

Highest Accuracy and F1-Score Non-Pretrained Models

ResNet-18	1	2	3	4	5
Female	0	0	0	0	0
Male	1	1	1	1	1
Inference time (s/image)	0.0537727				

VGG-11	1	2	3	4	5
Female	0	0	0	0	0
Male	1	1	1	1	1
Inference time (s/image)	0.0190841				

Inception V1	1	2	3	4	5
Female	0	0	0	0	0
Male	1	1	1	1	1
Inference time (s/image)	0.0398222				

Conclusion:

- CNN models that can classify gender based on images of human faces were successfully obtained.
- Comparing the classification performance of 3 different CNN models (VGG, ResNet, and GoogLeNet) in our testing reveals in general:
  - more **complex models** will have **increased training time**.
  - **ResNet and Inception** models have **relatively faster training time** compared to VGG models.
  - **Models** with initial **pretrained** weights yield **test results** with **higher and more consistent accuracy and F1-score** compared to those without.
  - For **binary classification**, it is better to just **use binary loss criterion** than multiclass loss criterion.
  - From **validation**, despite having lower test accuracy and F1-score, the **non-pretrained models have better prediction** capabilities than pretrained models

Future Works:

- **Expand the hyperparameters** for testing such as number of epochs, optimizers, batch size, etc.
- **Further study on validation tests** as to why higher test accuracy models didn’t guarantee good validation tests.

Thank You

The brain sure as hell doesn't work by somebody programming in rules.
GEOFFREY HINTON

CV-D (Geoffrey Hinton)	
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Calvin Christian Chandra ***(Team Leader)***	*Coding*, pembuatan PPT
Satrio Fatturahman	Coding, pembuatan PPT
Shania Salsabilla	Coding (Pretrain Model, Validation)
Eureka Labdawara	Pembuatan PPT
Alamul Yaqin	Pembuatan PPT