



FPT UNIVERSITY

BACHELOR OF ARTIFICIAL INTELLIGENCE THESIS

FRUIT TYPE AND WEIGHT RECOGNITION FOR PAYMENT PURPOSES USING COMPUTER VISION

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MR. BÙI VĂN HIỆU

- 
- 1 INTRODUCTION
 - 2 BUILDING MODEL
 - 3 IMPLEMENTATION
 - 4 DEMO
 - 5 CONCLUSION

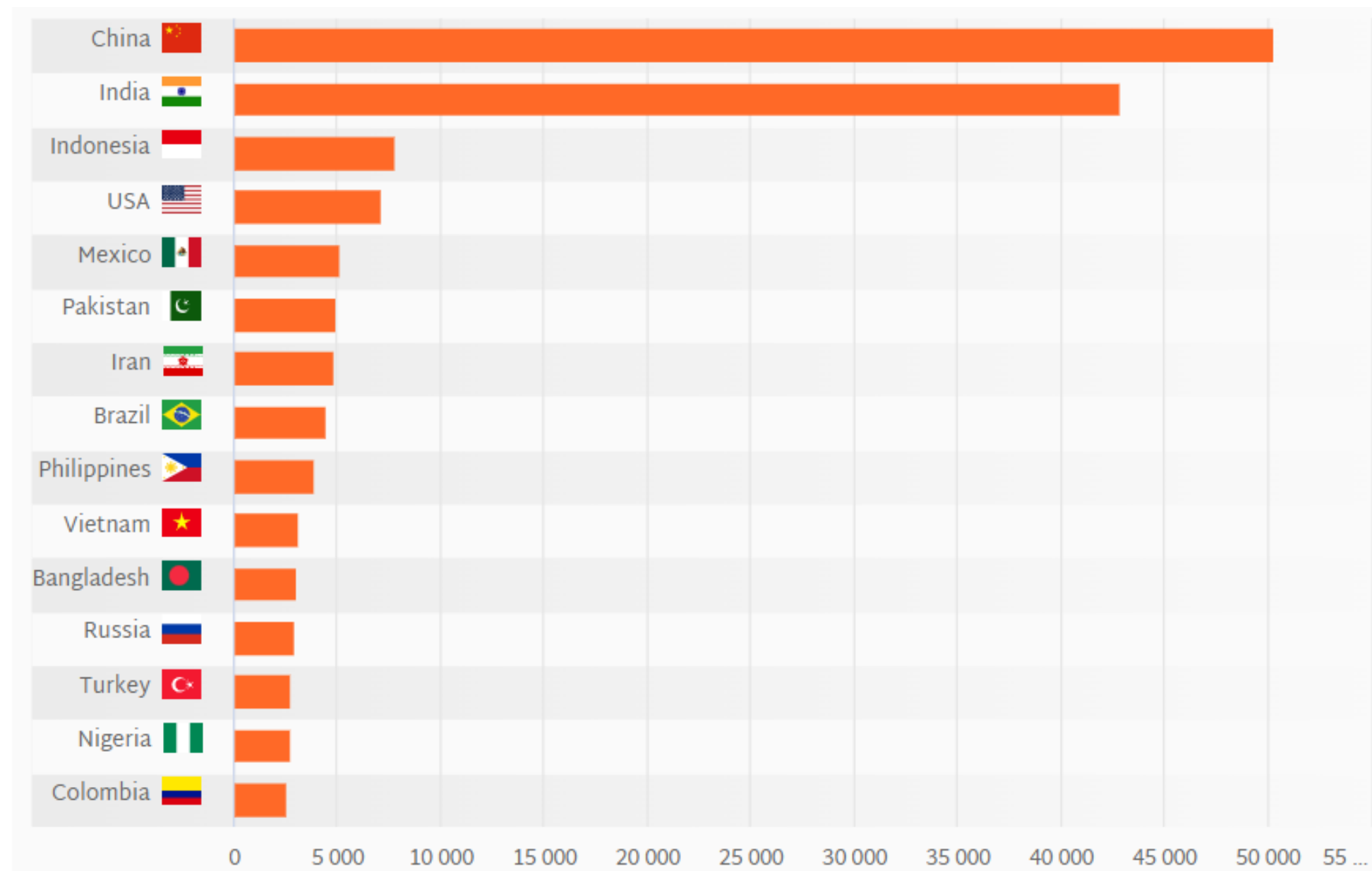


1

INTRODUCTION



WHY CHOOSE THIS WORK?



Current fruit checkout methods

Traditional methods: Fruits are recognized and scaled manually at the time of selling.

- Price is calculated by mental arithmetic or using a calculator.

Disadvantage:

- Take a variety of human efforts to calculate the price
- High risk of making mistakes: miscalculating or recognizing the wrong type of fruit or forgetting unit prices



Current fruit checkout methods

Electronic scale with the printer: Fruits are recognized manually to input code into the scale.

- Price is calculated and shown by scale after inputting code.

Disadvantage:

- Cost the owner time and money
- Chance of workers forgetting the fruit code or misremembering the fruit type
- Take time if having to look up paper



Current fruit checkout methods

Using barcode: The fruit is scaled and labeled before selling.

- Price is shown right after scanning the barcode.

Disadvantage:

Packed Fruits

- Make customers less choice in buying
- Release waste to the environment

Single fruit

- Take a numerous amount of human effort to weigh and add stickers to every fruit
- Can be harmful to human



Challenges

Fruit recognition:

- The fruit has multiple features: shape, size, color, ...
- Some fruits are similar to each other
- Effect of environmental factor



Scale:

- Building a scale that has the ability to connect and give parameters to another device in real-time

2

BUILDING THE MODEL

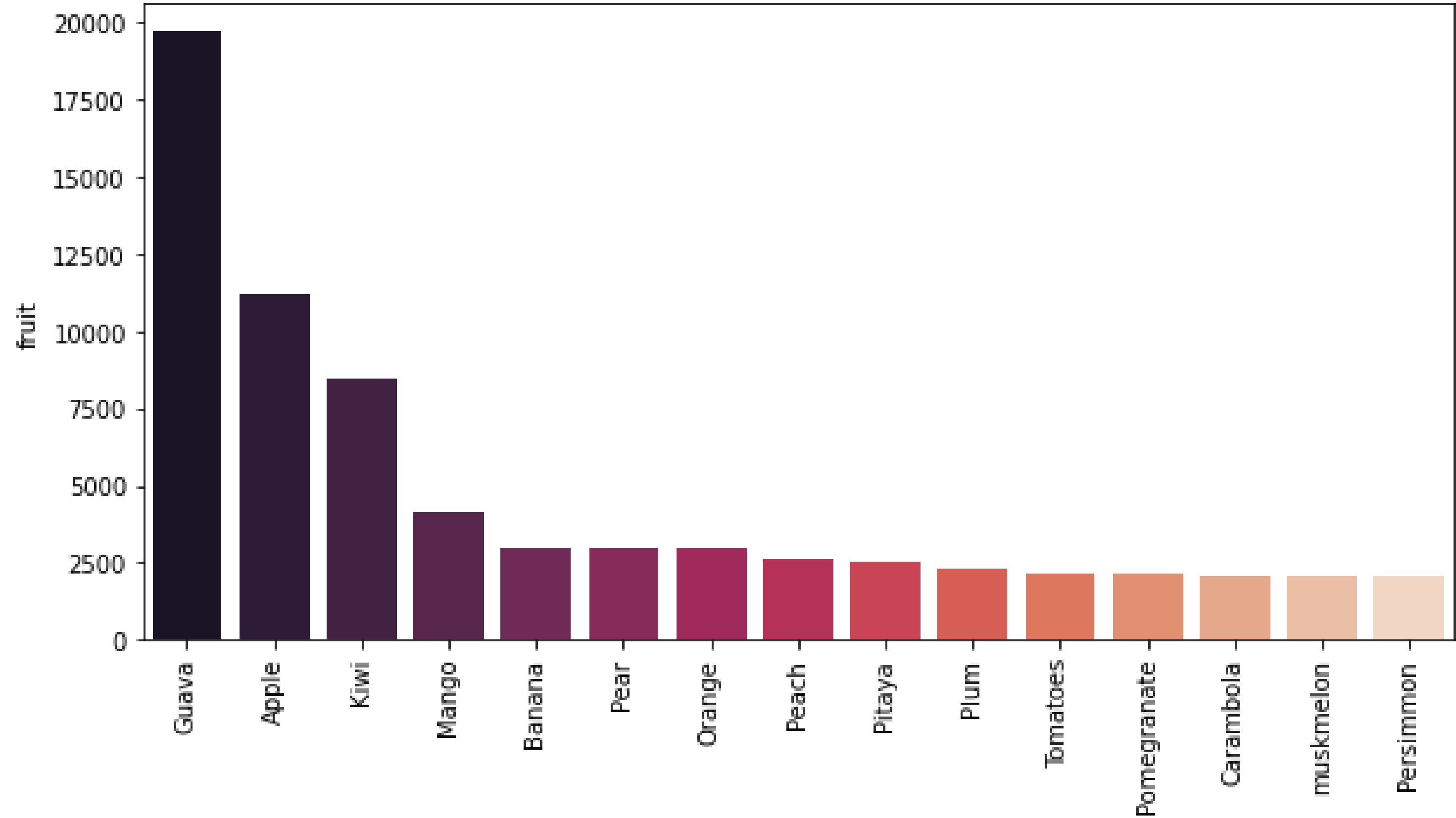


DATA PREPARATION

- CONSISTS OF 44406 IMAGES
- 15 KINDS OF FRUITS
- VARIOUS CONDITIONS LIKE POSES, ANGLES, LIGHTNING OR SHADOWS



Number of pictures of each category



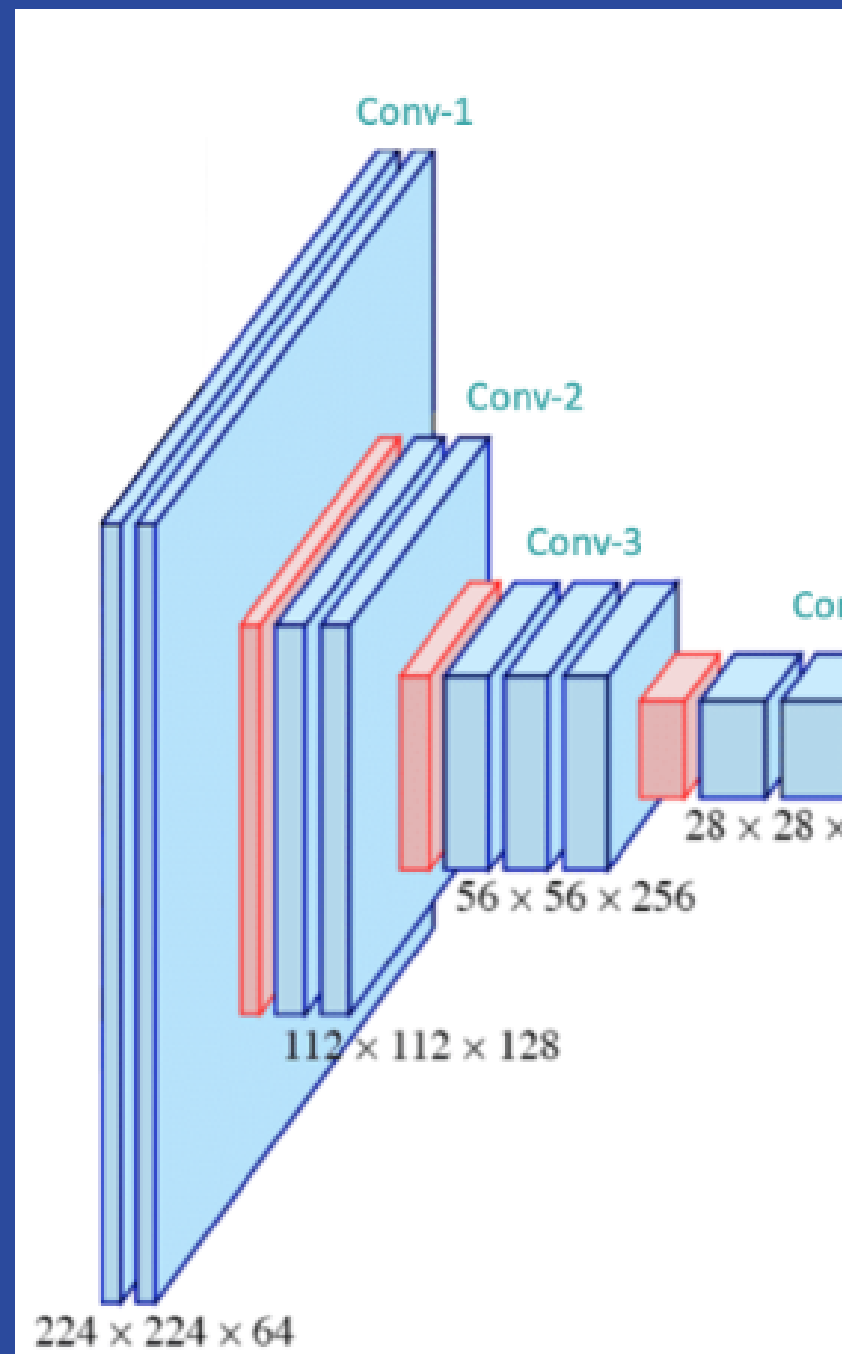
Apple Fruits

Fruit Name	Images				
Apple A	957				
Apple B	740				
Apple C	870				
Apple D	1033				
Apple E	664				
Apple F	1338				

WHY USE A CNN?

EFFICIENCY

- EXTRACTED THE MOST CORE FEATURES
- HIGH ACCURACY RATE
- ROBUST TO NOISE



EASE OF USE

- AUTOMATED, REQUIRED LITTLE HUMAN SUPERVISE
- SUITABLE FOR TRANSFER LEARNING



A BASIC CNN



What We See



08 02 22 97 98 15 00 40 00 75 04 05 07 78 52 12 50 77 91 08
49 49 99 40 17 81 18 57 40 87 17 40 98 43 49 48 04 54 42 00
81 49 31 73 55 79 14 29 93 71 40 47 53 88 30 03 49 13 34 45
52 70 95 23 04 40 11 42 89 24 88 54 01 32 54 71 37 02 34 91
22 31 14 71 51 47 43 89 41 92 34 54 22 40 40 28 44 33 13 80
24 47 32 40 99 03 45 02 44 75 33 53 78 34 84 20 35 17 12 50
32 98 81 28 44 23 47 10 24 38 40 47 59 34 70 44 18 38 44 70
47 24 20 48 02 42 12 20 95 43 94 39 43 08 40 91 44 49 94 21
24 55 58 05 44 73 99 24 97 17 78 78 94 83 14 88 34 89 43 72
21 34 23 09 75 00 74 44 20 43 35 14 00 41 33 97 34 31 33 95
78 17 53 28 22 75 31 47 15 94 03 80 04 42 14 14 09 53 54 92
14 39 05 42 94 35 31 47 55 58 88 24 00 17 54 24 34 29 85 57
84 54 00 48 35 71 89 07 05 44 44 37 44 40 21 58 51 54 17 58
19 80 81 48 05 94 47 49 28 73 92 13 84 52 17 77 04 89 55 40
04 52 08 83 97 35 99 14 07 97 57 32 14 24 24 79 33 27 98 44
88 34 48 87 57 42 20 72 03 44 33 47 44 55 12 32 43 93 53 49
04 42 14 73 38 25 39 11 24 94 72 18 08 44 29 32 40 42 74 34
20 49 34 41 72 30 23 88 34 42 99 49 82 47 59 85 74 04 34 14
20 73 35 29 78 31 90 01 74 31 49 71 48 84 81 14 23 57 05 54
01 70 54 71 83 51 54 49 14 92 33 48 41 43 52 01 89 19 47 48

What Computers See

A BASIC CNN



What We See

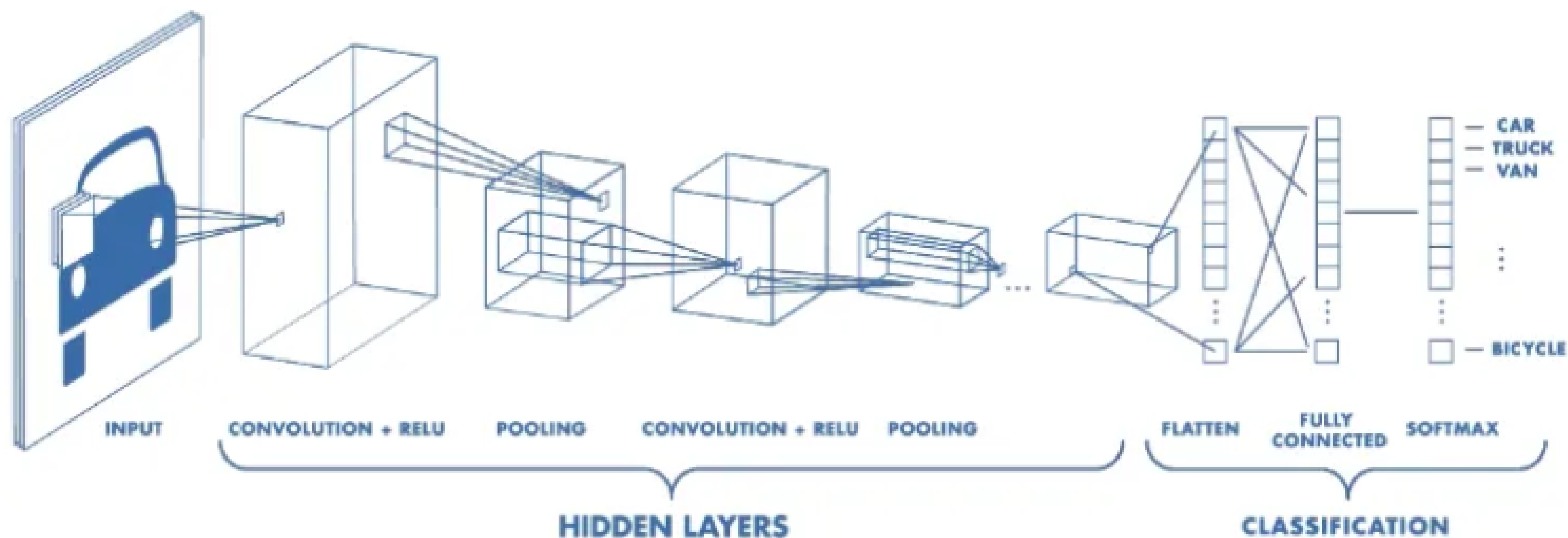


08 02 22 97 98 15 00 40 00 75 04 05 07 78 52 12 50 77 91 08
49 49 99 40 17 81 18 57 40 87 17 40 98 43 49 48 04 54 42 00
81 49 31 73 55 79 14 29 93 71 40 47 53 88 30 03 49 13 34 45
52 70 95 23 04 40 11 42 49 24 48 54 01 32 54 71 37 02 34 91
22 31 14 71 51 47 43 89 41 52 34 54 22 40 40 28 44 33 13 80
24 47 32 40 99 03 45 02 44 75 33 53 78 34 84 20 35 17 12 50
32 98 81 28 44 23 47 10 24 38 40 47 59 34 70 44 18 38 44 70
47 24 20 48 02 42 12 20 95 43 94 39 43 08 40 91 44 49 94 21
24 55 58 05 44 73 99 24 97 17 78 78 94 83 14 88 34 89 43 72
21 34 23 09 75 00 74 44 20 45 35 14 00 41 33 97 34 31 33 95
78 17 53 28 22 75 31 47 15 94 03 80 04 42 14 14 09 53 54 92
14 39 05 42 94 35 31 47 55 58 88 24 00 17 54 24 34 29 85 57
84 54 00 48 35 71 89 07 05 44 44 37 44 40 21 58 51 54 17 58
19 80 81 48 05 94 47 49 28 73 92 13 84 52 17 77 04 89 55 40
04 52 08 83 97 35 99 14 07 97 57 32 14 24 24 79 33 27 98 44
88 34 48 87 57 42 20 72 03 44 33 47 44 55 12 32 43 93 53 49
04 42 14 73 38 25 39 11 24 94 72 18 08 44 29 32 40 42 74 34
20 49 34 41 72 30 23 88 34 42 99 49 82 47 59 85 74 04 34 14
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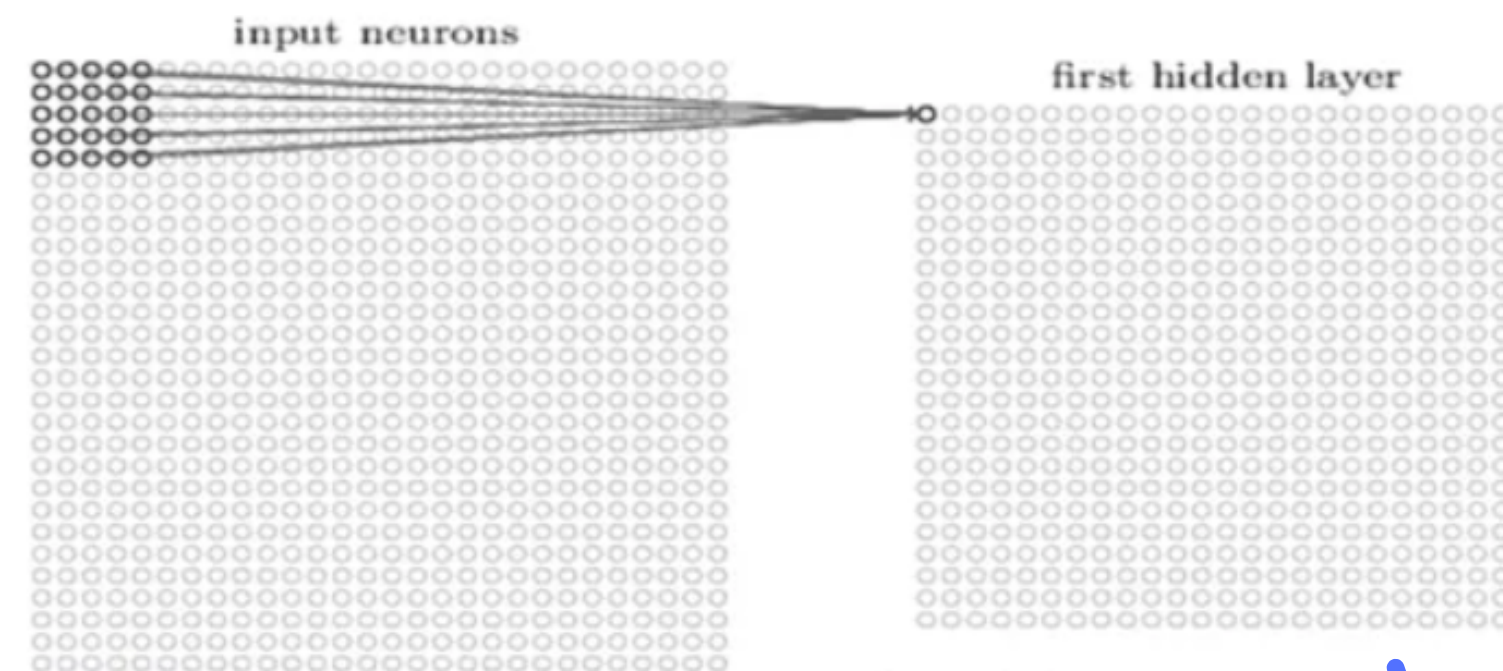
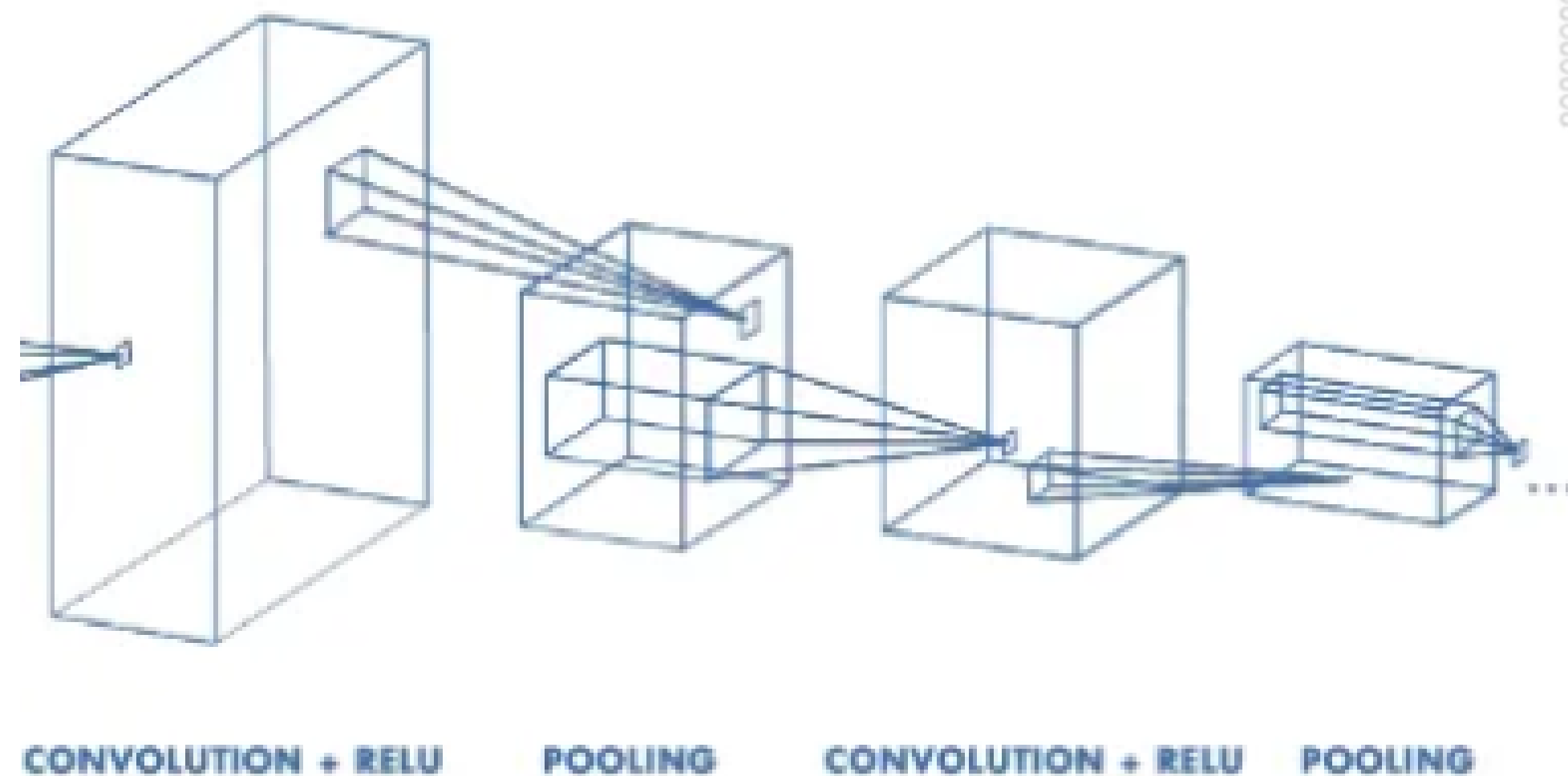
What Computers See

- FOCUS ON RELEVANT HIGH-LEVEL FEATURES.
- USE FILTERS TO SELECT LOW-LEVEL FEATURES LIKE EDGES AND CURVES, FROM THAT DEVELOP TO A MORE SOPHISTICATED DETAILS.

A BASIC CNN



A BASIC CNN



Max Pooling

29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2 x 2 pool size

100	184
12	45

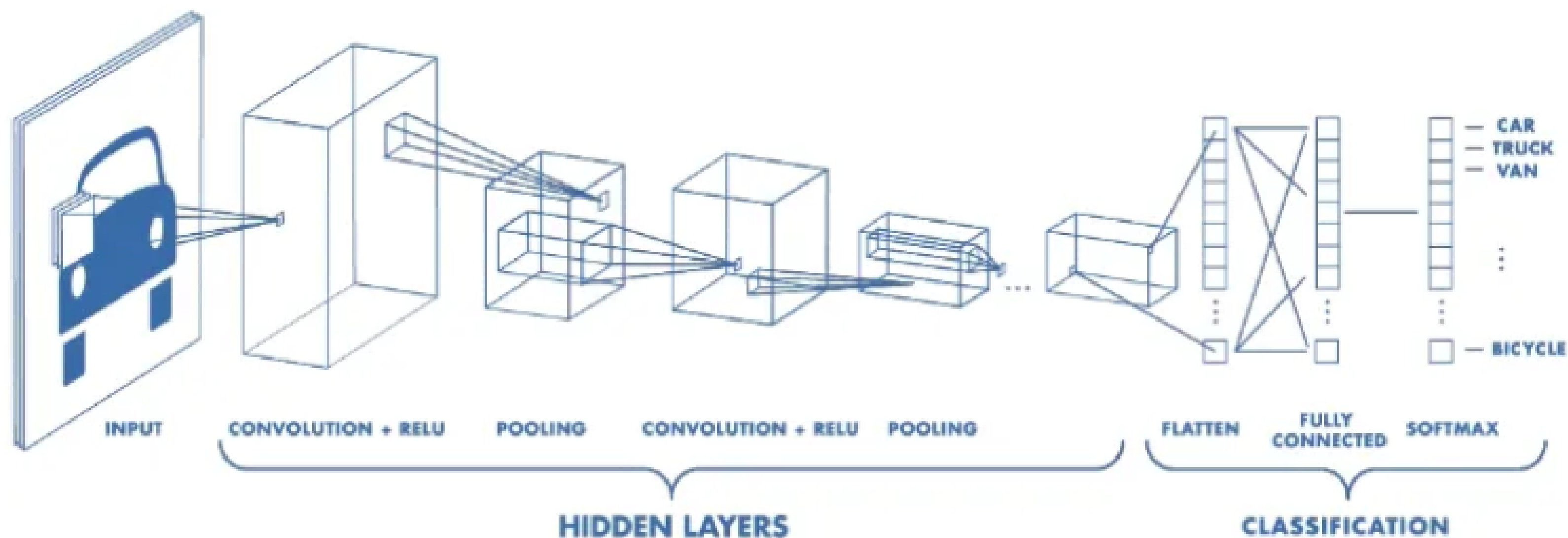
Average Pooling

31	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2 x 2 pool size

36	80
12	15

A BASIC CNN



A BASIC CNN

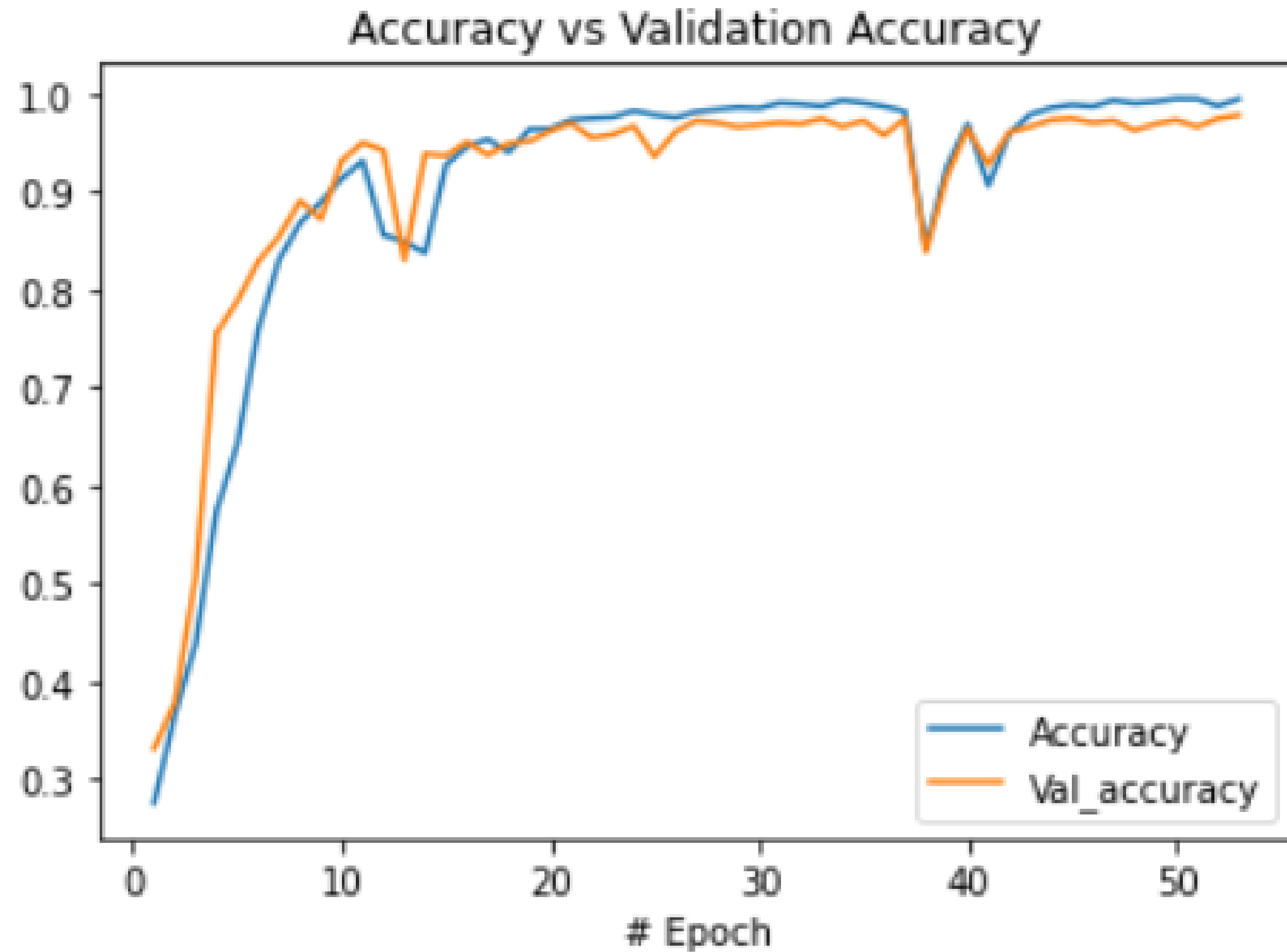
Layer	Details
Input	(150,150,3)
Convolution + Relu	number of filters: 32; kernel: 3x3
Max Pooling	2x2
Convolution + Relu	number of filters: 64; kernel: 3x3
Max Pooling	2x2
Convolution + Relu	number of filters: 64; kernel: 3x3
Max Pooling	2x2
Convolution + Relu	number of filters: 64; kernel: 3x3
Max Pooling	2x2
Convolution + Relu	number of filters: 64; kernel: 3x3
Max Pooling	2x2
Flatten	
Dense layer	size: 256 + reLu
Dense layer	size: 15
Softmax	
Output	

A BASIC CNN

- 6 CONVOLUTION LAYERS DEEP
- USING 1/5 OF DATASETS TO TRAIN
- ABOUT 100 EPOCHS

Layer	Details
Input	(150,150,3)
Convolution + Relu	number of filers: 32; kernel: 3x3
Max Pooling	2x2
Convolution + Relu	number of filers: 64; kernel: 3x3
Max Pooling	2x2
Convolution + Relu	number of filers: 64; kernel: 3x3
Max Pooling	2x2
Convolution + Relu	number of filers: 64; kernel: 3x3
Max Pooling	2x2
Convolution + Relu	number of filers: 64; kernel: 3x3
Max Pooling	2x2
Flatten	
Dense layer	size: 256 + reLu
Dense layer	size: 15
Softmax	
Output	

RESULT OF THE BASIC CNN



Apple	523	0	0	1	0	0	0	12	1	0	1	0	0	5	2
Banana	1	120	0	5	1	0	0	0	1	0	0	0	1	0	0
Carambola	0	0	109	0	0	0	0	0	0	0	0	0	0	0	0
Guava	0	0	0	1026	1	0	0	0	0	0	0	0	0	0	0
Kiwi	0	0	0	0	394	0	0	0	1	0	0	0	0	0	0
Mango	0	1	0	0	0	208	0	0	0	0	0	0	0	0	1
Orange	0	0	0	0	0	0	150	0	0	1	0	0	0	0	0
Peach	1	0	0	0	0	0	0	126	0	0	0	0	0	0	0
Pear	1	0	0	0	0	0	0	1	129	0	0	0	0	0	0
Persimmon	0	0	0	0	0	0	2	0	0	102	0	0	0	0	0
Pitaya	0	0	0	0	0	0	0	1	0	0	130	0	0	0	0
Plum	0	0	0	0	0	0	0	0	0	0	0	107	0	0	0
Pomegranate	0	1	0	0	0	1	0	0	2	0	0	0	125	0	0
Tomatoes	12	0	0	0	0	0	0	0	0	0	0	0	0	117	0
muskmelon	13	0	0	0	0	0	0	0	0	0	0	0	0	0	90
Apple ·	Apple ·	Banana ·	Carambola ·	Guava ·	Kiwi ·	Mango ·	Orange ·	Peach ·	Pear ·	Persimmon ·	Pitaya ·	Plum ·	Pomegranate ·	Tomatoes ·	muskmelon ·

[illegible]

True label: Apple
Predicted label: Apple



True label: Persimmon
Predicted label: Orange



True label: Apple
Predicted label: Apple



True label: Guava
Predicted label: Guava



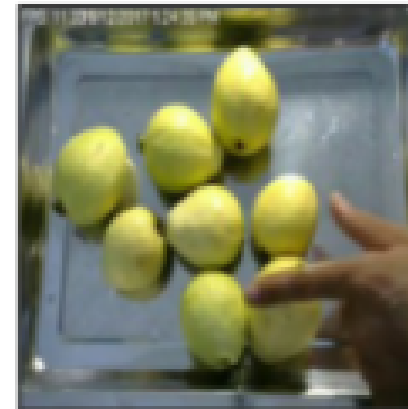
True label: Carambola
Predicted label: Carambola



True label: Plum
Predicted label: Plum



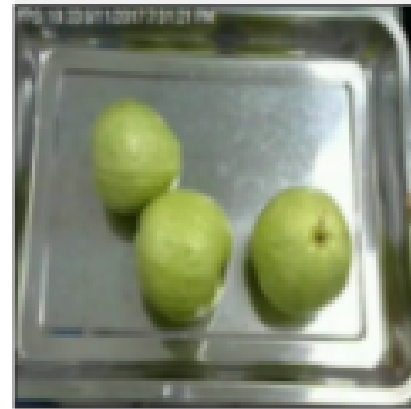
True label: Guava
Predicted label: Guava



True label: Mango
Predicted label: Mango



True label: Guava
Predicted label: Guava



True label: Apple
Predicted label: Apple



True label: Orange
Predicted label: Orange



True label: Orange
Predicted label: Mango



True label: Kiwi
Predicted label: Kiwi



True label: Guava
Predicted label: Guava



True label: Guava
Predicted label: Guava

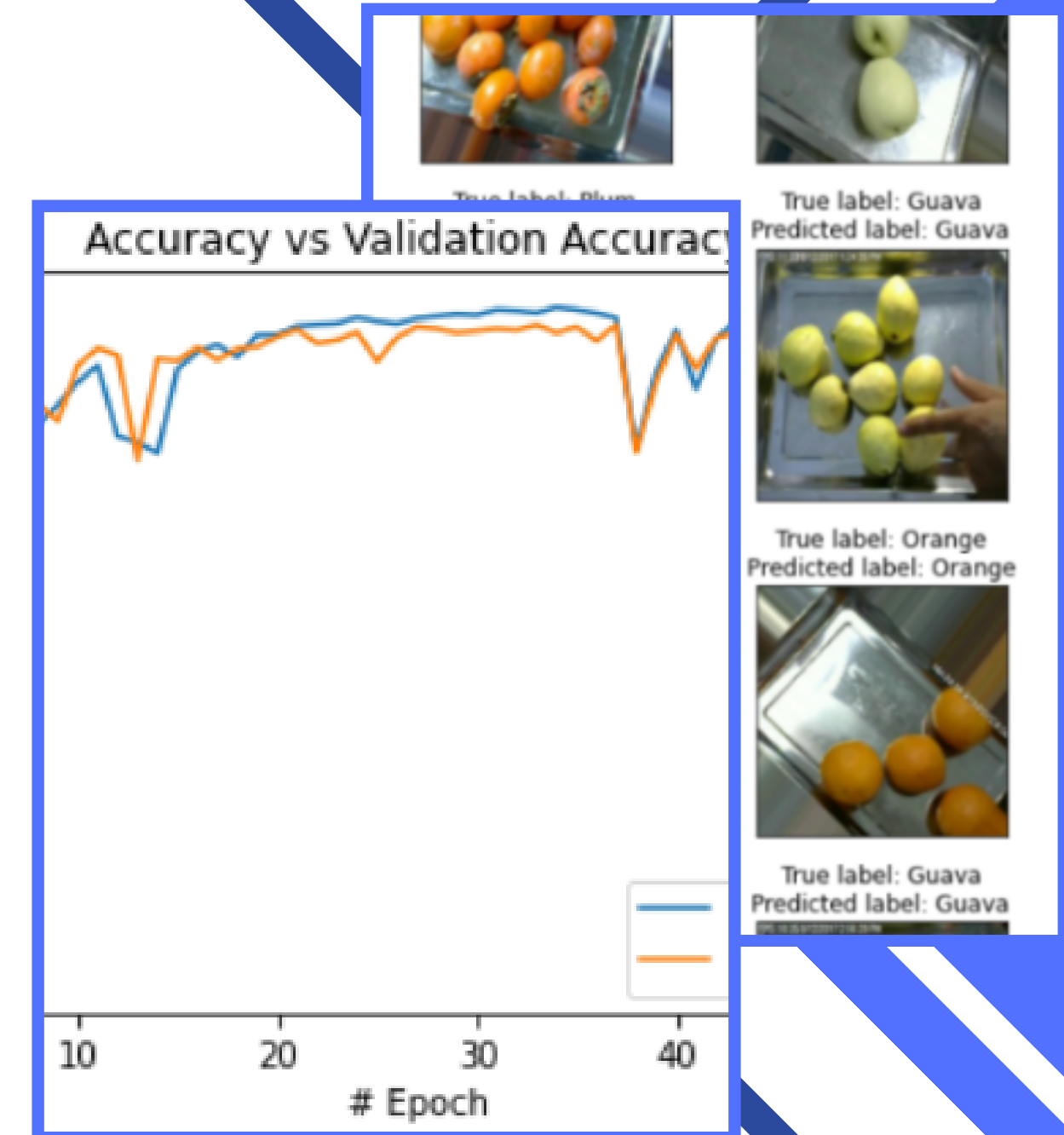


True label: Orange
Predicted label: Apple

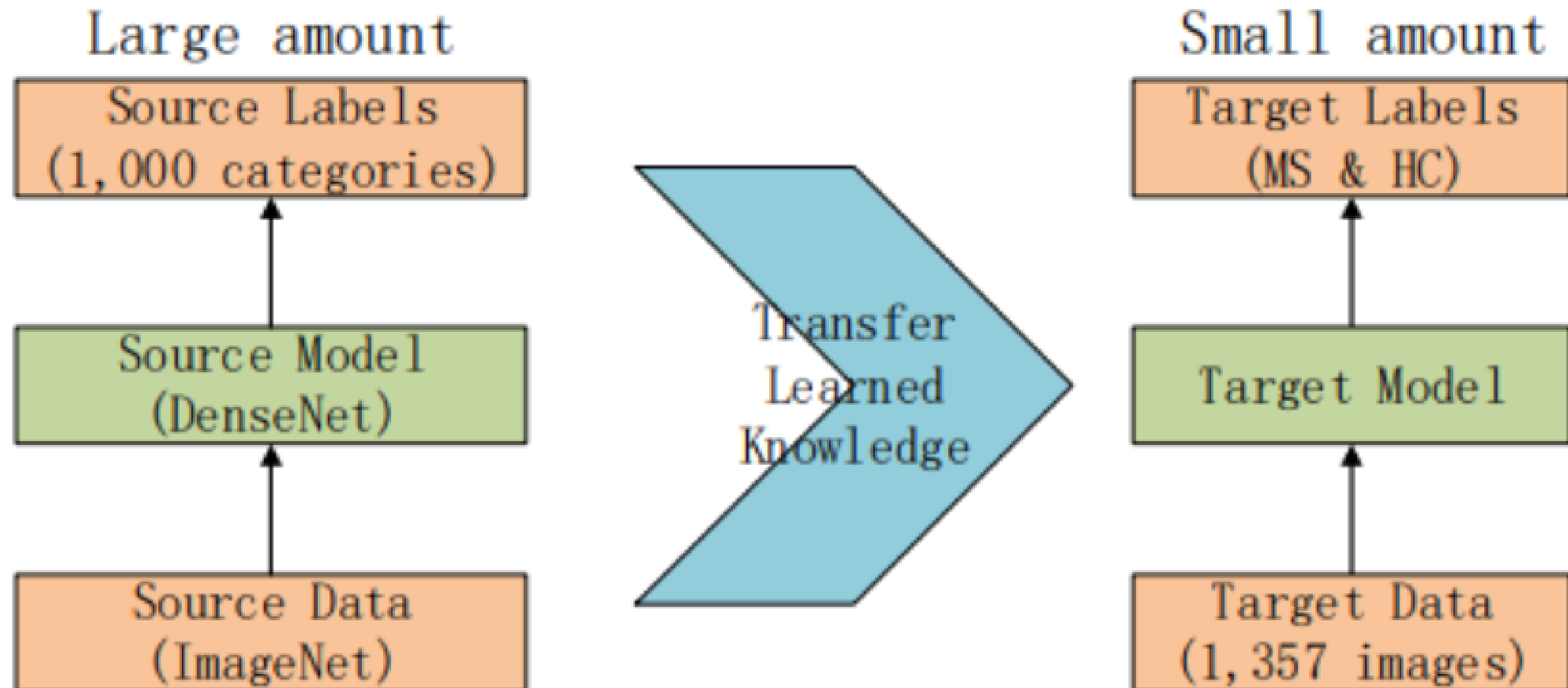


DISCUSSION

- IMPRESSIVE RESULT: 97,6 %
- PERFORMS WELL ENOUGH ON MOST PARTS EVEN WITH ONLY 20% OF THE DATASET
- SEEMS TO BE STRUGGLE TO RECOGNIZE FRUITS WITH SIMILAR SHAPE AND COLOR LIKE ORANGE, APPLE, PERSIMMON OR TOMATO.



TRANSFER LEARNING

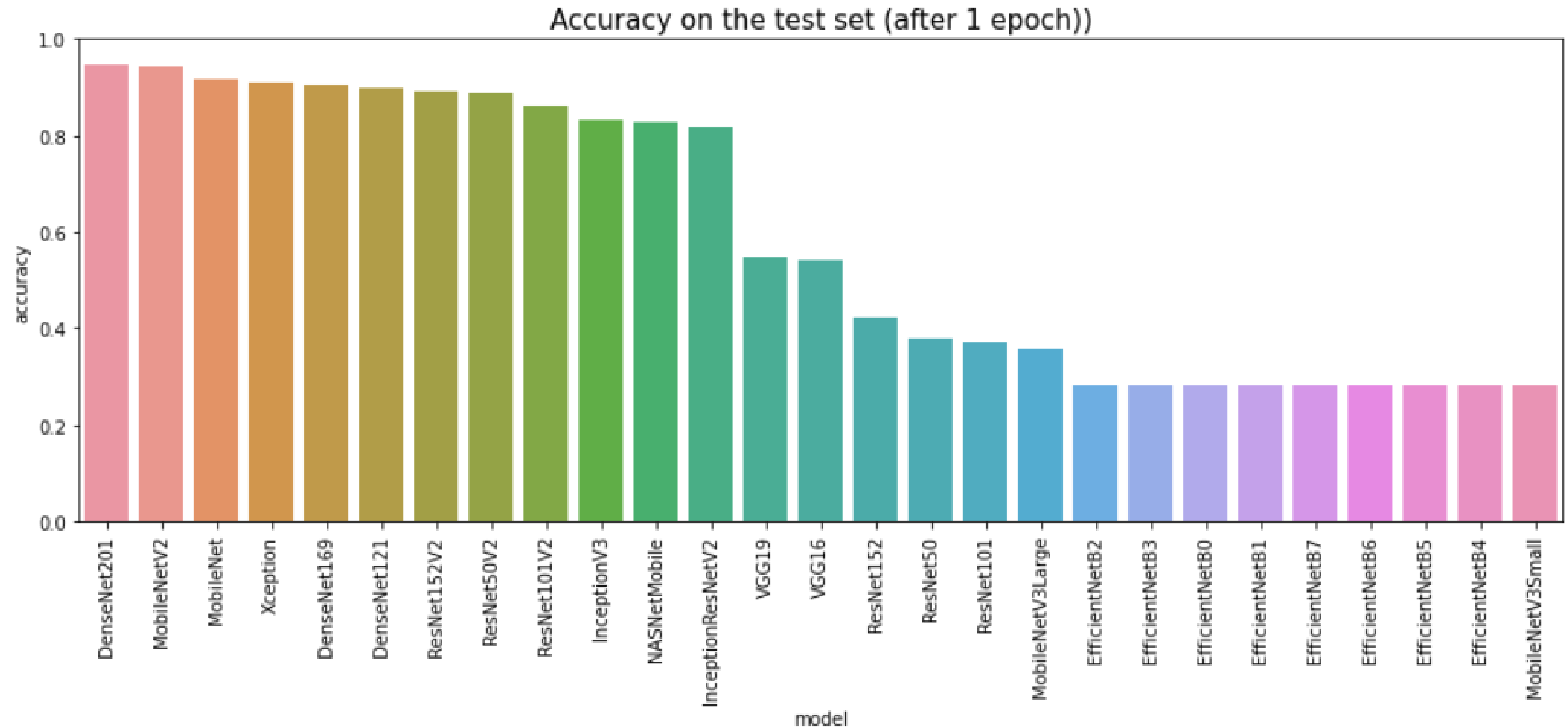


PRETRAINED MODEL

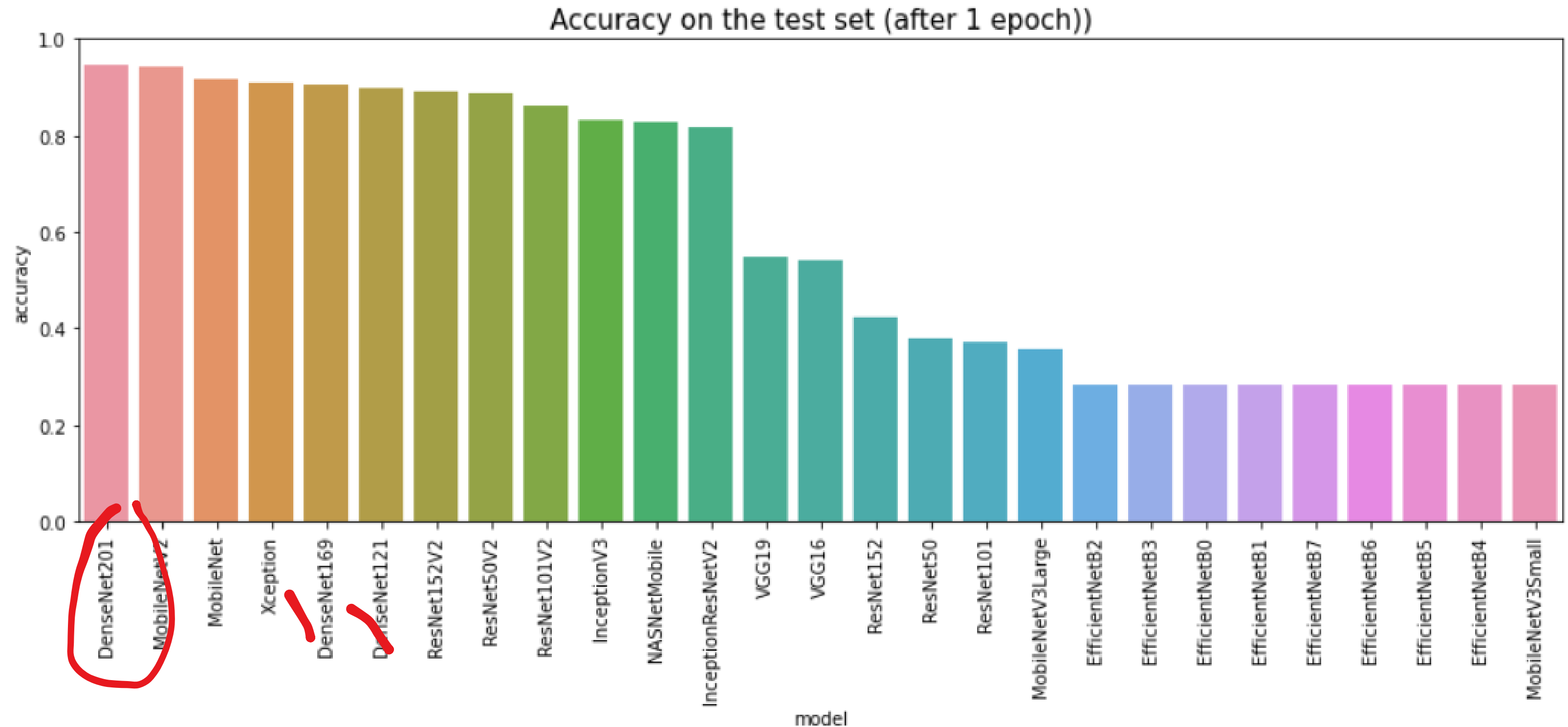
- 27 MODELS AVAILABLE
- USING 1/10 OF THE DATASET
- TRAIN AND TEST THE ACCURACY AFTER 1 EPOCHS



PRETRAINED MODEL

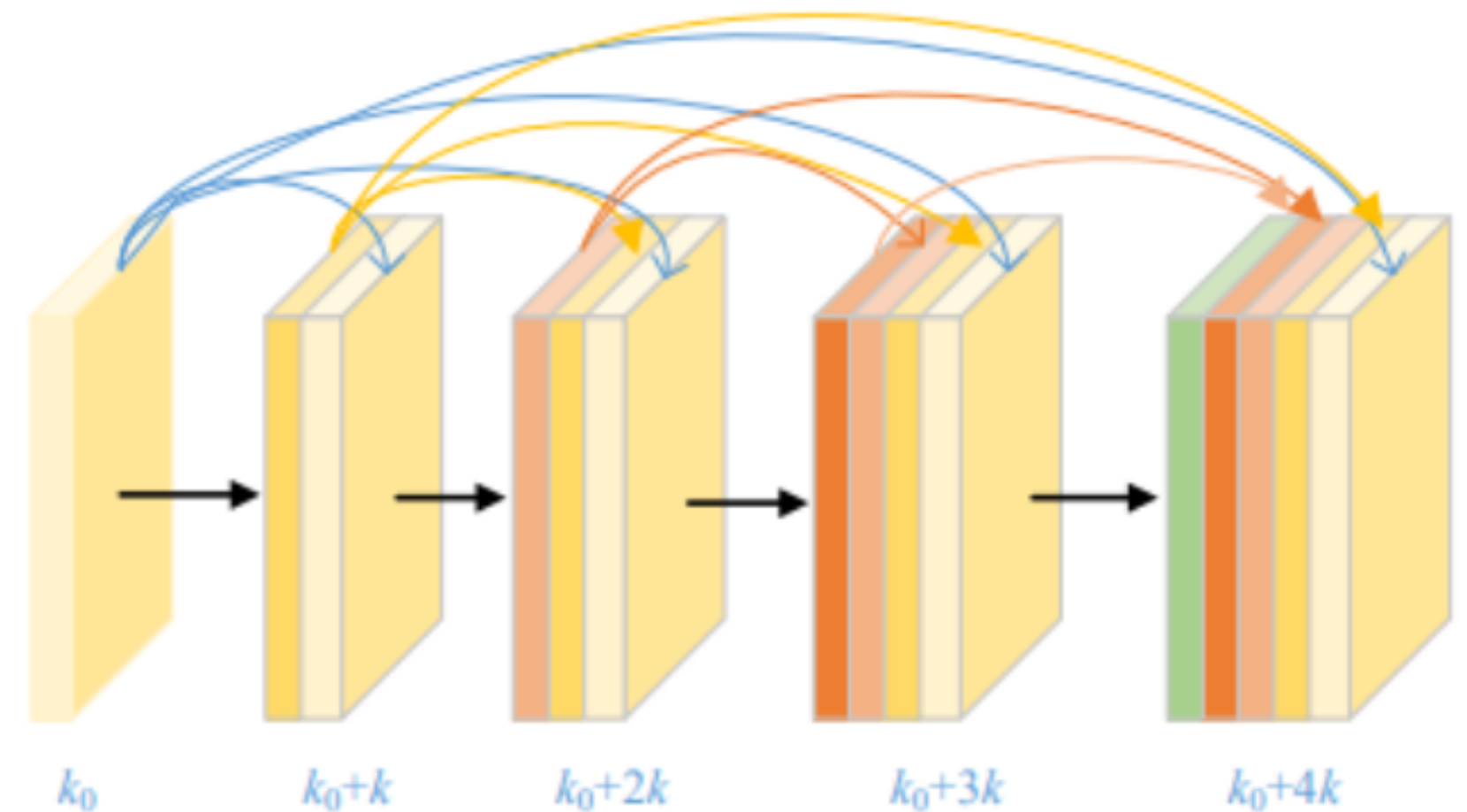


PRETRAINED MODEL

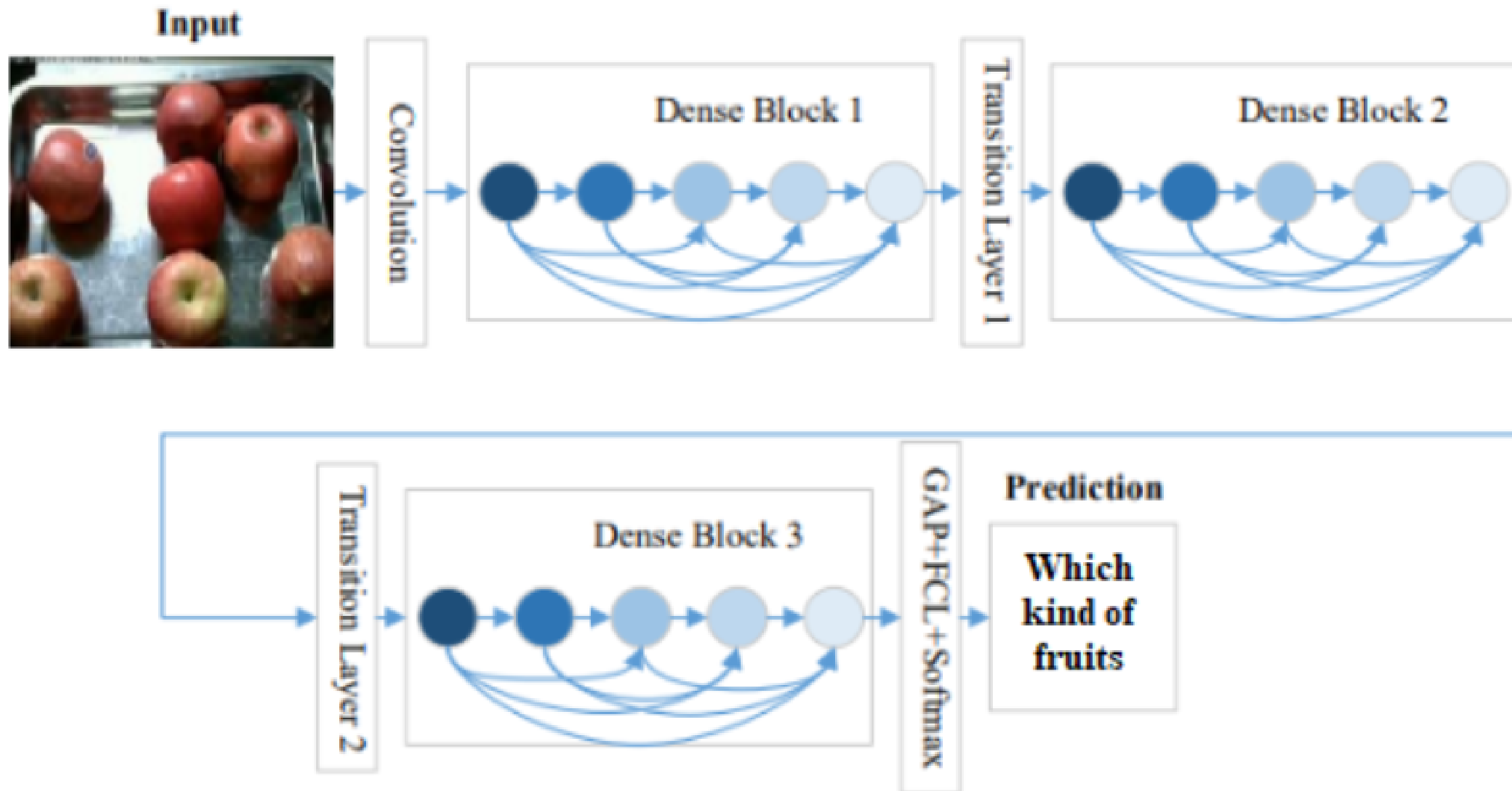


DENSENET

- THE DEFINED FEATURE: THE DENSE BLOCKS.
- CONSISTS OF ALL FEATURE MAPS OF ALL PREVIOUS CONVOLUTIONAL PROCESS

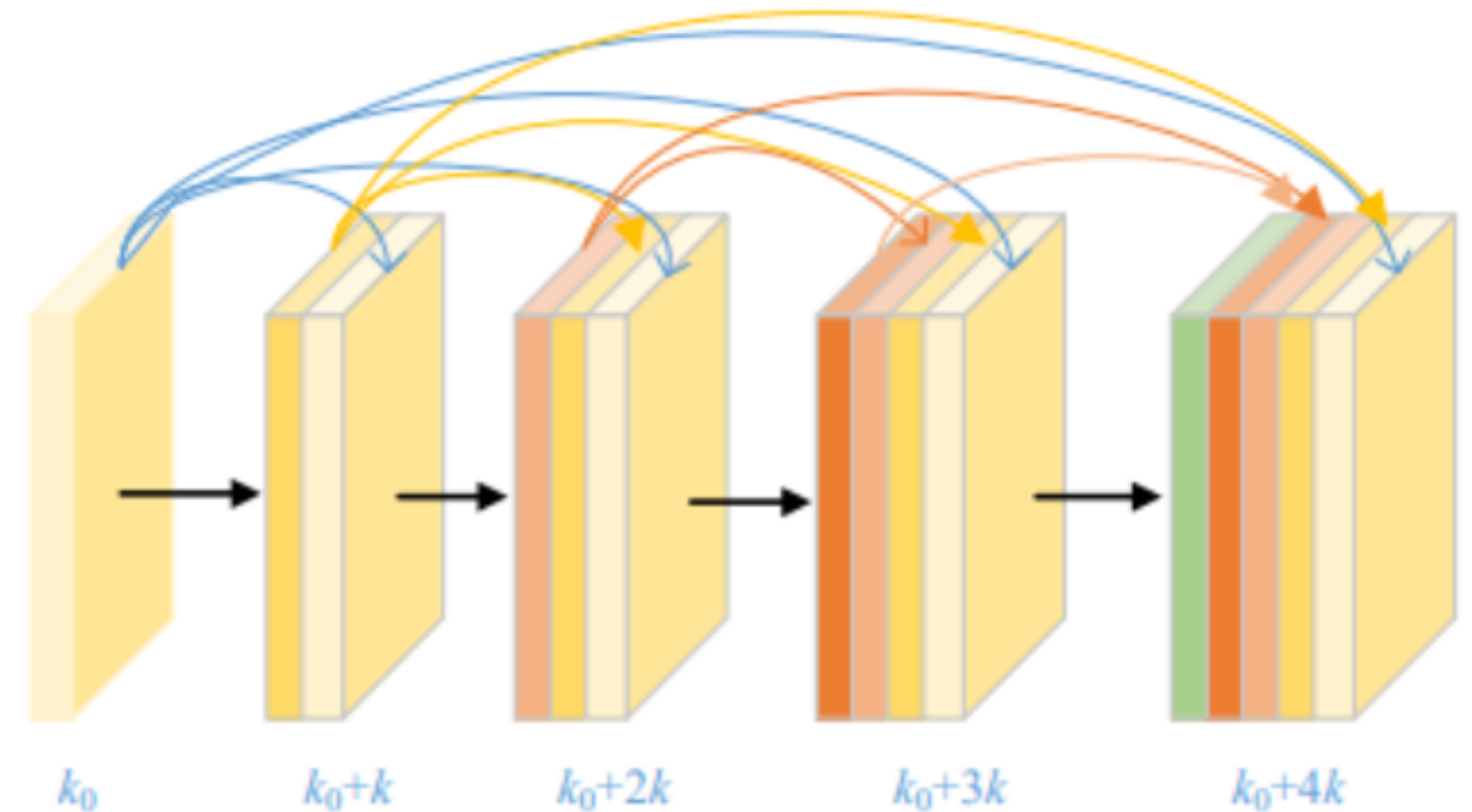


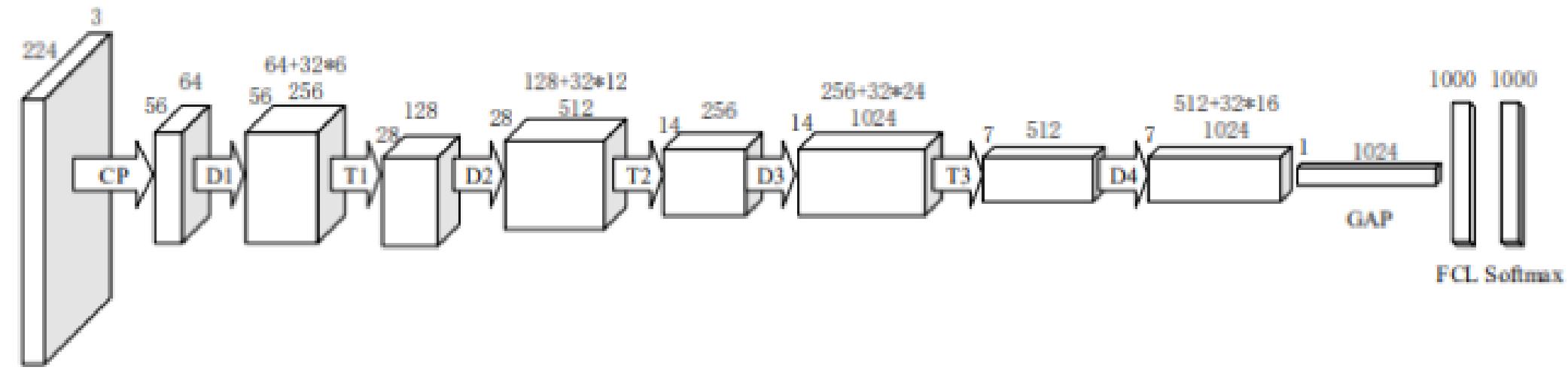
DENSENET



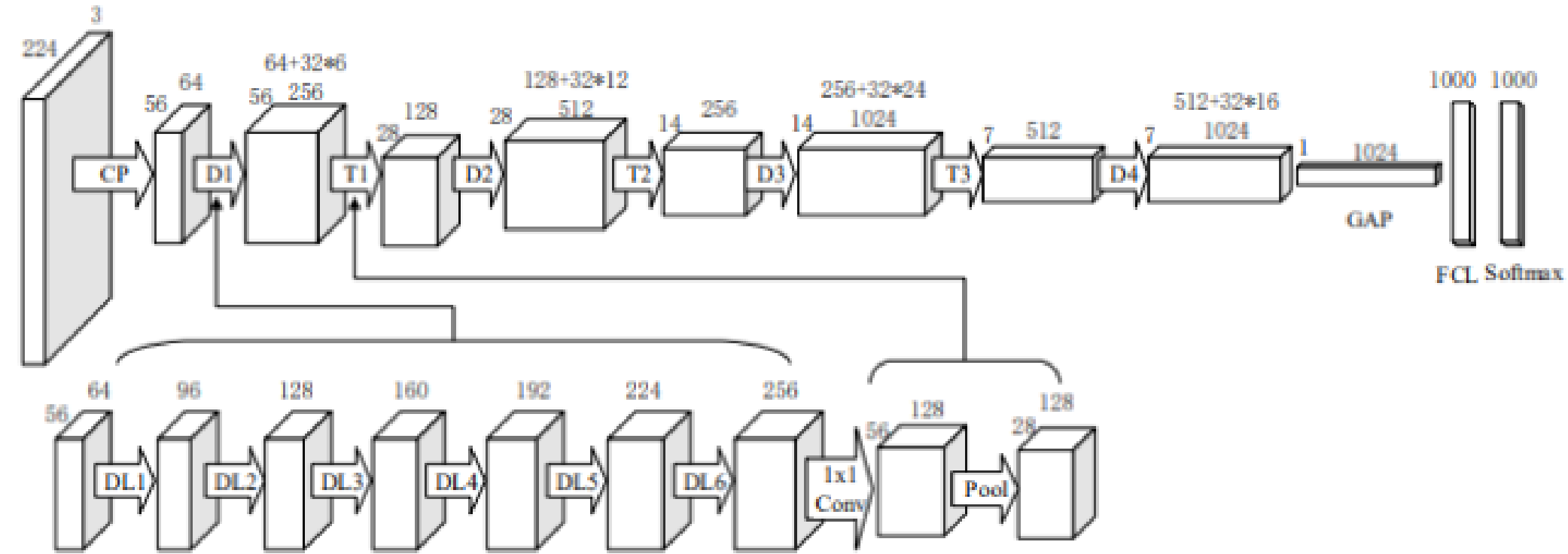
DENSENET

- THE DEFINED FEATURE: THE DENSE BLOCKS.
- CONSISTS OF ALL FEATURE MAPS OF ALL PREVIOUS CONVOLUTIONAL PROCESS
- EXTREME POOLING (1X1) IS NEEDED TO MAKE THE COMPUTATION VIABLE

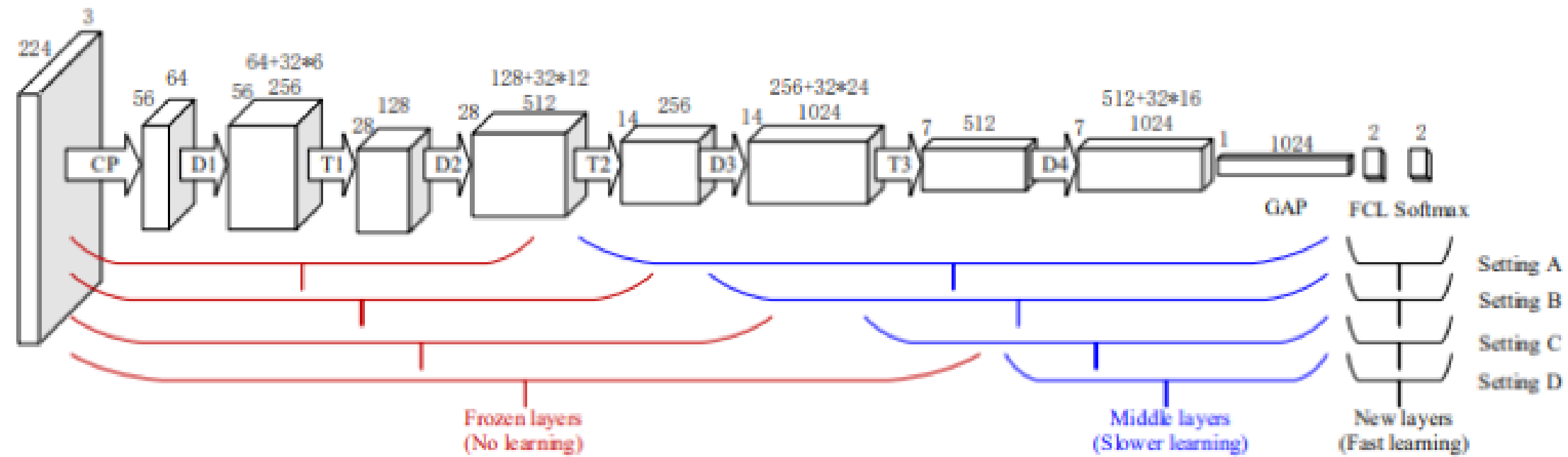




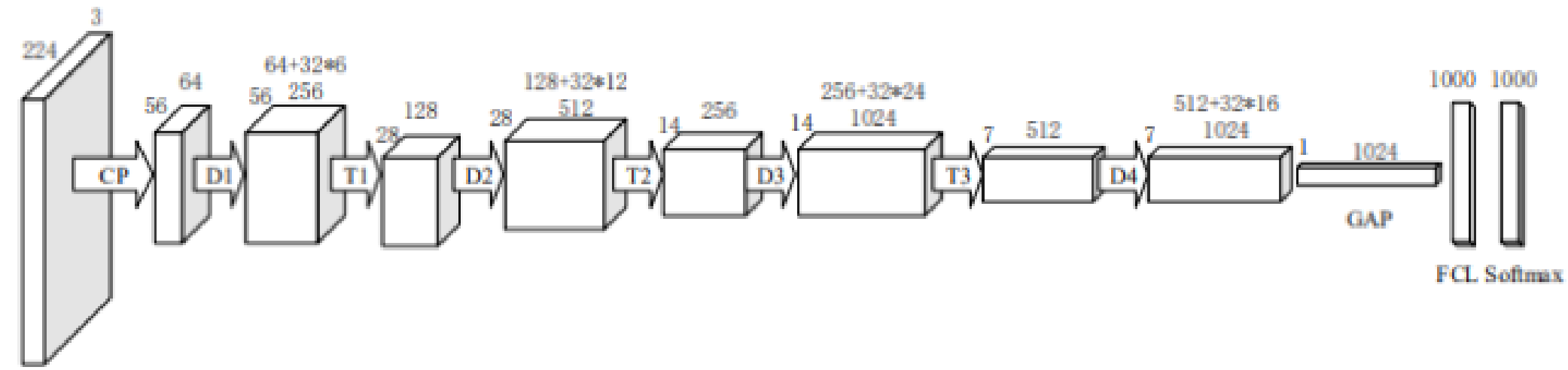
(a) Original pretrained DenseNet-121



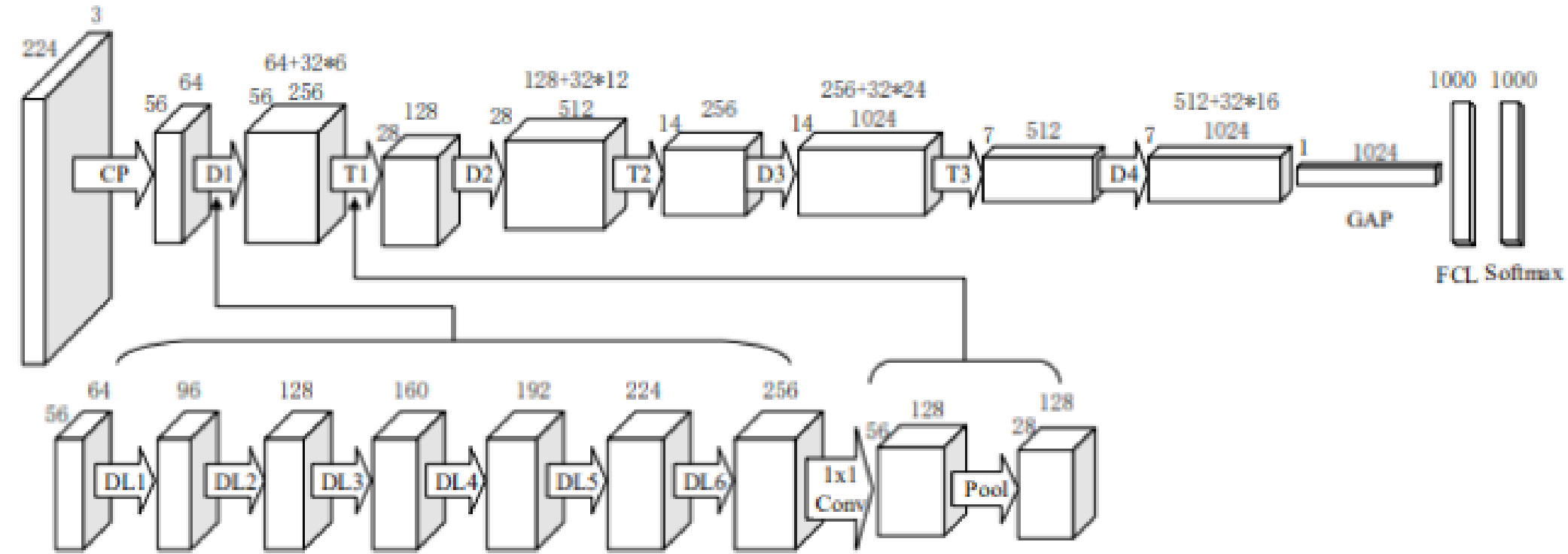
(b) one level deeper view of DenseNet-121



(c) DenseNet-121 transferred to our task

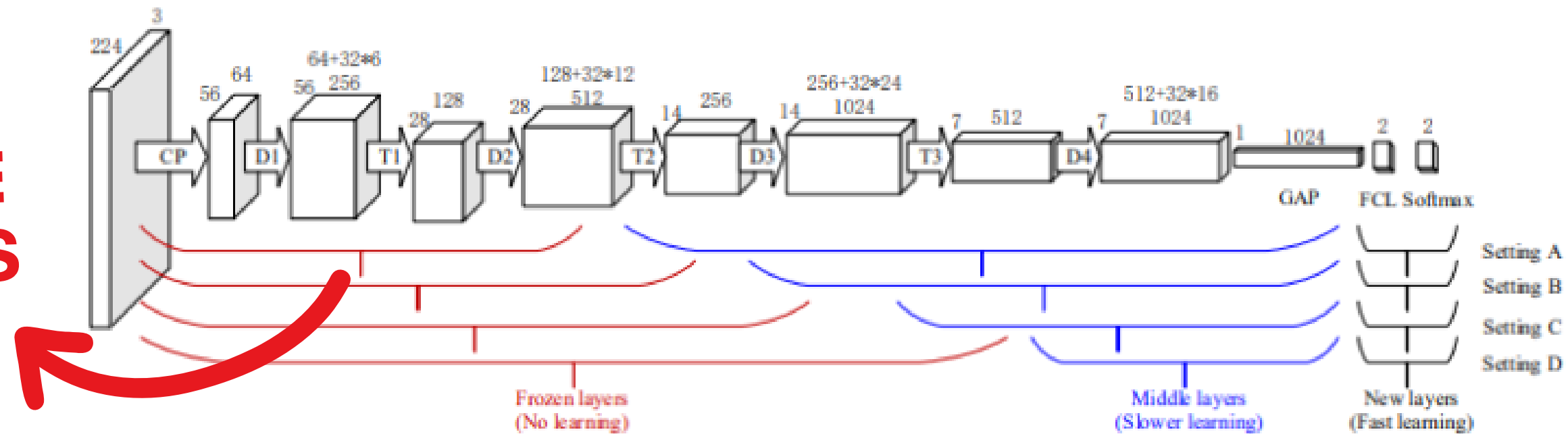


(a) Original pretrained DenseNet-121

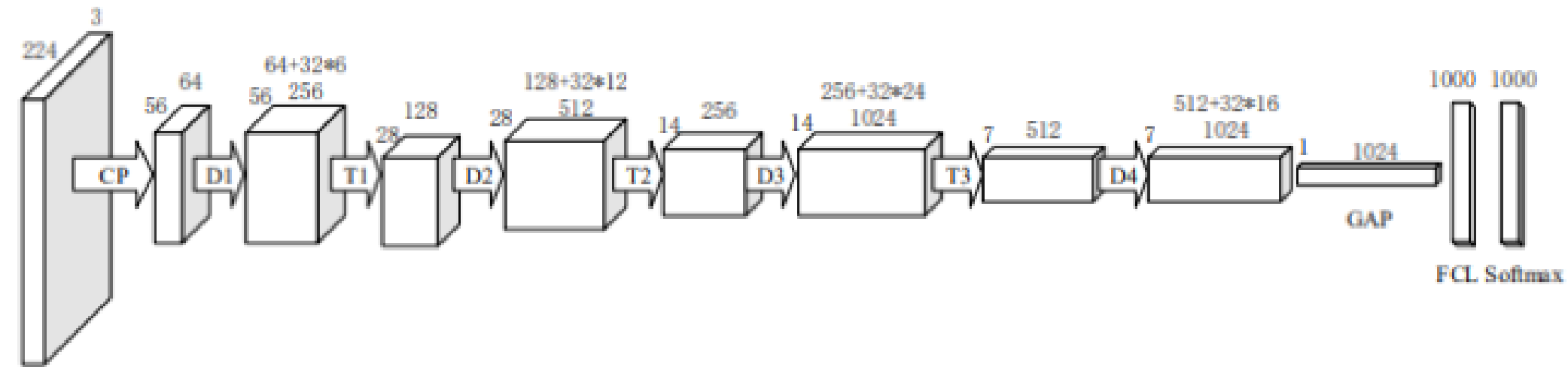


(b) one level deeper view of DenseNet-121

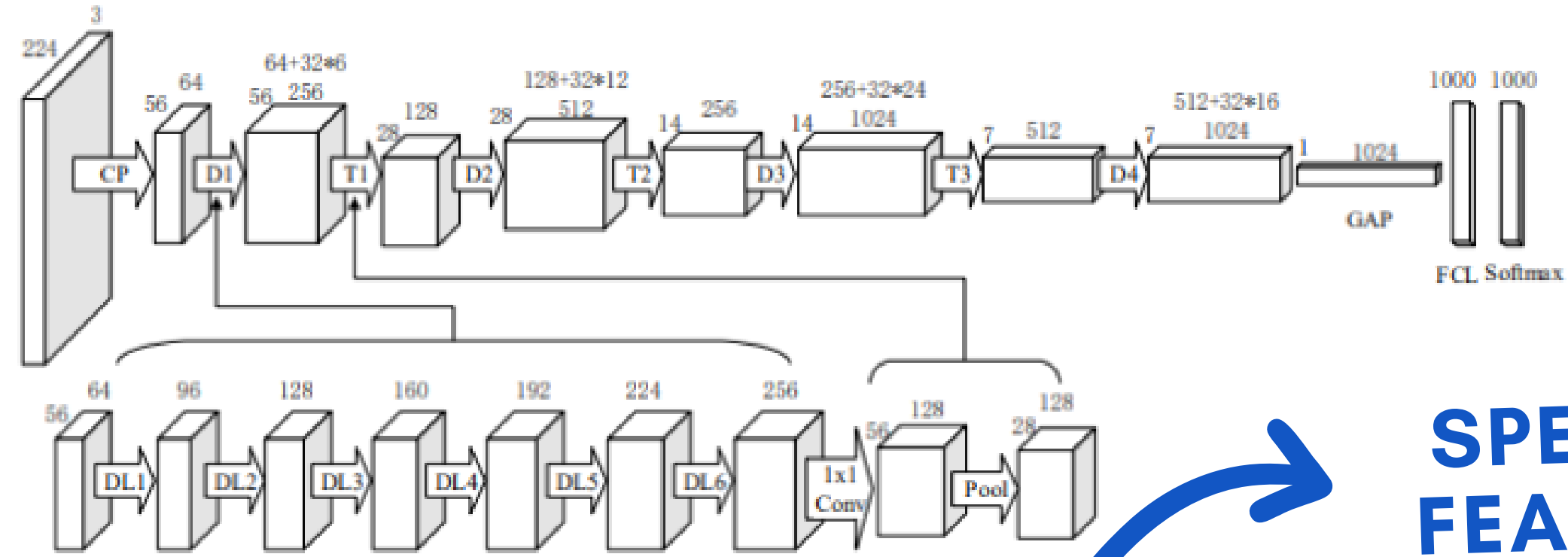
**PRIMITIVE
FEATURES**



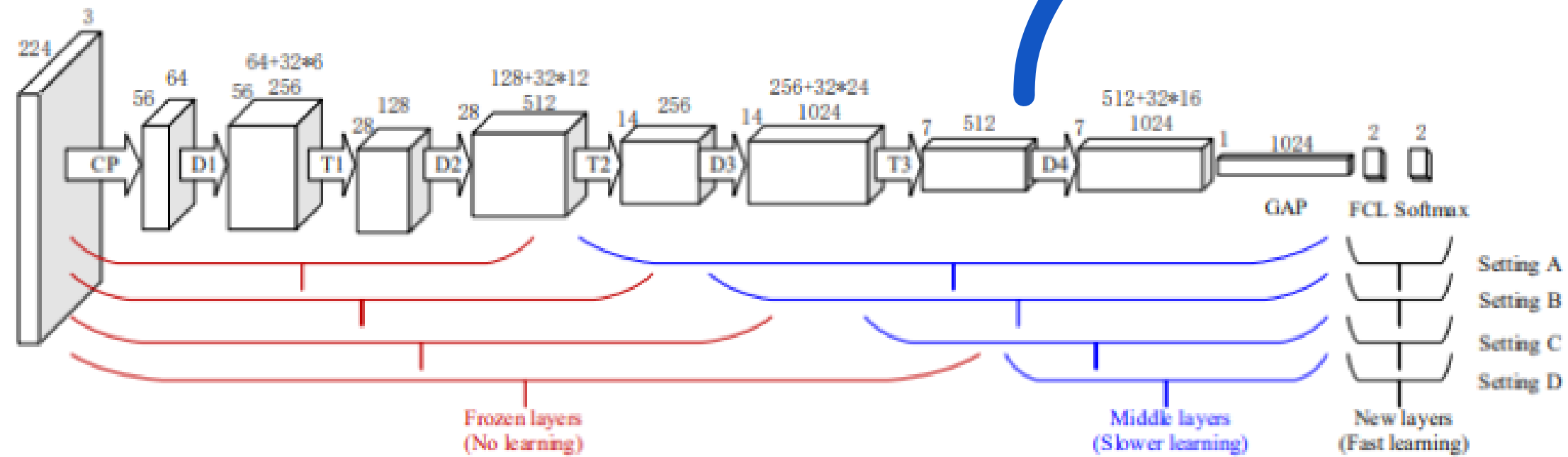
(c) DenseNet-121 transferred to our task



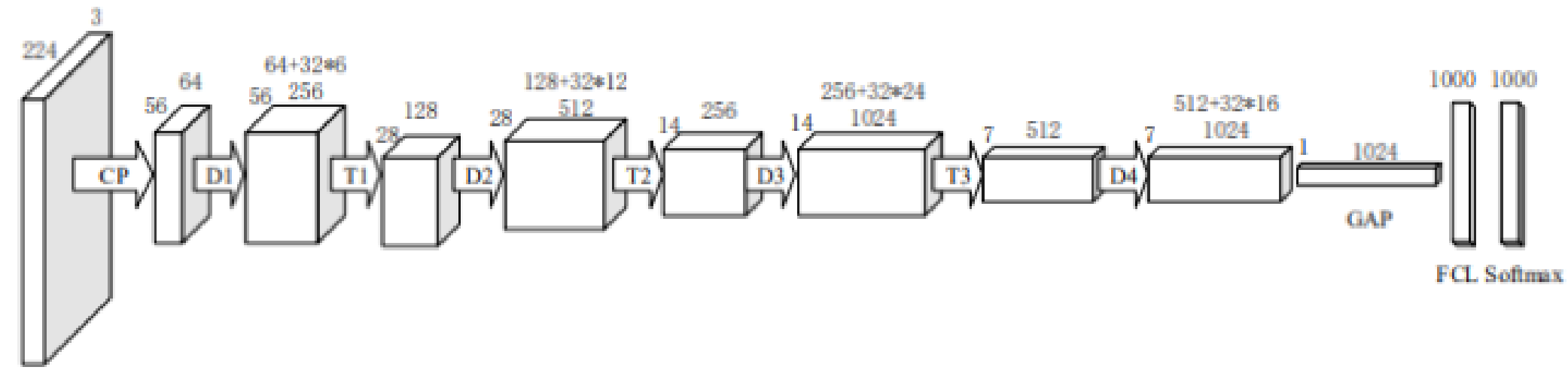
(a) Original pretrained DenseNet-121



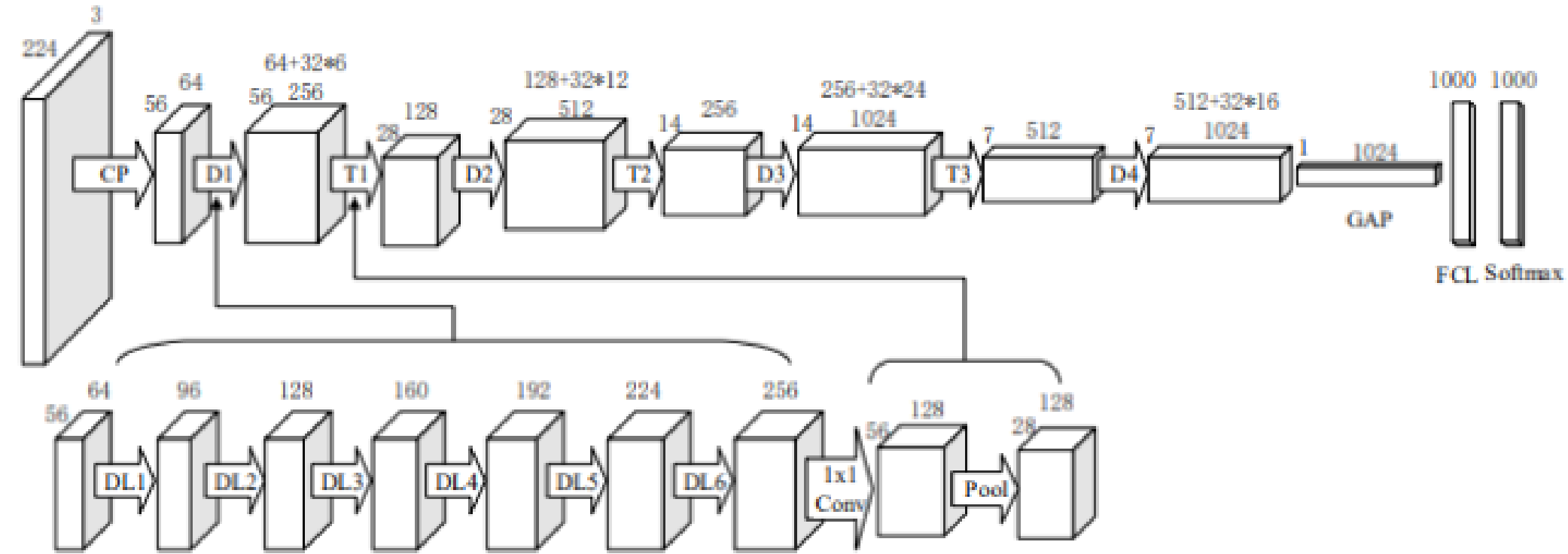
(b) one level deeper view of DenseNet-121



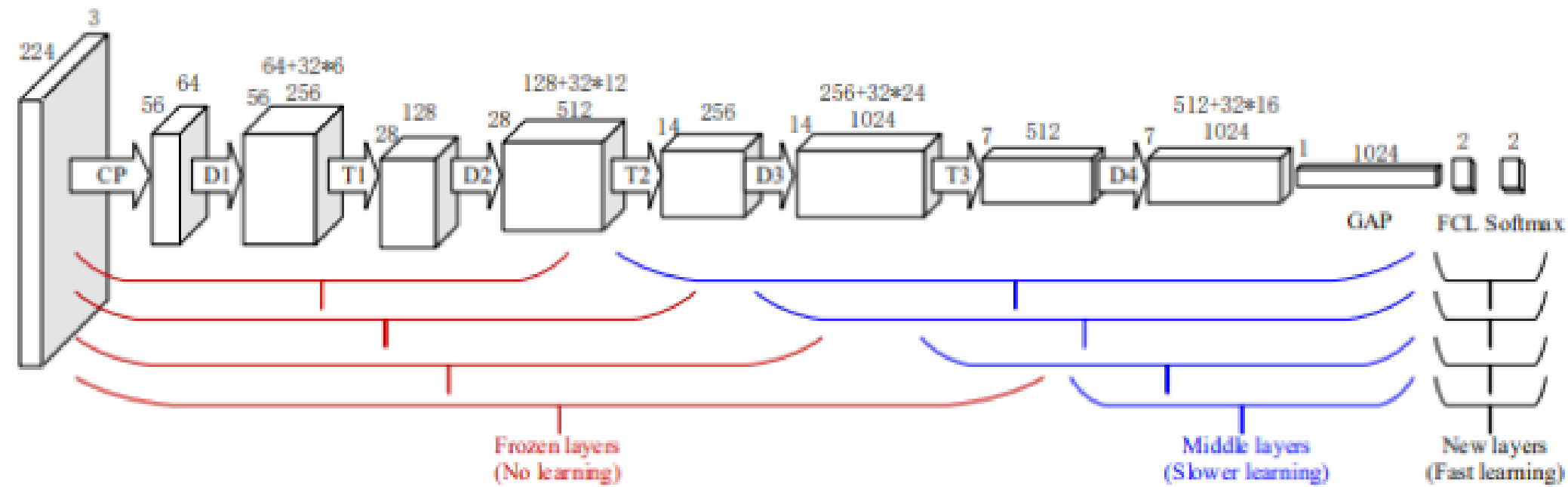
(c) DenseNet-121 transferred to our task



(a) Original pretrained DenseNet-121



(b) one level deeper view of DenseNet-121



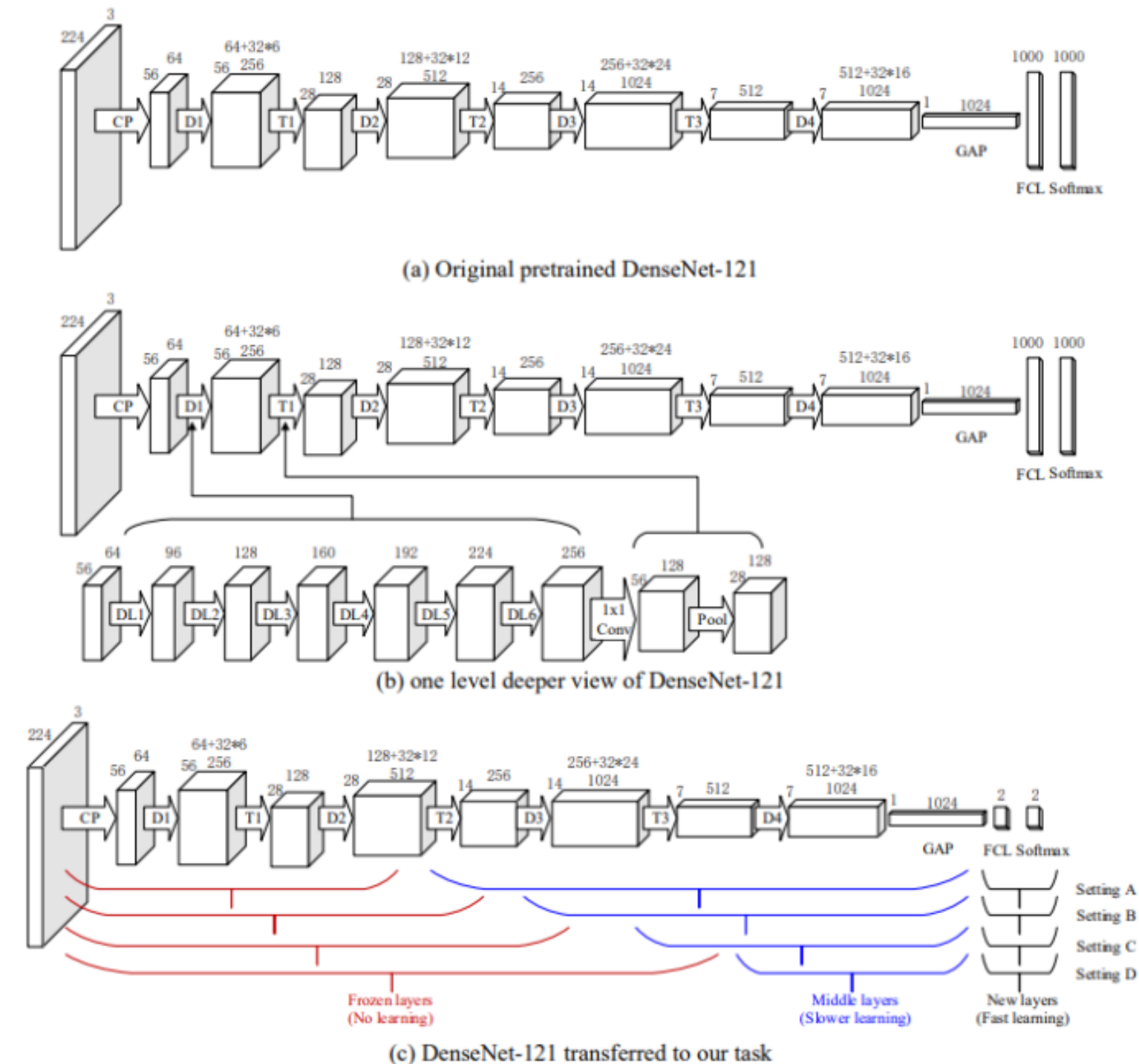
(c) DenseNet-121 transferred to our task

**NEWLY
CLASSIFICATION
LAYER**

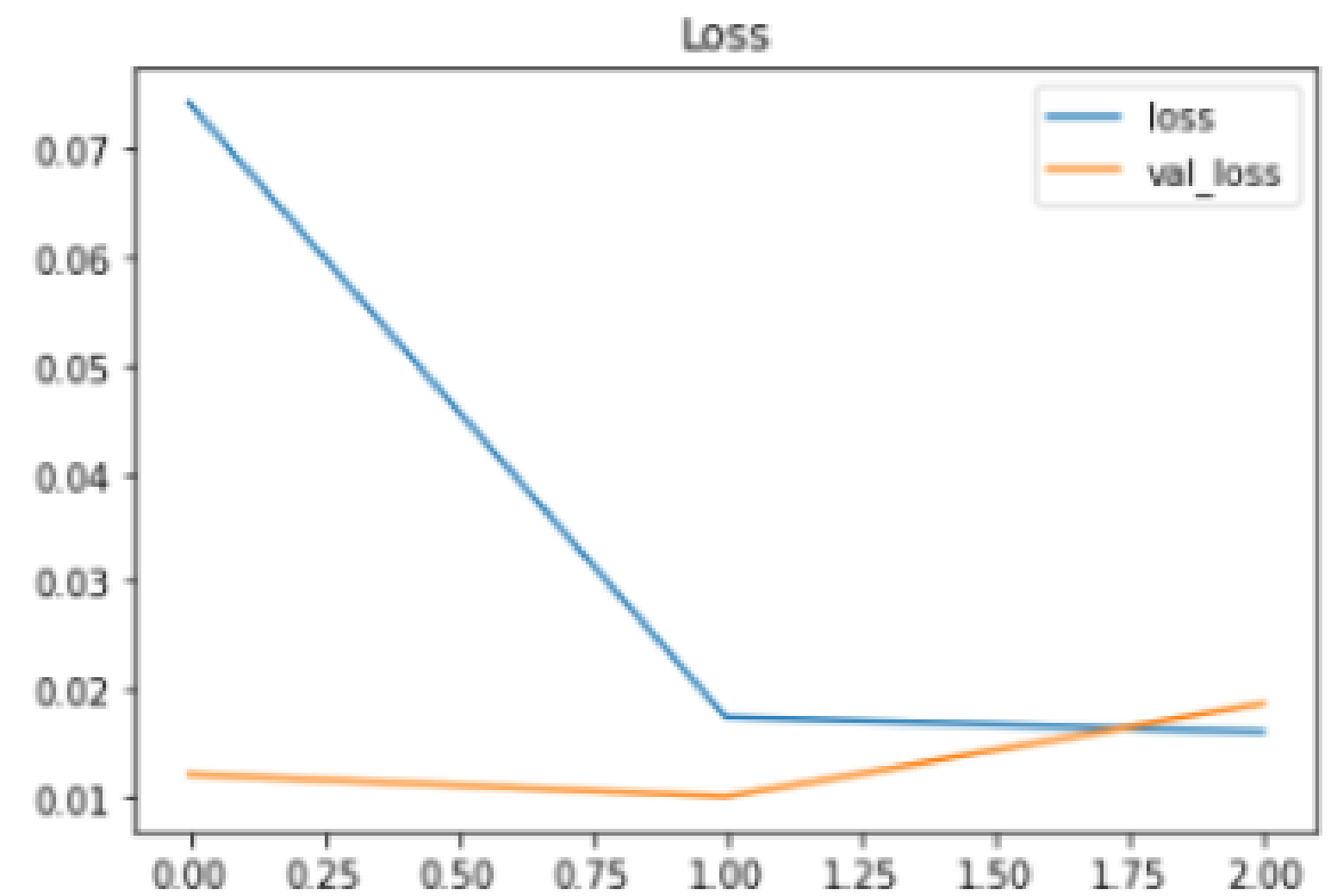
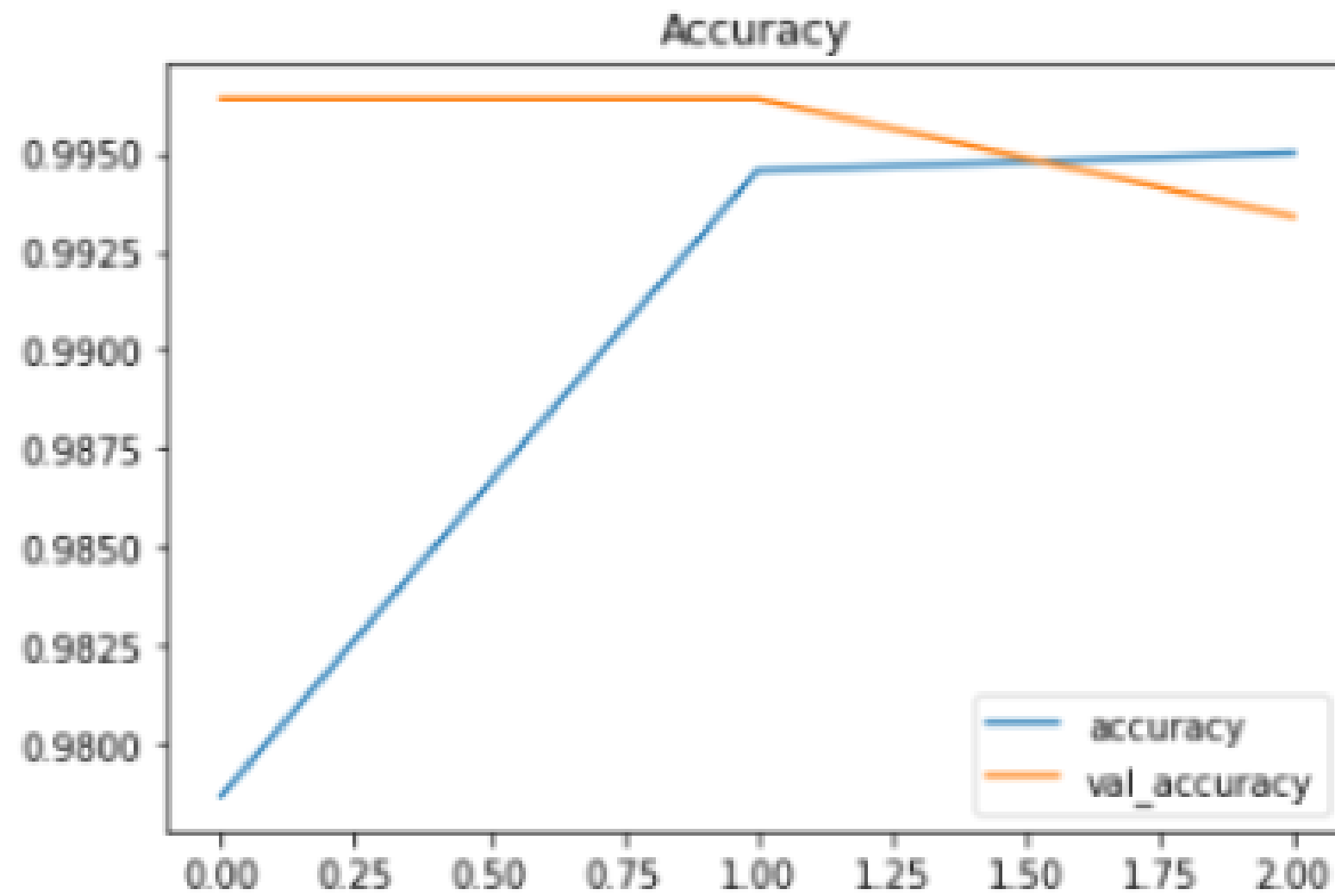


TRANSFER PROCESS

- FROZEN COUPLE FIRST LAYERS WHERE BASIC FEATURE IS TRAINED
- LATER DENSE LAYERS NEED TO BE SLOWLY RETRAINED TO EXTRACT FEATURE MOST REPRESENTATIVE FOR THE TASKS
- COMPLETELY RETRAIN THE CLASSIFICATION AND THE FCL.



RESULT OF DENSENET



True: Guava
Predicted: Guava



True: Apple
Predicted: Apple



True: Kiwi
Predicted: Kiwi



True: Apple
Predicted: Apple



True: Apple
Predicted: Apple



True: Kiwi
Predicted: Kiwi



True: Tomatoes
Predicted: Tomatoes



True: Guava
Predicted: Guava



True: Pomegranate
Predicted: Pomegranate



True: Kiwi
Predicted: Kiwi



True: Guava
Predicted: Guava



True: Apple
Predicted: Apple



True: Apple
Predicted: Apple



True: Peach
Predicted: Peach



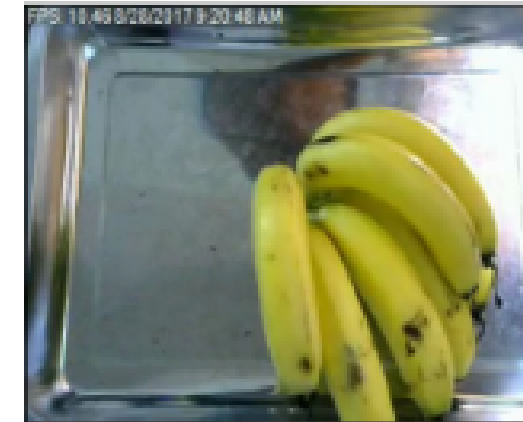
True: Mango
Predicted: Mango



True: Guava
Predicted: Guava



True: Banana
Predicted: Banana



True: Plum
Predicted: Plum



True: Kiwi
Predicted: Kiwi



True: Pear
Predicted: Pear



True: muskmelon
Predicted: muskmelon



True: Apple
Predicted: Apple



True: Guava
Predicted: Guava

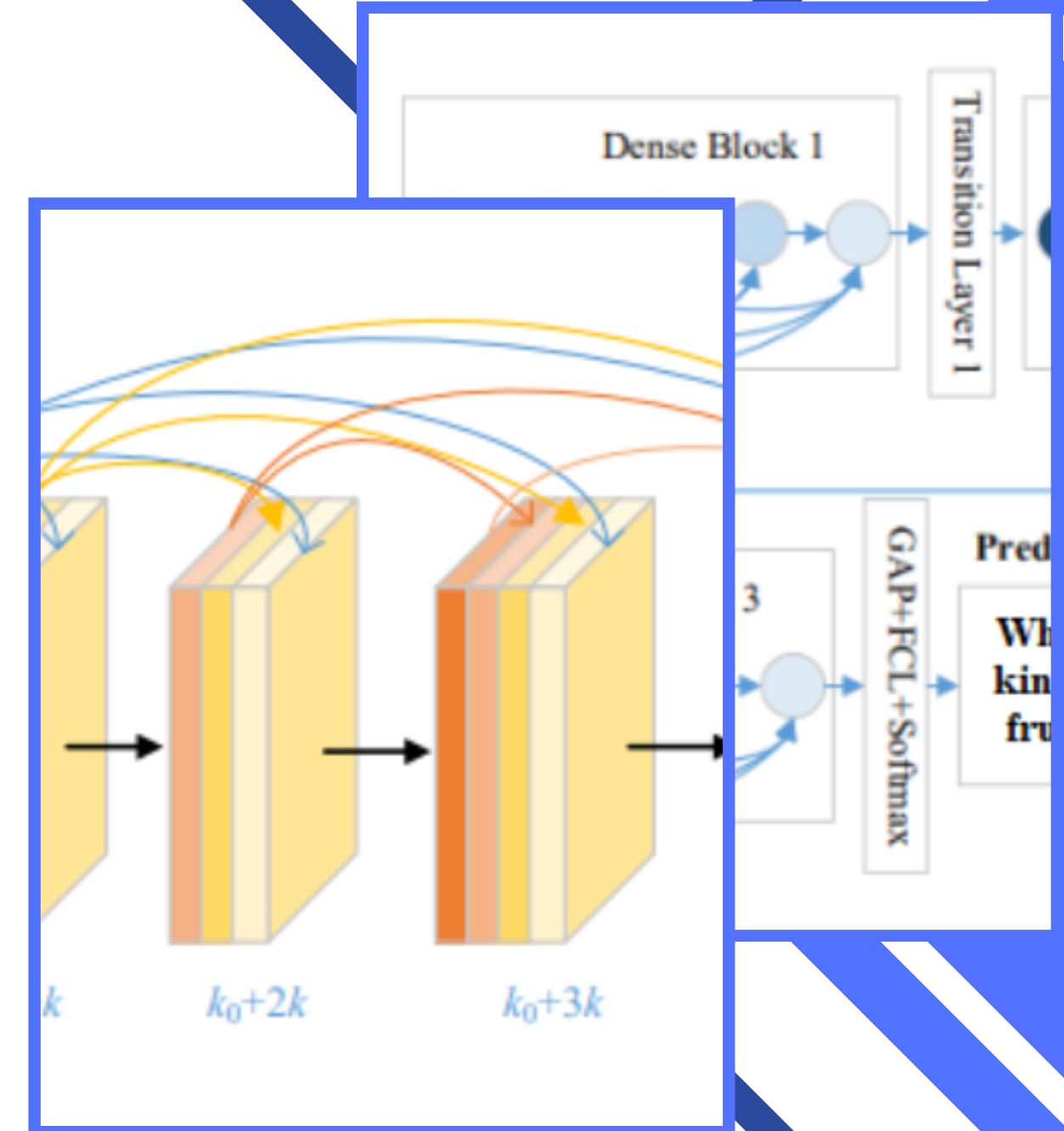


True: muskmelon
Predicted: muskmelon



DISCUSSION

- IMPRESSIVE RESULT: 99,6 %
- MUCH MORE STABLE IN PREDICTING SIMILAR FRUIT PRODUCT COMPARED TO BASIC CNN



3

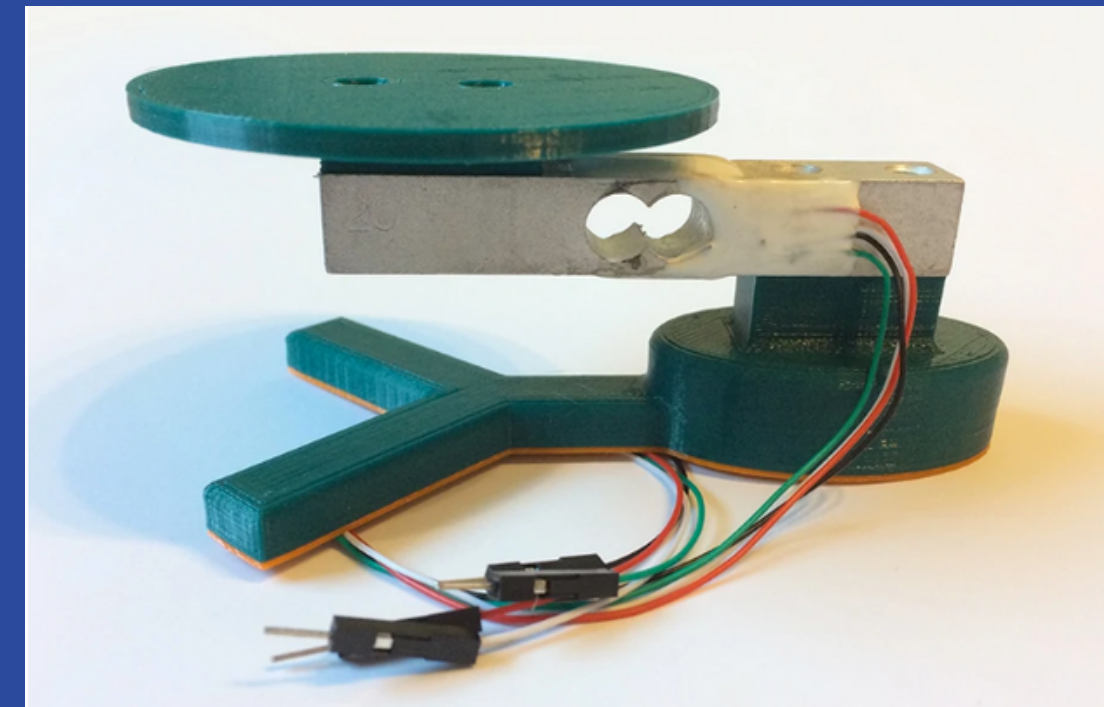
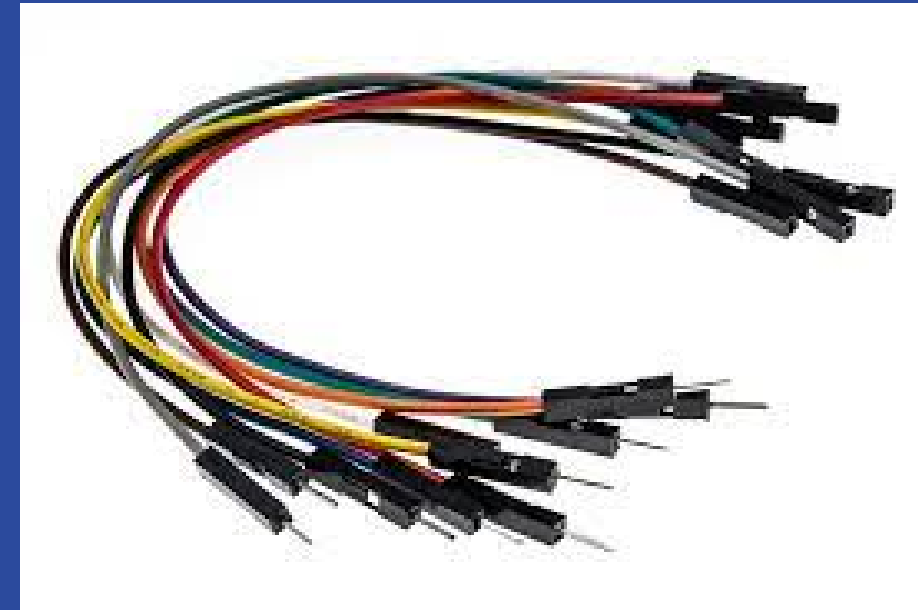
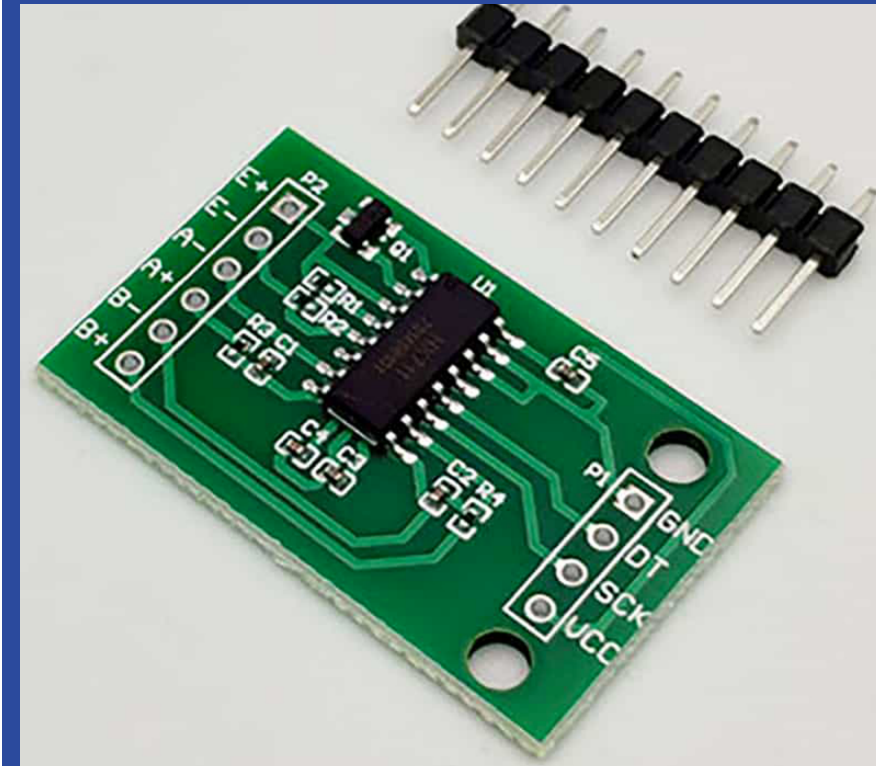
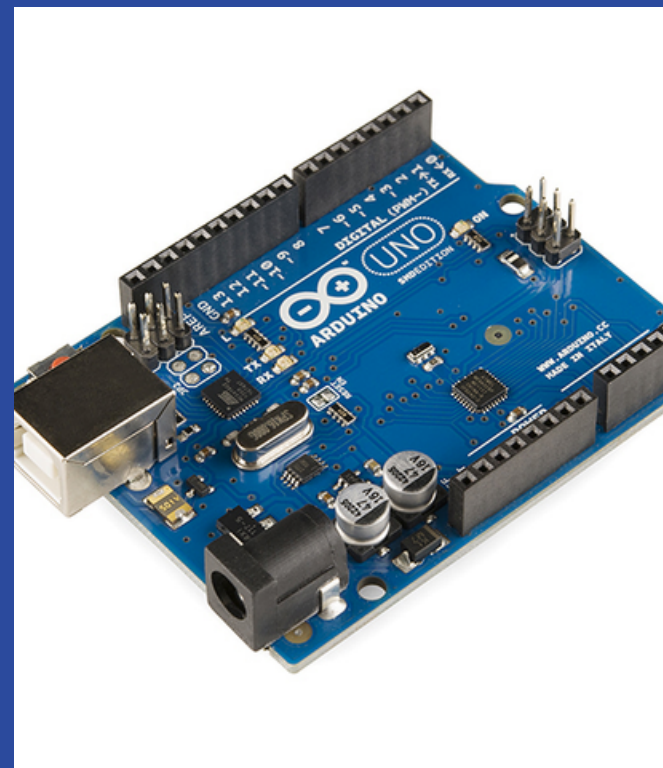
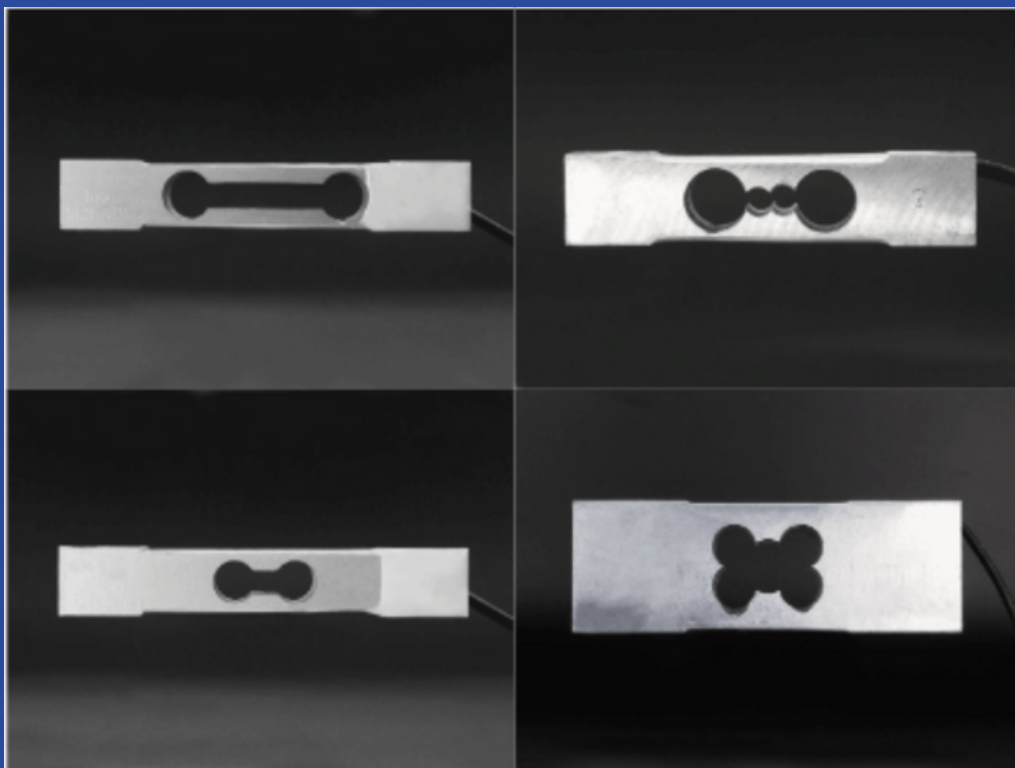
IMPLEMENTATION



WEIGHT SCALE

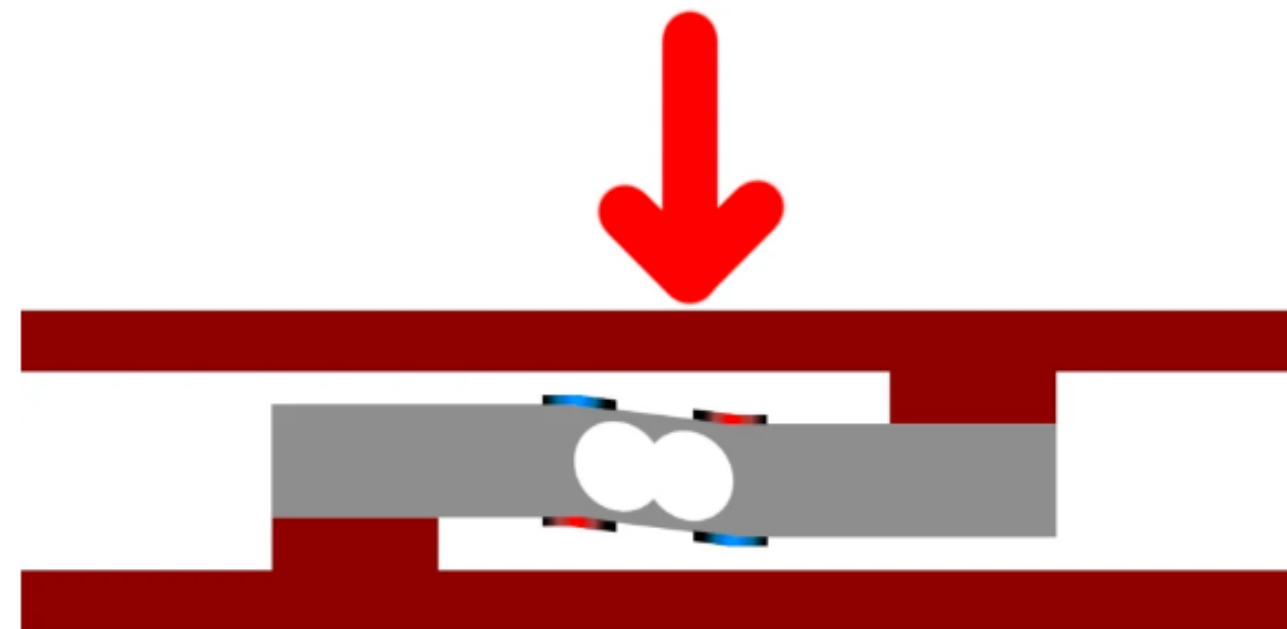
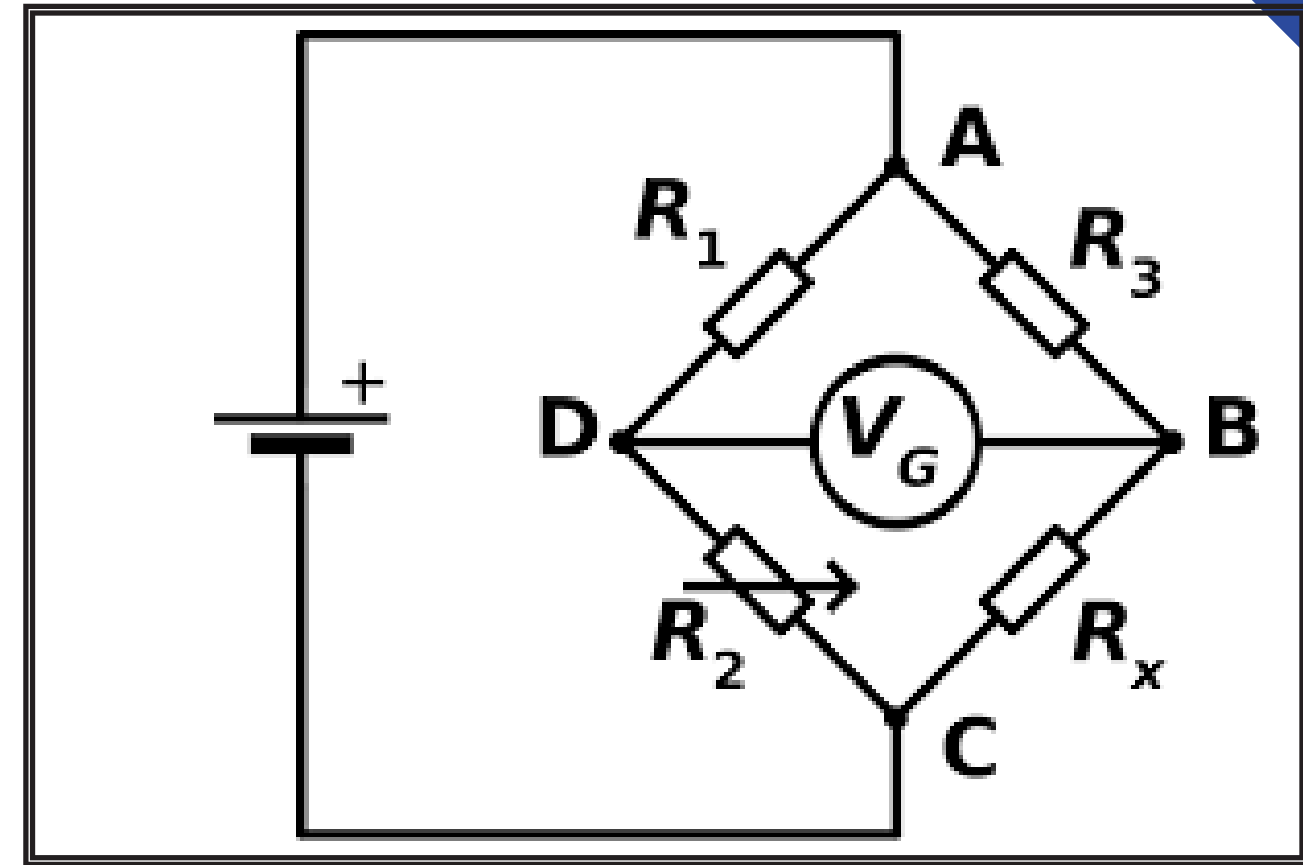
COMPONENTS

- Load cell 10kg
- Arduino kit (Arduino Uno, jumper wires)
- HX711 module
- Scale base



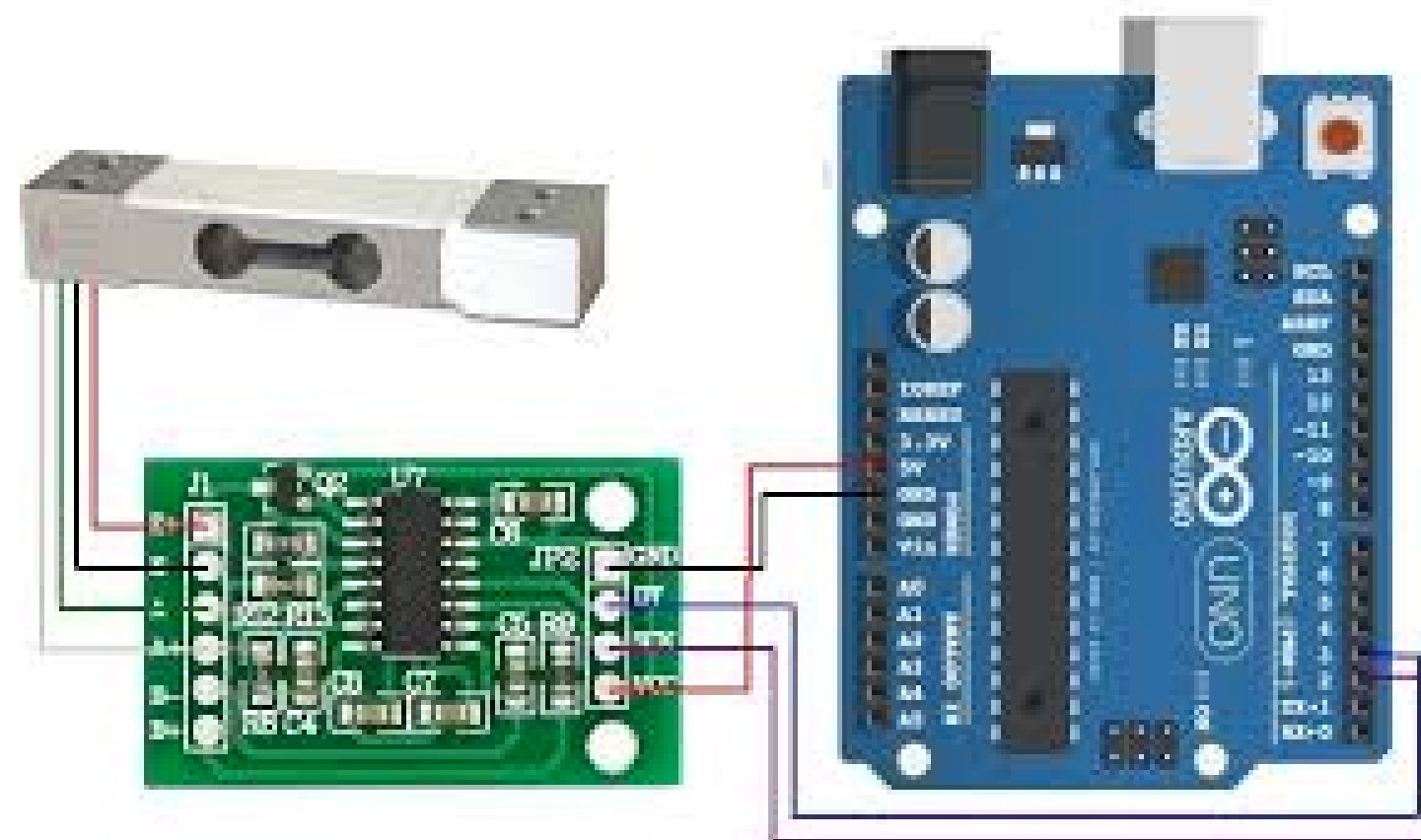
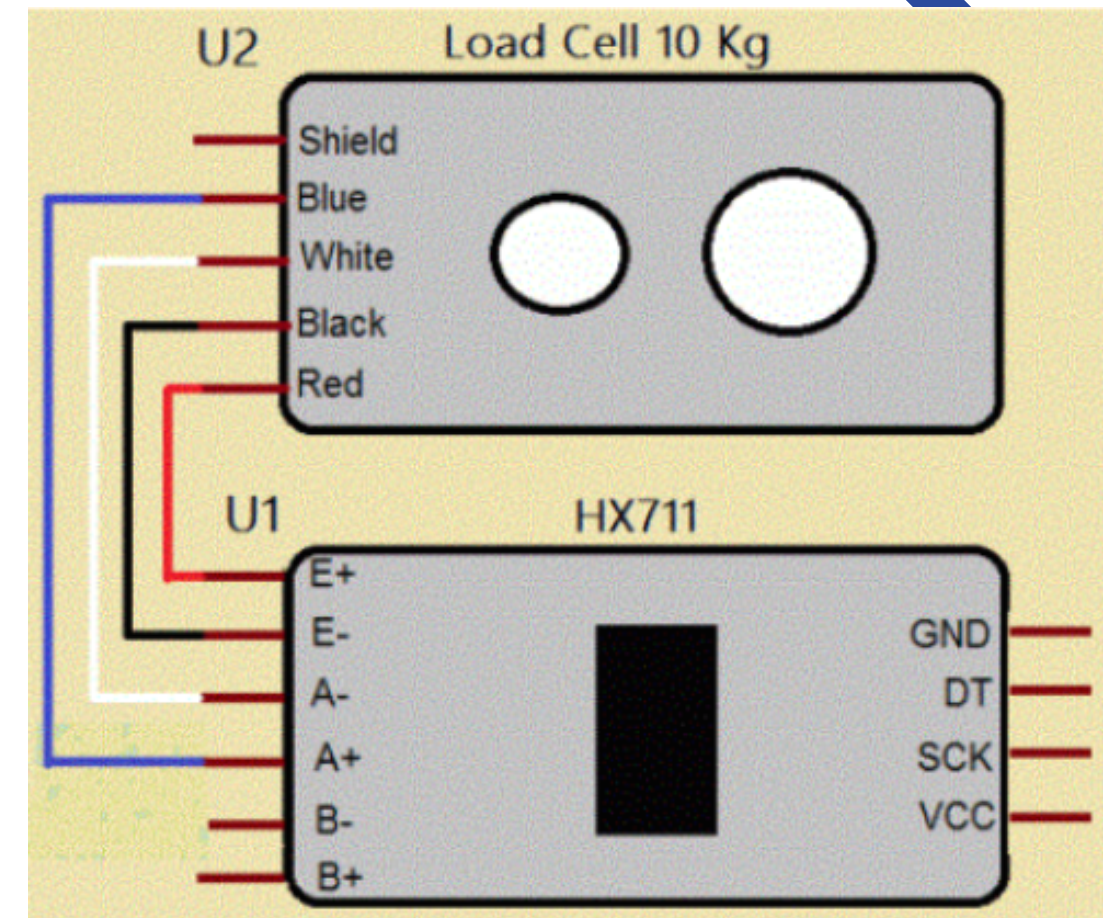
LOAD CELL

- The load cell has 4 strain gauges that are formed as the Wheatstone bridge formation.
- A transducer device for measuring strain and then converting forces into electrical energy that can be measured
- When applying force to the load cell, 2 of the 4 strain gauges will compress (marked red) while the rest will stretch (marked blue).



HX711 MODULE

- Also known as HX711 Load Cell Amplifier
- Connect to a microcontroller helps read changes in the resistance of the load cell
- Communicates using a two-wire interface, namely Clock and Data
- HX711_ADC library helps with the calibration:
https://github.com/olkal/HX711_ADC



OTHERS

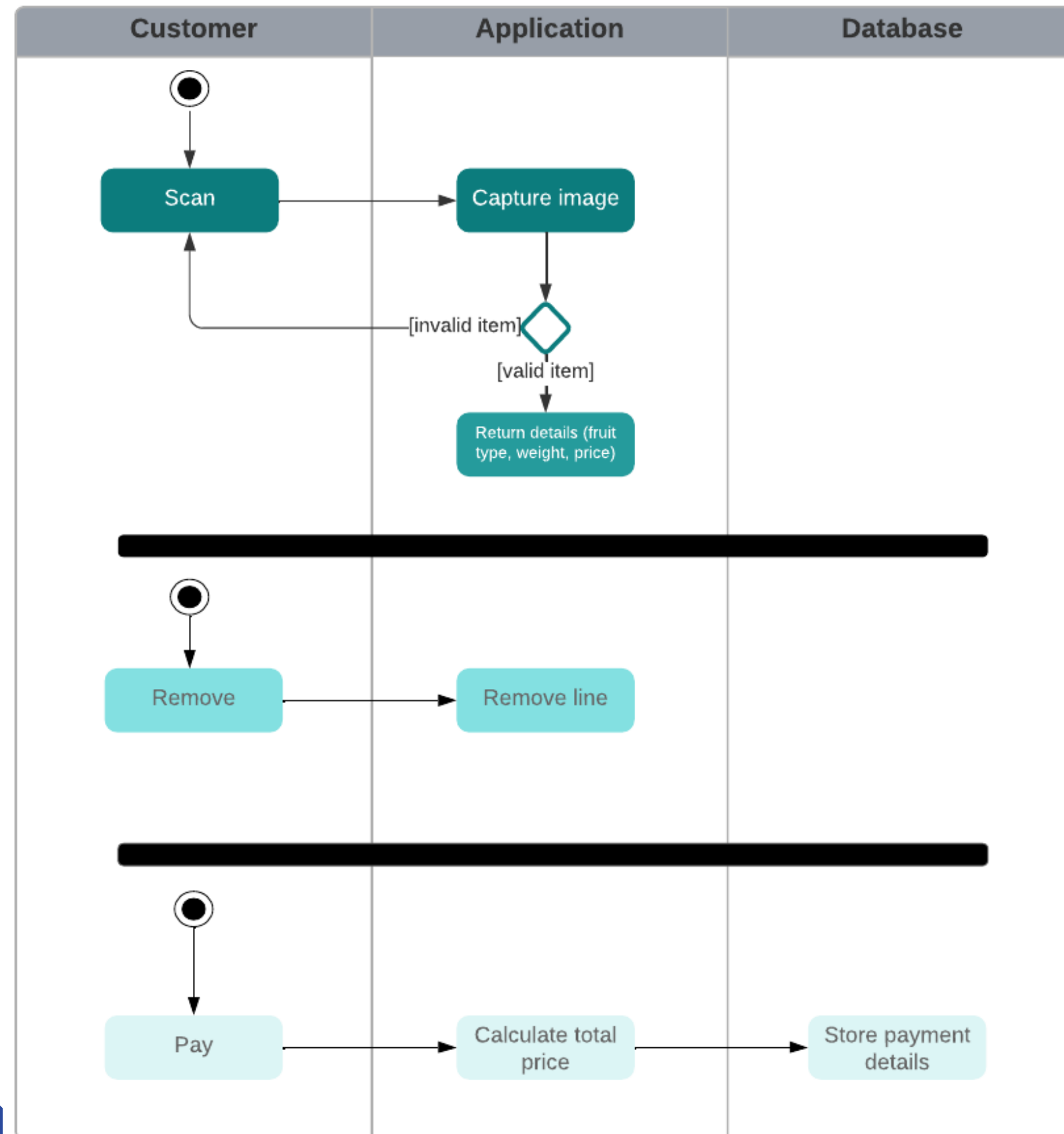


*CoolTerm for
transmitting
weight values*

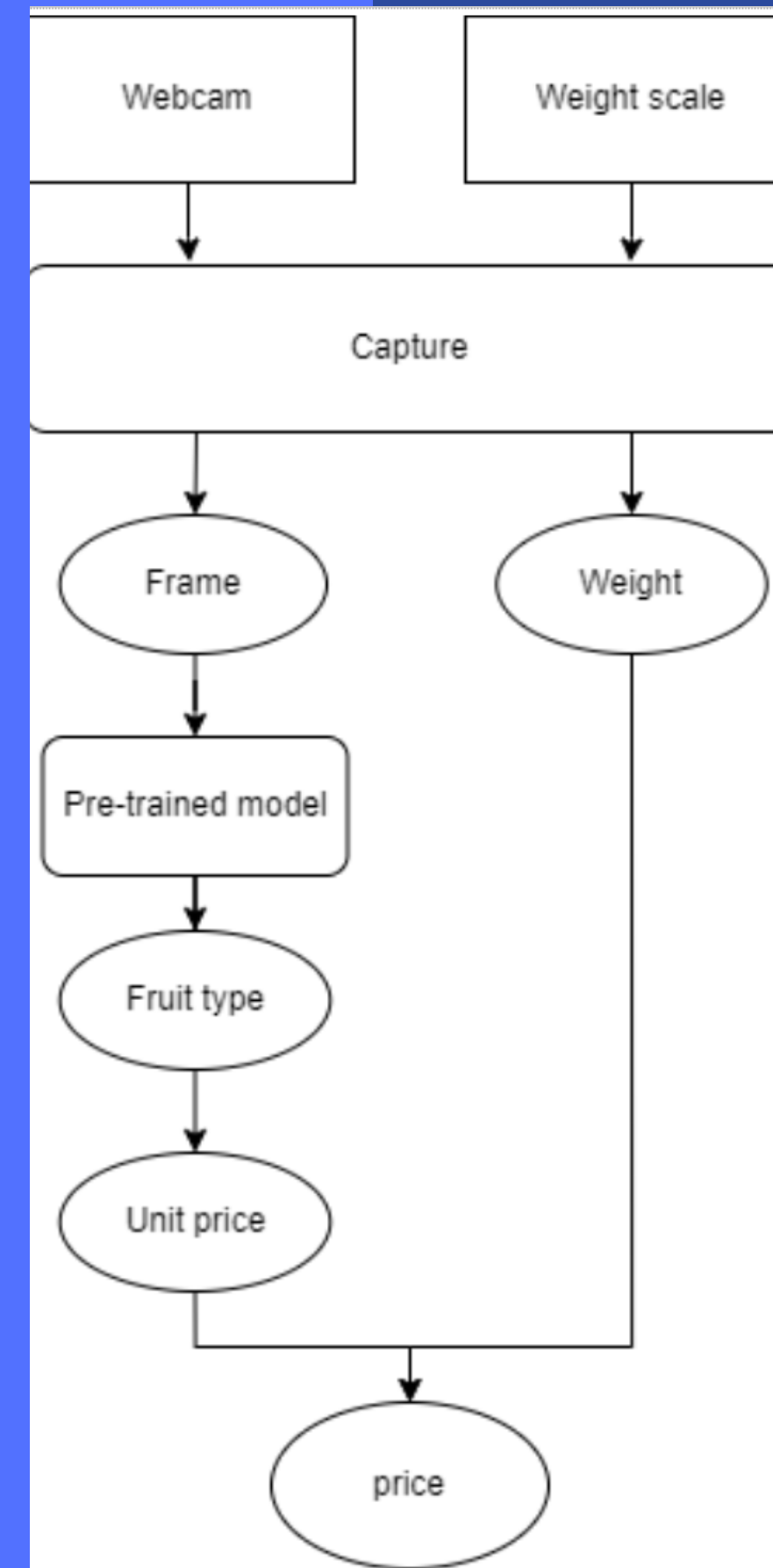


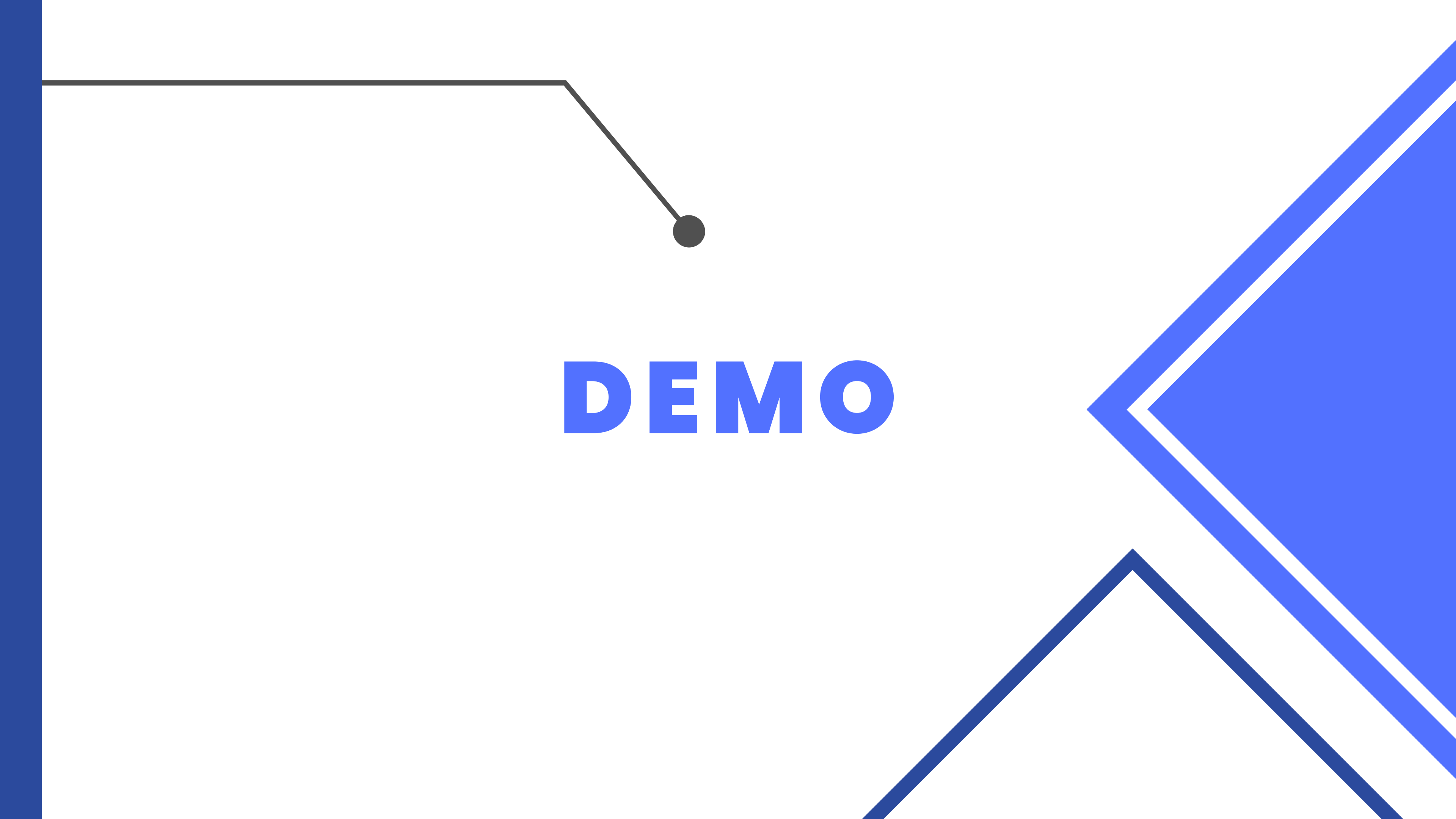
*HIKVISION
webcam with a
resolution of
 1920×1080 and
a USB plug-in*

WORKFLOW



FLOWCHART





DEMO

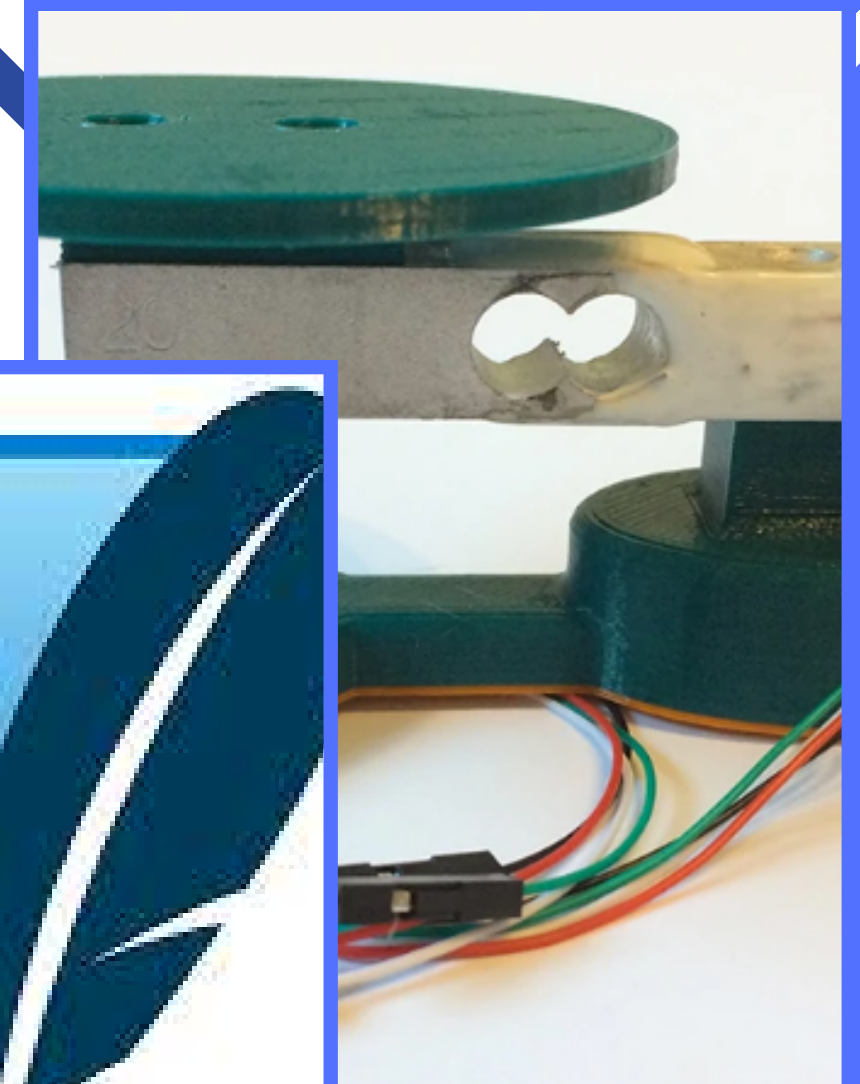
5

CONCLUSION



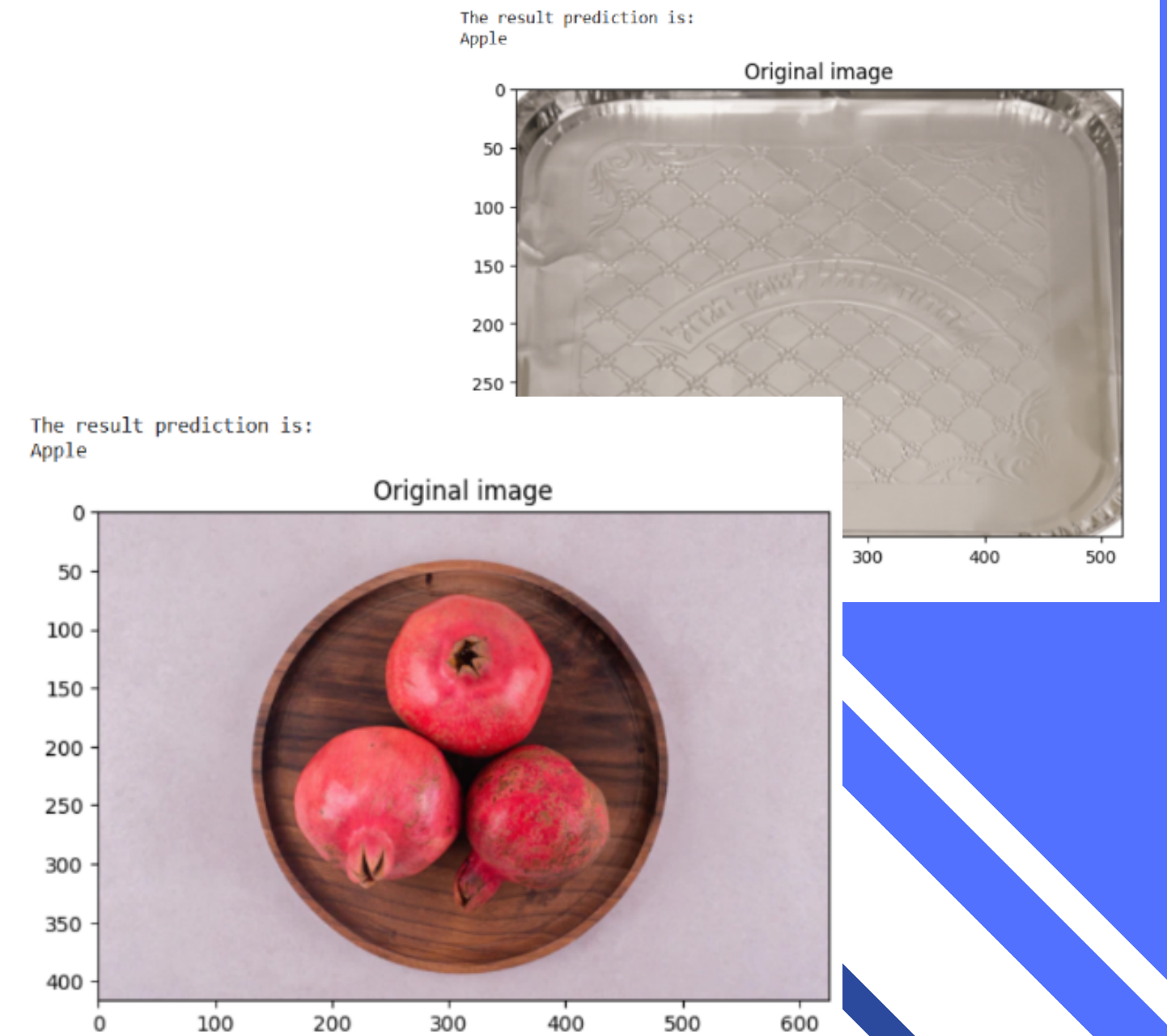
ACHIEVEMENTS

- A CNN model recognize up to 15 fruit varieties, and detecting anomalies.
- A sketch model of a weight scale.
- Transmit data value from the weight via a third-party application, which helps to utilize memory capacity.
- An application with a user-friendly interface, high stability, and utilized running time that connects all pieces and performs real-time recognition and price result.
- Established a connection with a database feature for storing payment and sales details.



IMPROVE THE MODEL

- Improve the recognition ability



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- Implement segmentation to detect mixed fruits situation
- Widen the range of fruits available to the model



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- Widen the range of fruits available to the model
- Improve the ability to detect obstacles or non-fruit anomaly
- Upgrade computing power (using GPU) for faster starting, processing time



IMPROVE THE HARDWARE

- The quality and stability of a weighting machine can be improved with more up-to-date and high-end equipment
- Increase the number of sensors, typically load cells, instead of one, thus increase accuracy
- Upgrade to a higher resolution camera for better image quality



IMPROVE THE SOFTWARE

- Adding numerous features like a QR code generator comprised of details such as type, weight, and total price for payment and billing purposes.
- Incorporate with a database feature for storing payments and sales, useful for managing a large supply chain.





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**THANKS FOR
WATCHING**