



Revolutionizing Disease Detection

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Topics

- INTRODUCTION
- DEEP LEARNING MODELS FOR IMAGE CLASSIFICATION
- INCEPTIONRESNET V2 ARCHITECTURE
- A QUICK COMPARISON OF THE MODELS THAT WERE USED
- PRACTICAL APPLICATION
- CONCLUSION





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INTRODUCTION



Introduction

Challenge

Threat:

Plant diseases → Crop loss, economic damage, food

Insecurity:

Traditional Methods:

Manual inspection → **Slow**, ineffective for early diagnosis.





Introduction

Solution

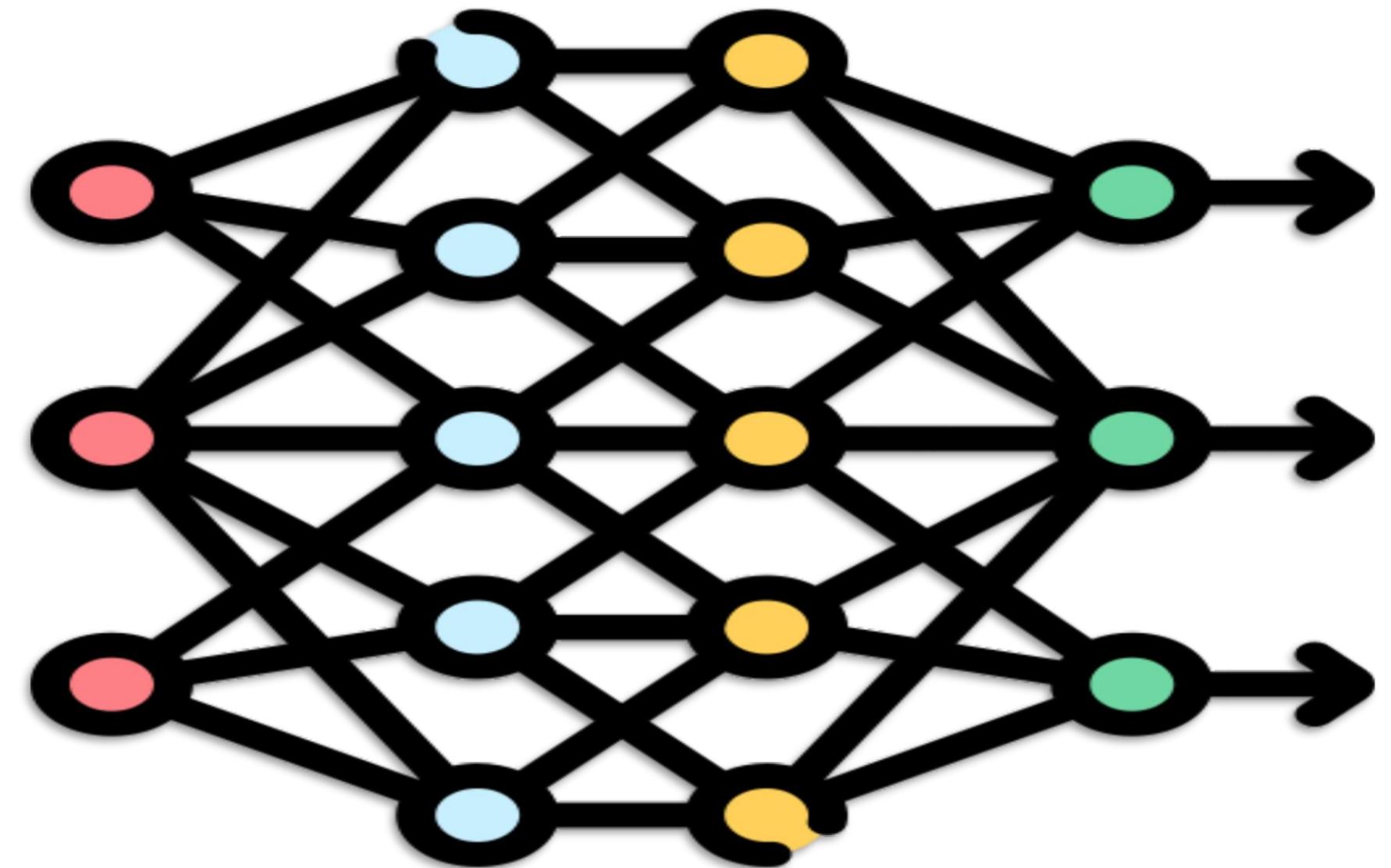
Deep Learning (DL):

Automates detection via image analysis →
Speed, accuracy, scalability.

InceptionResNetV2:

Hybrid architecture (Inception + Residual Networks).

Detects subtle symptoms → Early-stage diagnosis.



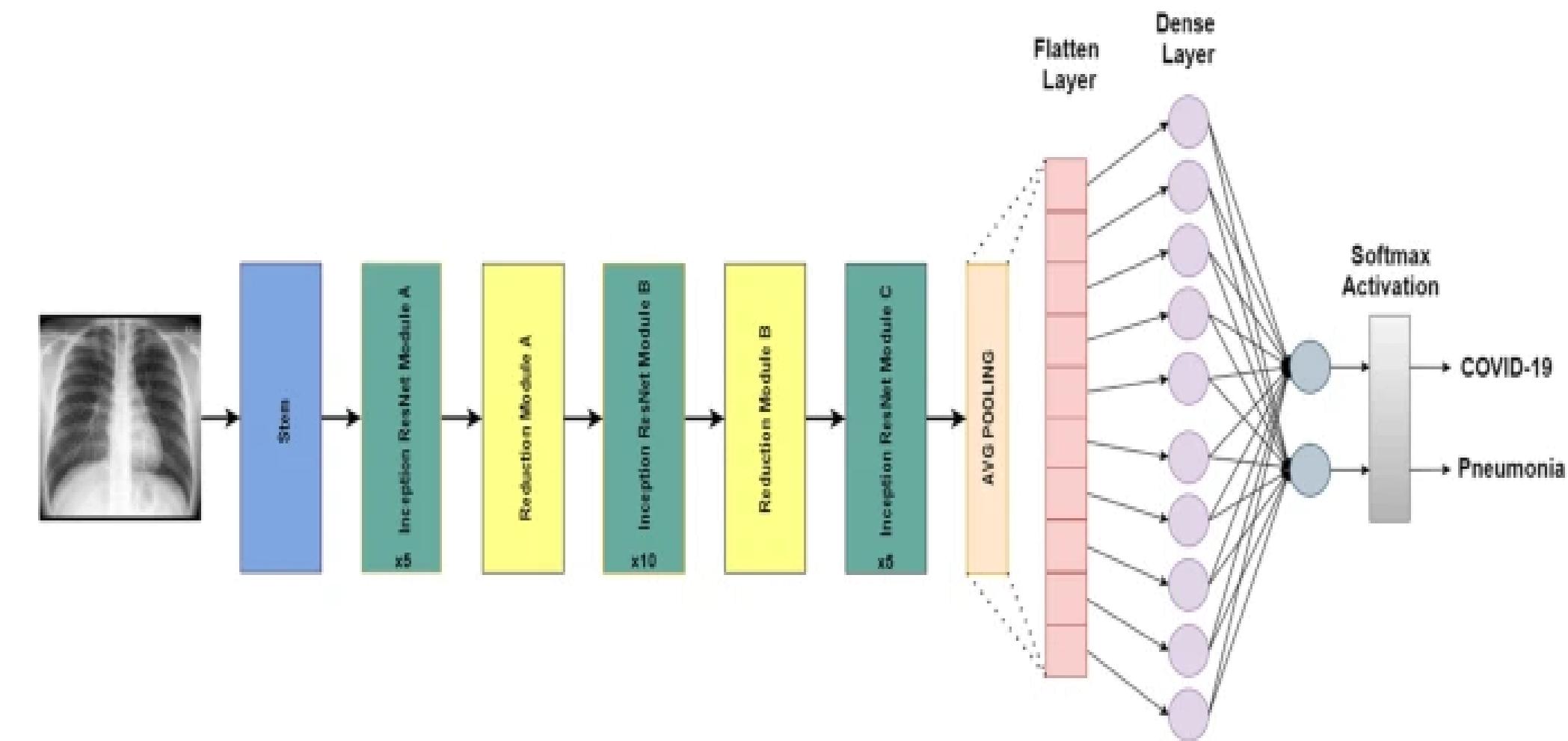


Introduction

Objective

Highlight AI's role in bridging agricultural gaps.

Showcase InceptionResNetV2 as a game-changer for sustainable farming.





DEEP LEARNING MODELS FOR IMAGE CLASSIFICATION



Deep learning models for image classification

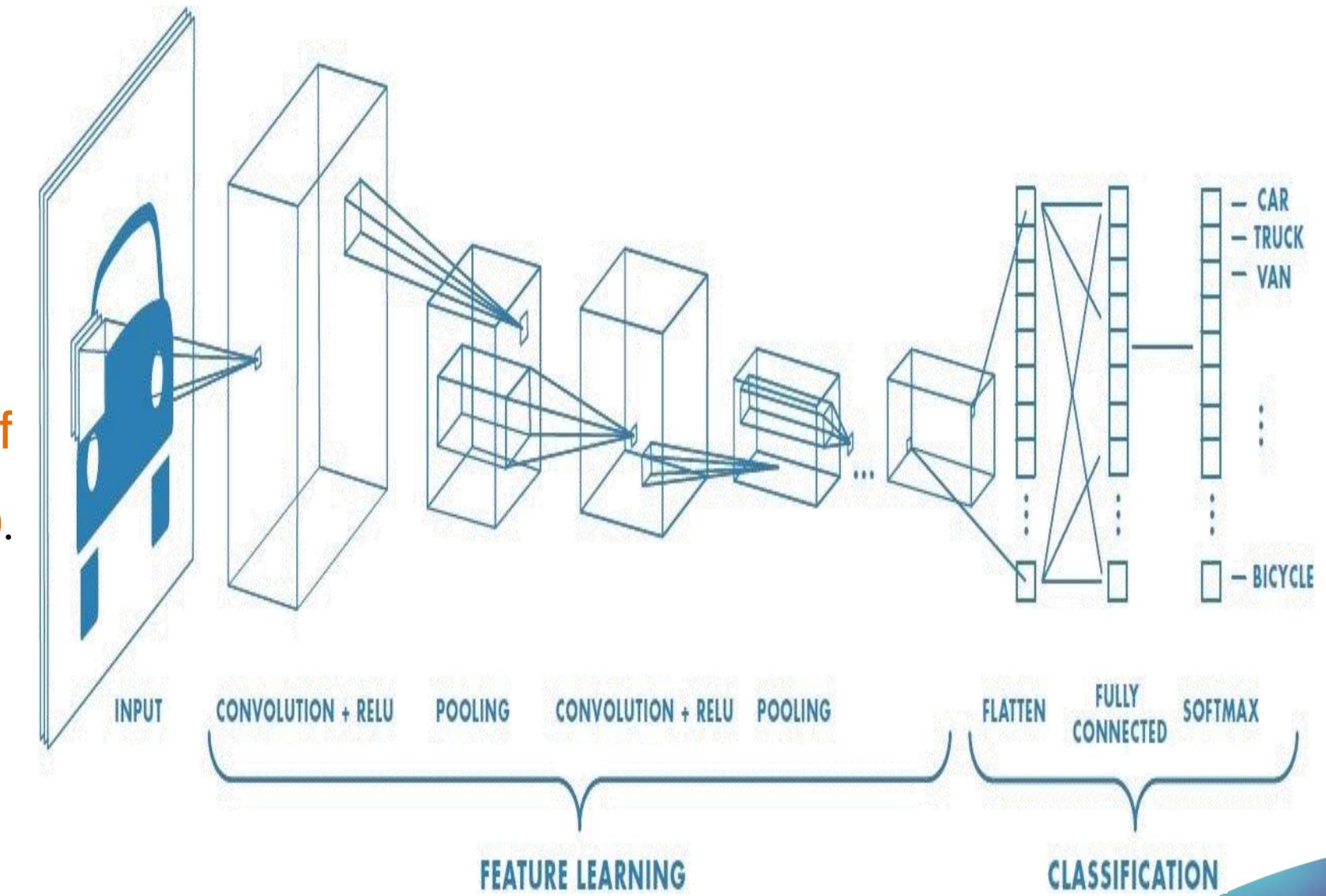
Convolutional Neural Networks (CNNs)

Description

Convolutional Neural Networks (CNNs) are a specialized **type of deep learning model** designed to **analyze visual data (as Images)**.

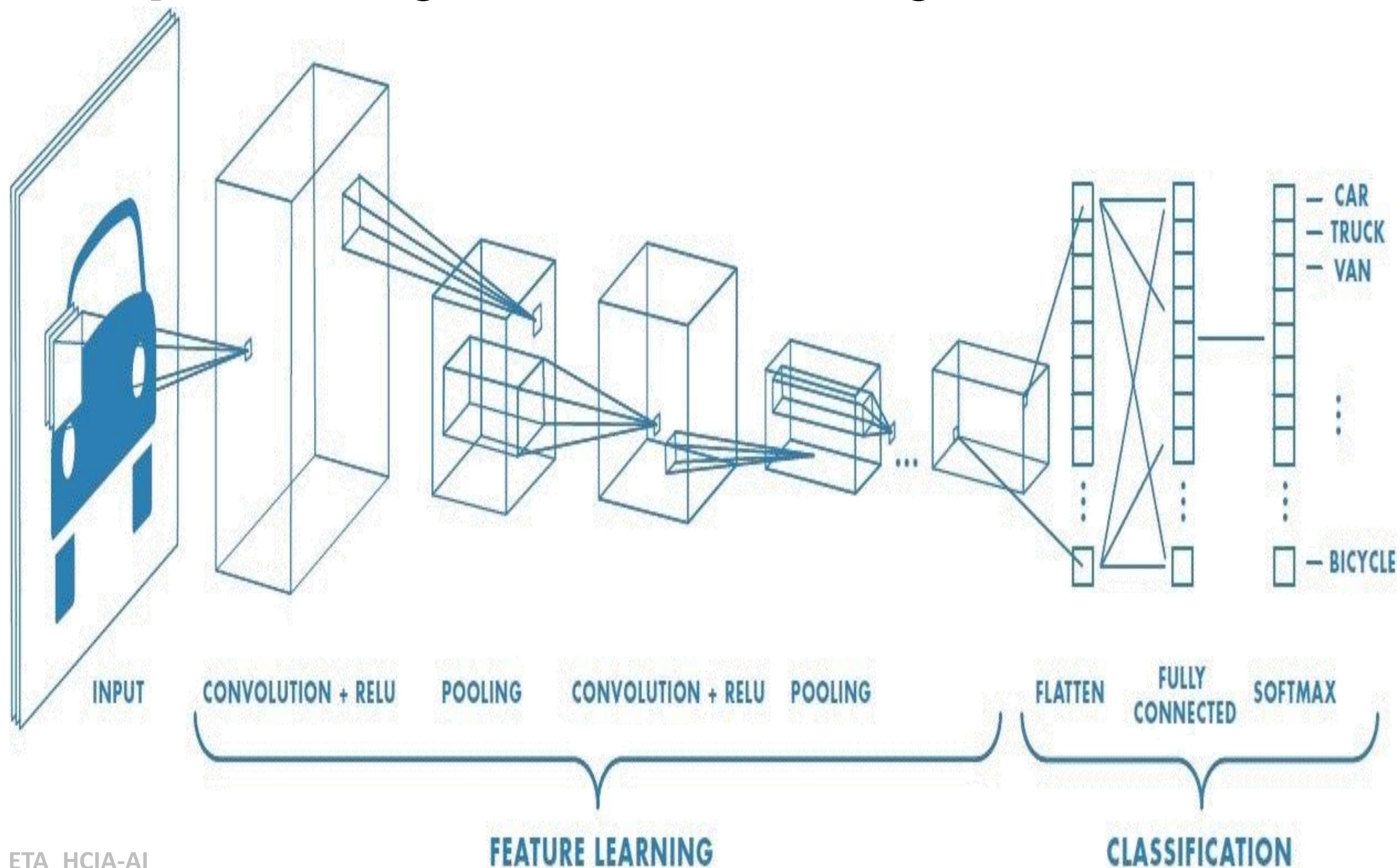
A typical CNN consists of:

- Convolutional layers
- Pooling layers
- Fully connected layers





Deep learning models for image classification





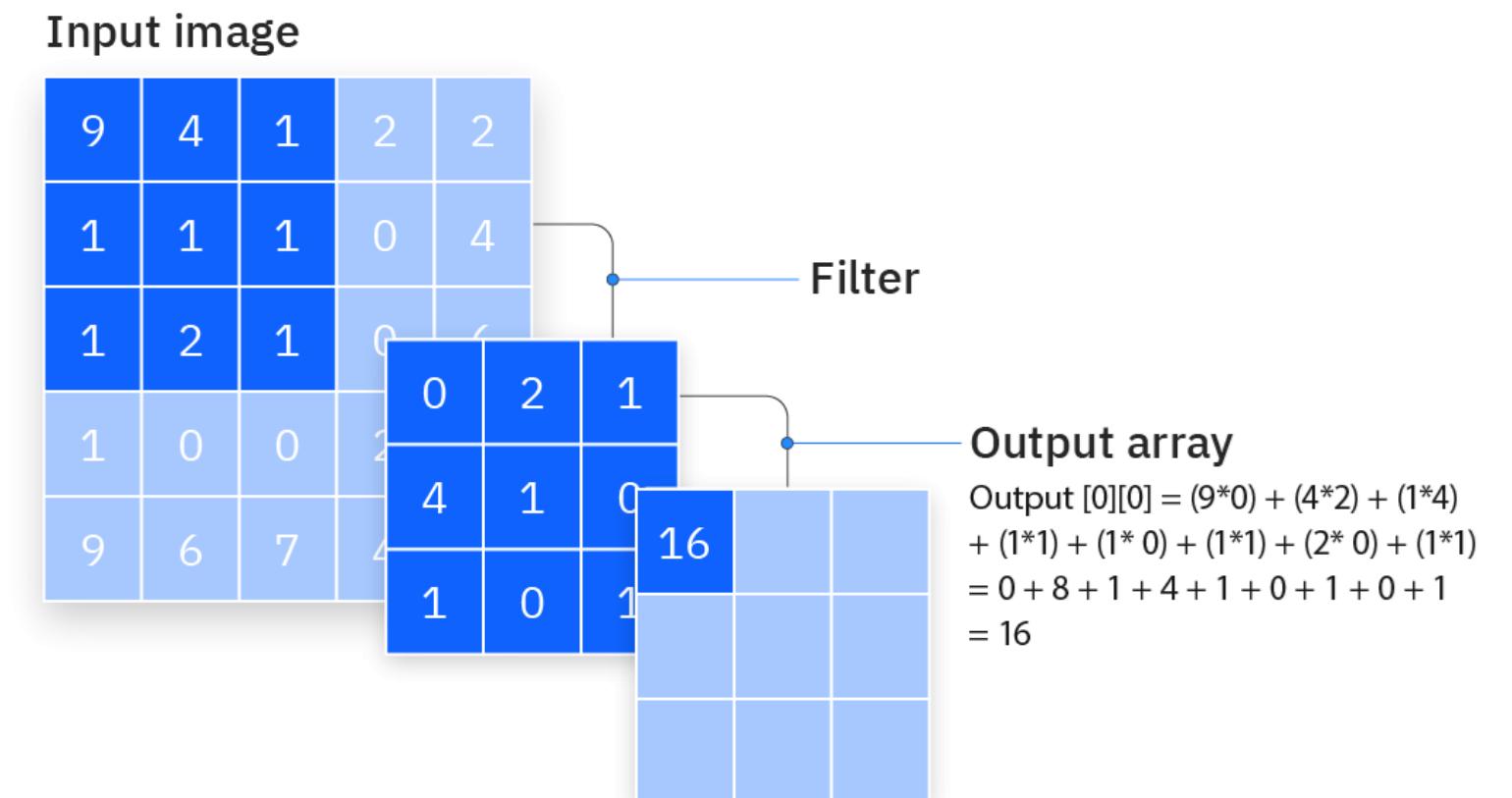
Deep learning models for image classification

◆ *1. Convolution Layer*

How it works

The convolution layer applies a **set of filters (kernels)** to the input image.

Each filter slides across the image, performing a dot product between the **filter** and **local regions of the image** to **produce a feature map**.





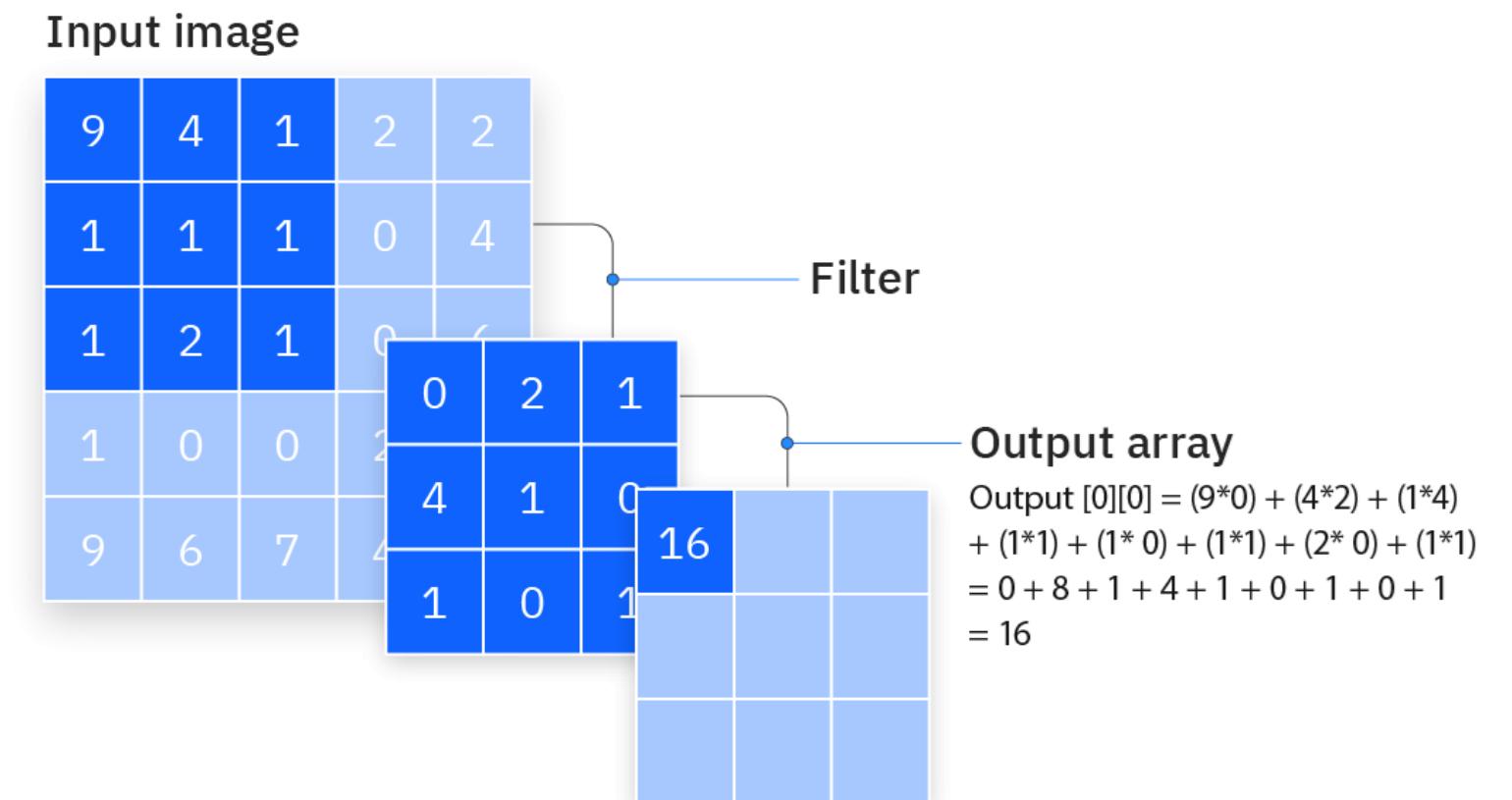
Deep learning models for image classification

◆ *1. Convolution Layer*

1. Filters & Output Depth

Role: Each filter extracts **unique features** (edges, textures).

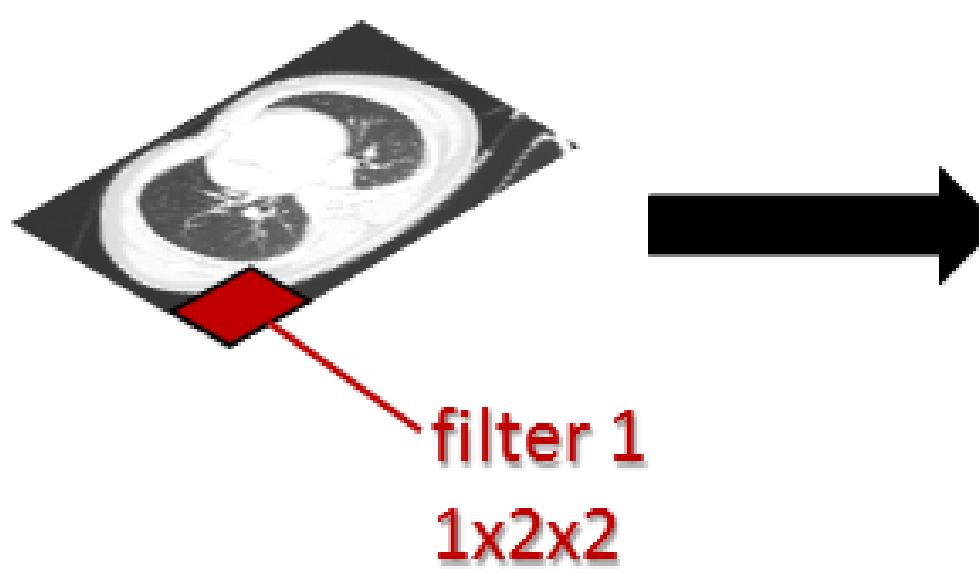
Example: 3 filters → 3 feature maps → Output depth = 3.



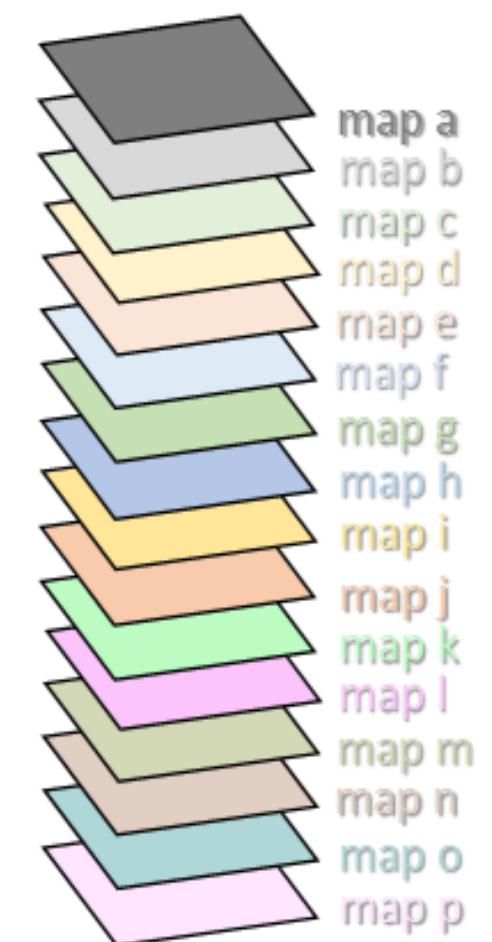
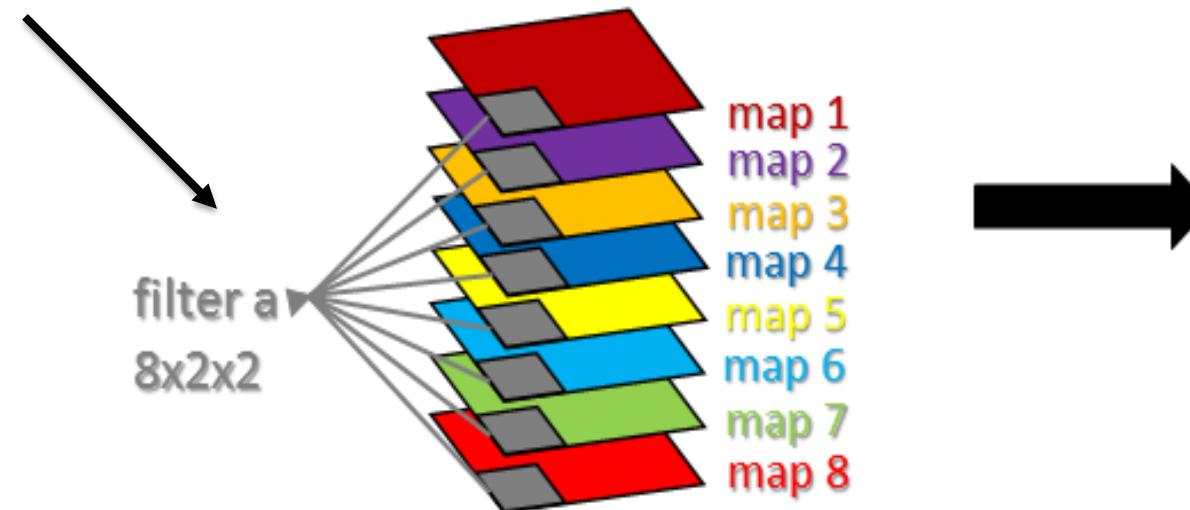


Deep learning models for image classification

first CNN layer with 8 filters



second CNN layer with 16 filters





Deep learning models for image classification

$$\begin{matrix} 60 & 7 & 98 & 14 & 19 \\ 165 & 159 & 147 & 196 & 169 \\ 187 & 204 & 165 & 41 & 111 \\ 209 & 30 & 201 & 23 & 203 \\ 58 & 79 & 218 & 59 & 118 \end{matrix} * \begin{matrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{matrix} =$$



Deep learning models for image classification

1. Convolution Layer

2. Stride & Output Size

Definition: Steps the kernel takes across the input (e.g., stride=1 or 2).

Impact: Larger stride → Smaller output size.

Example: Stride=2 halves output dimensions.

(a) Stride = 1

1	2	3	1	3	5
2	2	5	4	2	5
0	6	9	6	2	2
2	0	1	9	4	0
5	5	4	6	7	6
6	1	3	7	1	5

(b) Stride = 2

1	2	3	1	3	5
2	2	5	4	2	5
0	6	9	6	2	2
2	0	1	9	4	0
5	5	4	6	7	6
6	1	3	7	1	5

$$\begin{matrix} \begin{matrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{matrix} * \begin{matrix} 1 & 2 & 3 & 1 & 3 & 5 \\ 2 & 2 & 5 & 4 & 2 & 5 \\ 0 & 6 & 9 & 6 & 2 & 2 \\ 2 & 0 & 1 & 9 & 4 & 0 \\ 5 & 5 & 4 & 6 & 7 & 6 \\ 6 & 1 & 3 & 7 & 1 & 5 \end{matrix} \end{matrix} = \begin{matrix} \begin{matrix} -14 & -1 & 10 & -1 \\ -11 & -11 & 7 & 12 \\ -7 & -10 & 1 & 13 \\ 5 & -16 & -4 & 10 \end{matrix} \end{matrix}$$

$$\begin{matrix} \begin{matrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{matrix} * \begin{matrix} 1 & 2 & 3 & 1 & 3 & 5 \\ 2 & 2 & 5 & 4 & 2 & 5 \\ 0 & 6 & 9 & 6 & 2 & 2 \\ 2 & 0 & 1 & 9 & 4 & 0 \\ 5 & 5 & 4 & 6 & 7 & 6 \\ 6 & 1 & 3 & 7 & 1 & 5 \end{matrix} \end{matrix} = \begin{matrix} \begin{matrix} -14 & 10 \\ -7 & 1 \end{matrix} \end{matrix}$$



Deep learning models for image classification

(a) Stride = 1

	1	2	3	1	3	5
	2	2	5	4	2	5
	0	6	9	6	2	2
Stride = 1	2	0	1	9	4	0
	5	5	4	6	7	6
	6	1	3	7	1	5

$$\begin{matrix} * & \begin{matrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{matrix} \end{matrix} =$$

-14	-1	10	-1
-11	-11	7	12
-7	-10	1	13
5	-16	-4	10

(b) Stride = 2

	1	2	3	1	3	5
	2	2	5	4	2	5
	0	6	9	6	2	2
Stride = 2	2	0	1	9	4	0
	5	5	4	6	7	6
	6	1	3	7	1	5

$$\begin{matrix} * & \begin{matrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{matrix} \end{matrix} =$$

-14	10
-7	1



Deep learning models for image classification

$$\begin{matrix} \begin{matrix} 60 & 7 & 98 & 14 & 19 \\ 165 & 159 & 147 & 196 & 169 \\ 187 & 204 & 165 & 41 & 111 \\ 209 & 30 & 201 & 23 & 203 \\ 58 & 79 & 218 & 59 & 118 \end{matrix} & * & \begin{matrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{matrix} & = & \end{matrix}$$



Deep learning models for image classification

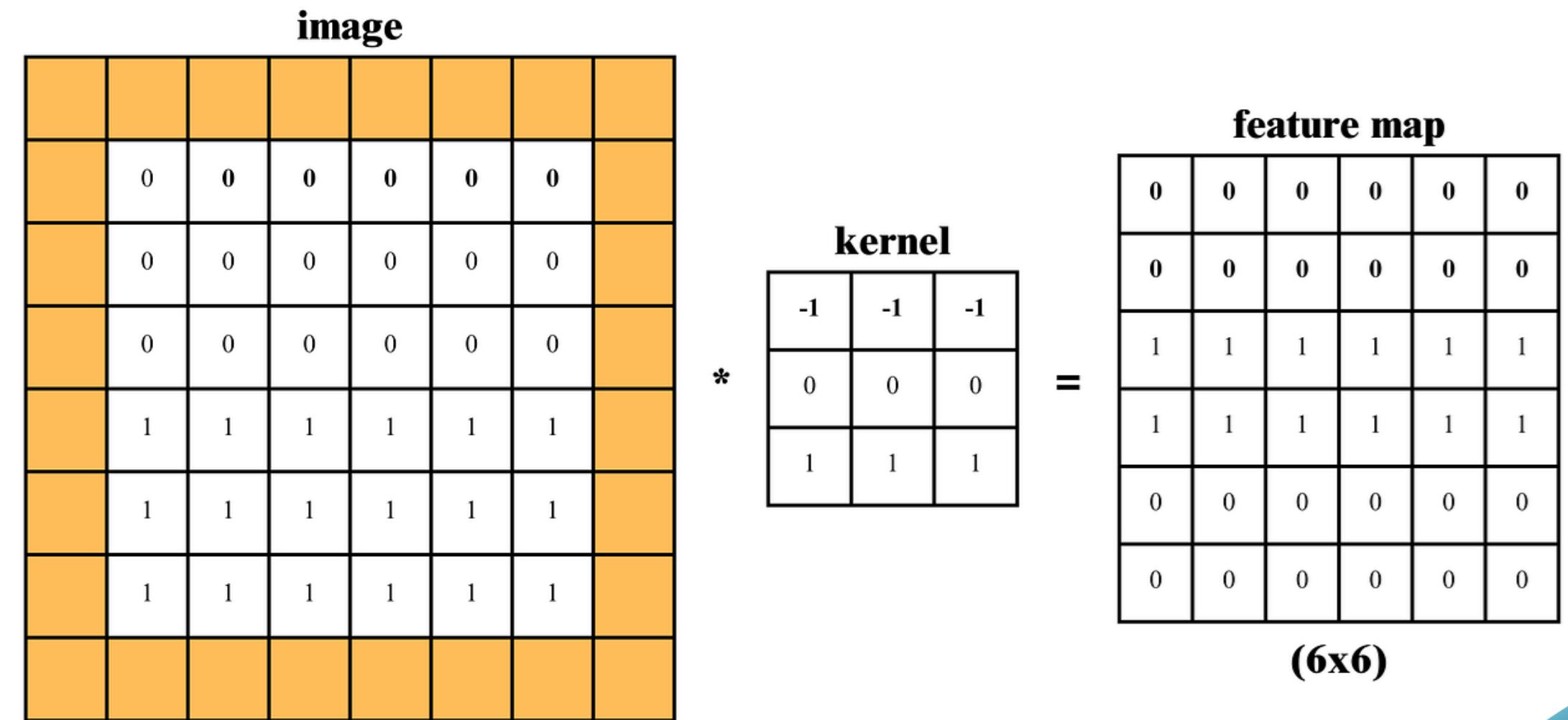
1. Convolution Layer

3.Padding Types:

Valid: No padding → Output ≤ input.

Same: Output = input (adds zeros).

Full: Output > input (maximal zero padding).





Deep learning models for image classification

image

	0	0	0	0	0	0	
	0	0	0	0	0	0	
	0	0	0	0	0	0	
	1	1	1	1	1	1	
	1	1	1	1	1	1	
	1	1	1	1	1	1	

*

kernel

-1	-1	-1
0	0	0
1	1	1

*

feature map

0	0	0	0	0	0
0	0	0	0	0	0
1	1	1	1	1	1
1	1	1	1	1	1
0	0	0	0	0	0
0	0	0	0	0	0

=

(6x6)



Deep learning models for image classification

60	7	98	14	19
165	159	147	196	169
187	204	165	41	111
209	30	201	23	203
58	79	218	59	118

*

1	0	-1
1	0	-1
1	0	-1

=



Deep learning models for image classification

1. Convolution Layer

Output size in a Convolutional Neural Network (CNN)

$$\text{Output Size} = \left\lfloor \frac{W - F + 2P}{S} \right\rfloor + 1$$

Variables:

- W: Input width/height (e.g., 32x32 image → W = 32).
- F: Filter/kernel size (e.g., 3x3 filter → F = 3).
- P: Padding (number of zeros added around the input).
- S: Stride (steps the filter moves).
- $\lfloor \cdot \rfloor$ = Floor function (rounds down to the nearest integer)



Deep learning models for image classification

◆ 1. Convolution Layer

Output size in a Convolutional Neural Network (CNN)

Example Calculations

1. Input: 28x28 (**W = 28**). Filter: 3x3 (**F = 3**). Stride: 1 (**S = 1**).
Padding: 1 (**P = 1**):

$$\frac{28 - 3 + 2(1)}{1} + 1 = 28 \quad (\text{Same padding!})$$

2. Input: 32x32 (**W = 32**). Filter: 5x5 (**F = 5**). Stride: 2
(**S = 2**). Padding: 0 (**P = 0**):

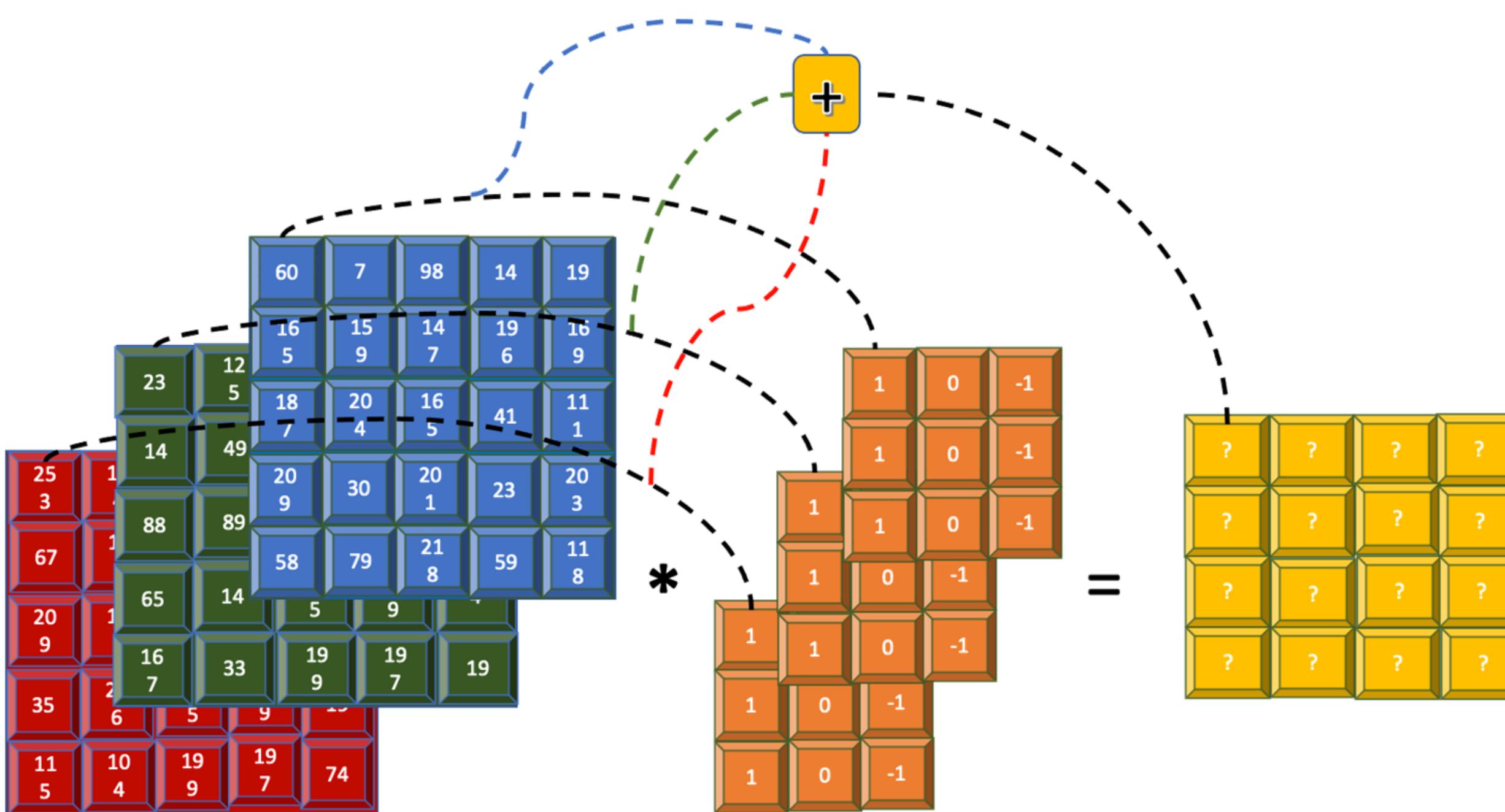
$$\frac{32 - 5 + 2(0)}{2} + 1 = 14.5$$

→ Floor to 14 (Valid padding!)



Deep learning models for image classification

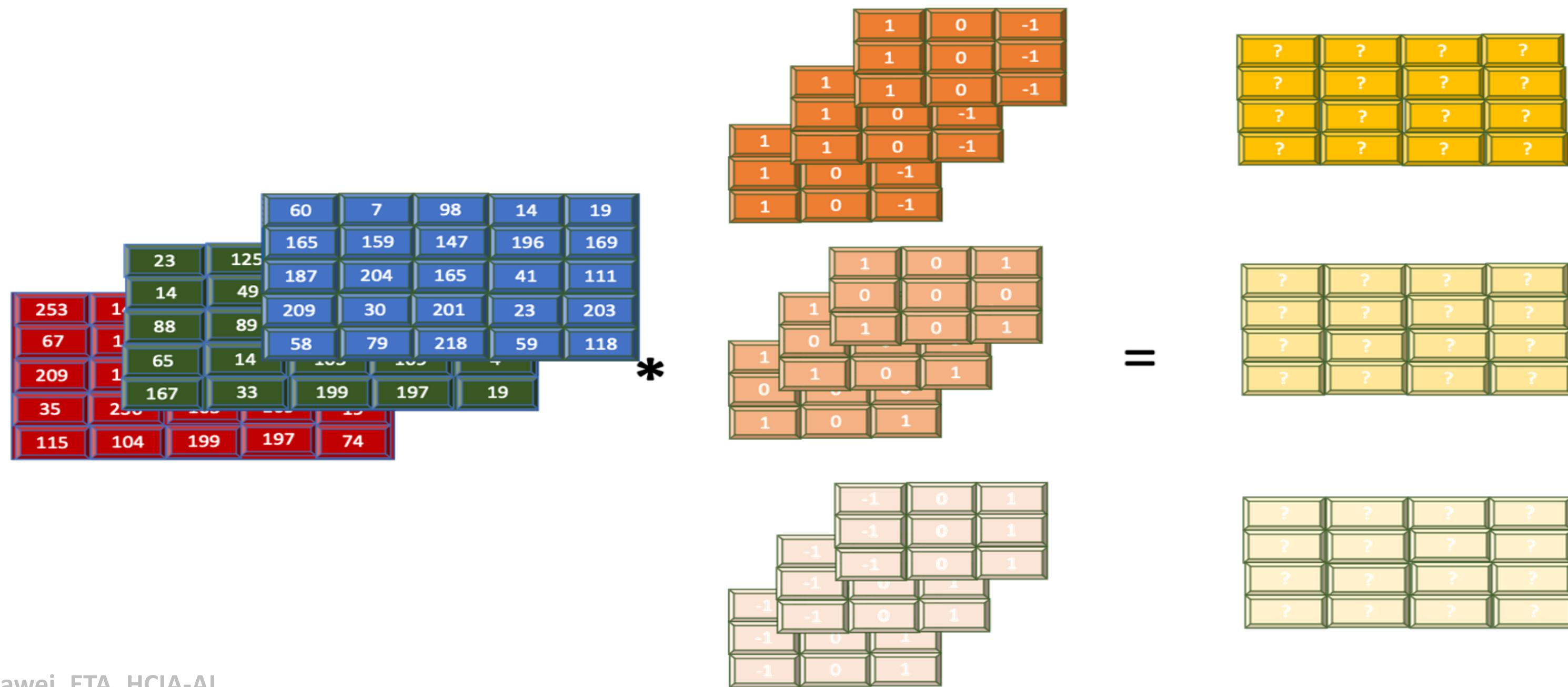
1. Convolutions applied over the RGB channels





Deep learning models for image classification

1. Convolutions applied over the RGB channels





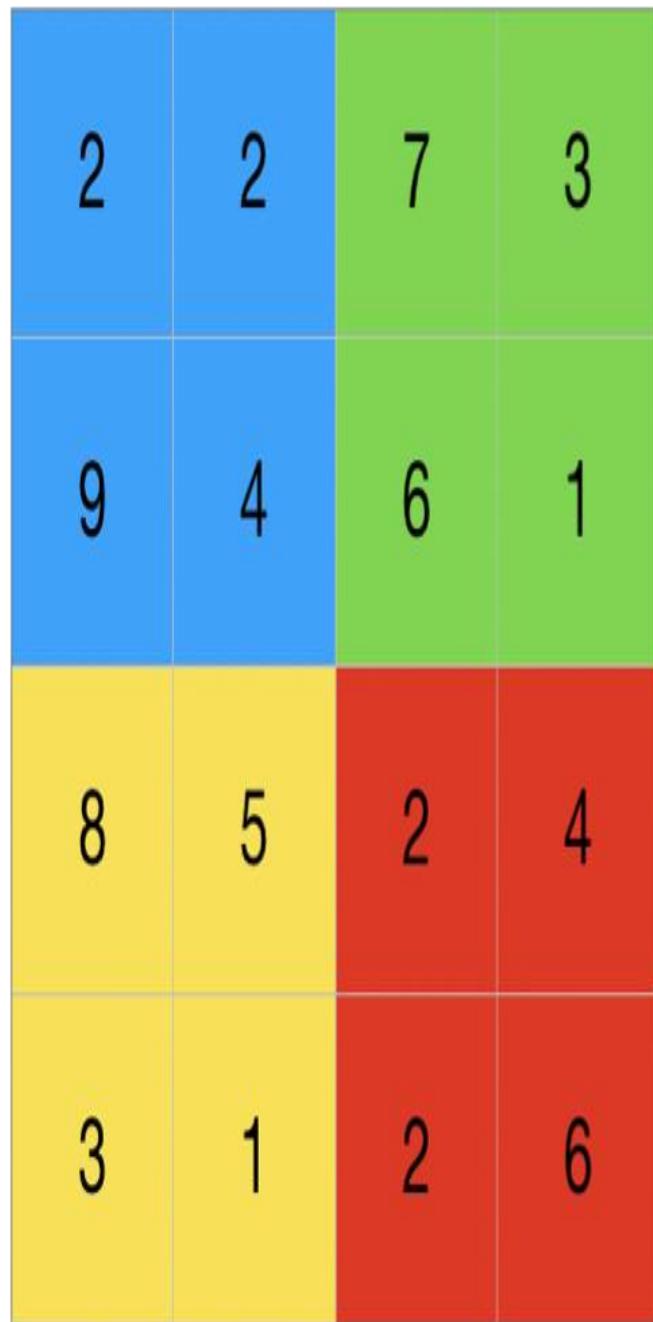
Deep learning models for image classification

2. Max Pooling Layer

How it works

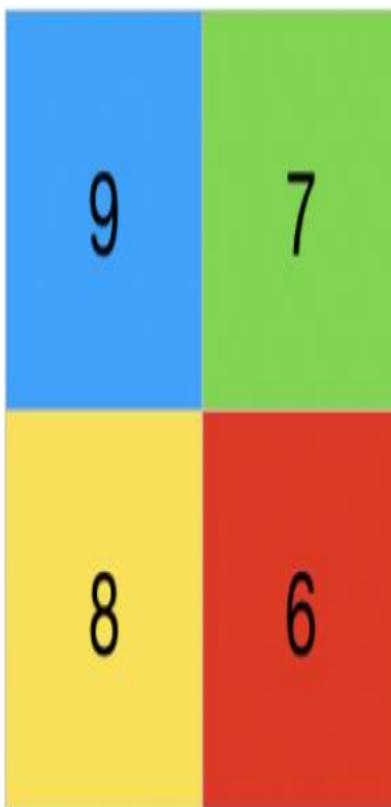
Mechanism:

Slides a window (e.g., 2×2) over **feature maps** → **selects maximum value** in each region.



Max Pool
→

Filter - (2×2)
Stride - $(2, 2)$





Deep learning models for image classification

2. Max Pooling Layer

Purpose

Down sampling: Reduces spatial dimensions (e.g., $4 \times 4 \rightarrow 2 \times 2$).

Efficiency: Lowers computational load.

Translation Invariance: Focuses on strongest features (e.g., edges, patterns), regardless of exact location.

3	13	17	11
5	3	1	23
7	1	2	3
11	17	1	4

Max Pooling →

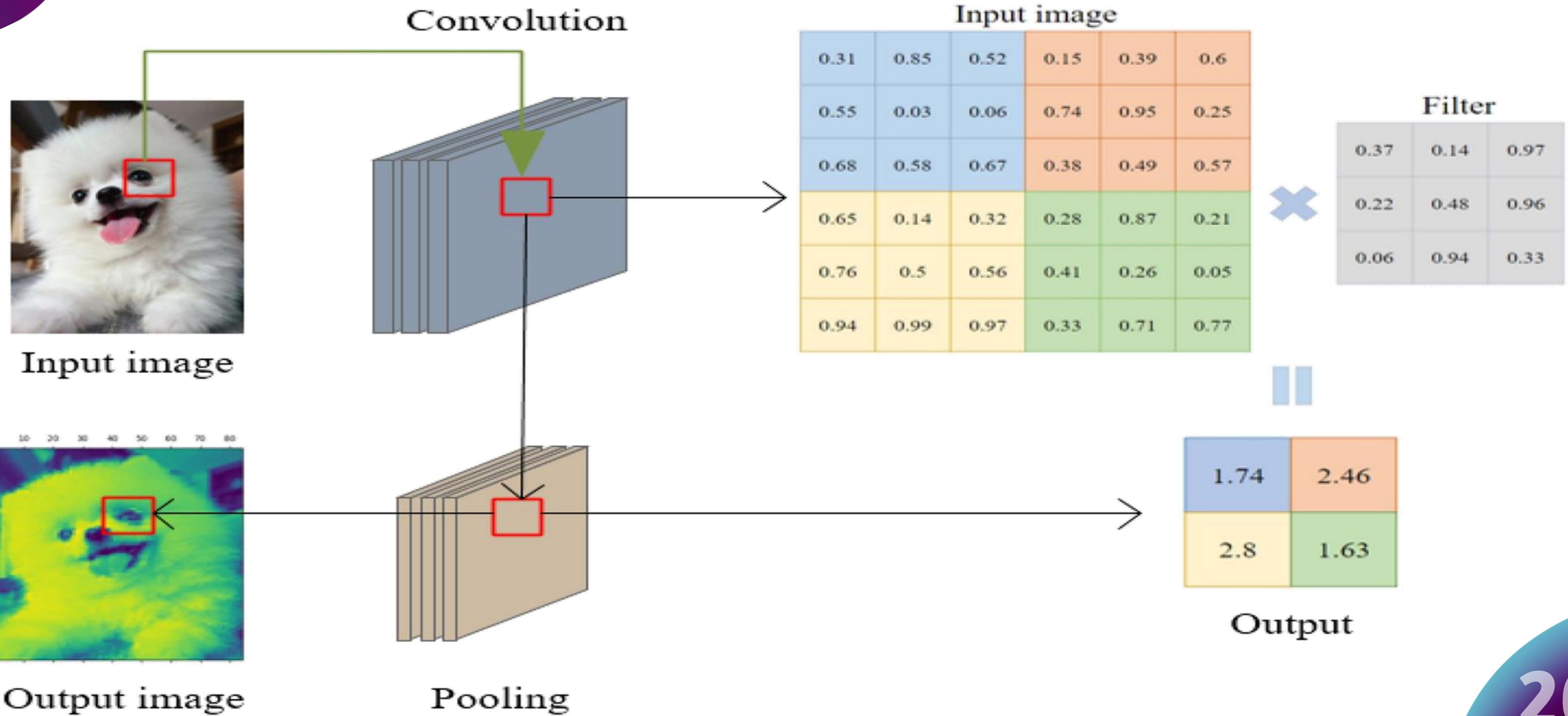
13	23
17	4

Average Pooling →

6	13
9	2.5



Deep learning models for image classification





Deep learning models for image classification

$$\begin{bmatrix} -166 & -20 & -44 & 57 & 210 \\ 370 & 11 & 119 & 111 & 251 \\ 393 & 48 & 133 & 30 & 260 \\ -313 & -130 & 190 & 152 & 123 \\ -109 & -158 & 27 & 98 & 82 \end{bmatrix} =$$



Deep learning models for image classification

3. *Flatten Layer*

How it works

The flatten layer **converts** the **2D** feature maps (after convolution and pooling) into a **1D vector**.

1	1	0
4	2	1
0	2	1

Pooled Feature Map

Flattening

1
1
0
4
2
1
0
2
1



Deep learning models for image classification

3. *Flatten Layer*

Purpose

Prepares the **data** for the **fully connected** layers (which act like a traditional neural network classifier).

1	1	0
4	2	1
0	2	1

Pooled Feature Map

Flattening

1
1
0
4
2
1
0
2
1

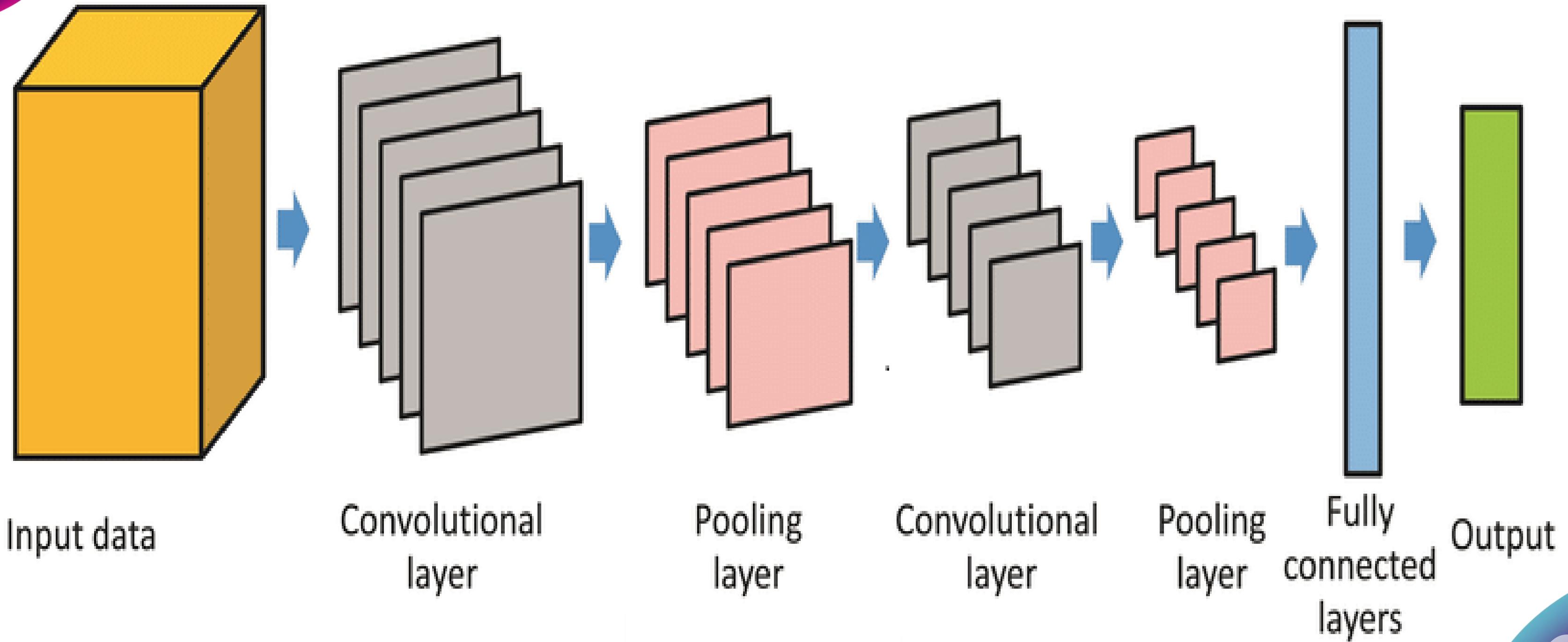


Deep learning models for image classification

$$\begin{matrix} 11 & 119 & 119 & 251 \\ 393 & 119 & 119 & 260 \\ 393 & 190 & 190 & 260 \\ -109 & 190 & 190 & 152 \end{matrix} =$$



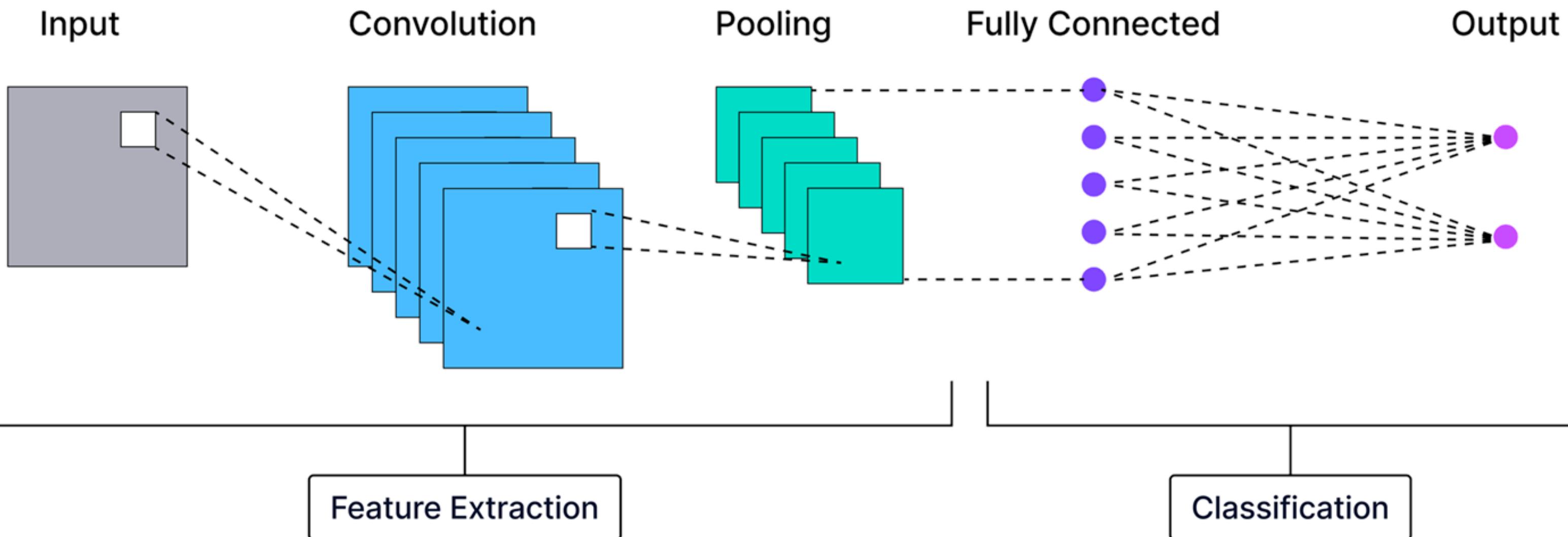
Deep learning models for image classification





Deep learning models for image classification

The Architecture of Convolutional Neural Networks





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INCEPTIONRESNET V2 ARCHITECTURE





Deep learning models for image classification

InceptionResNetV2 Architecture

Description

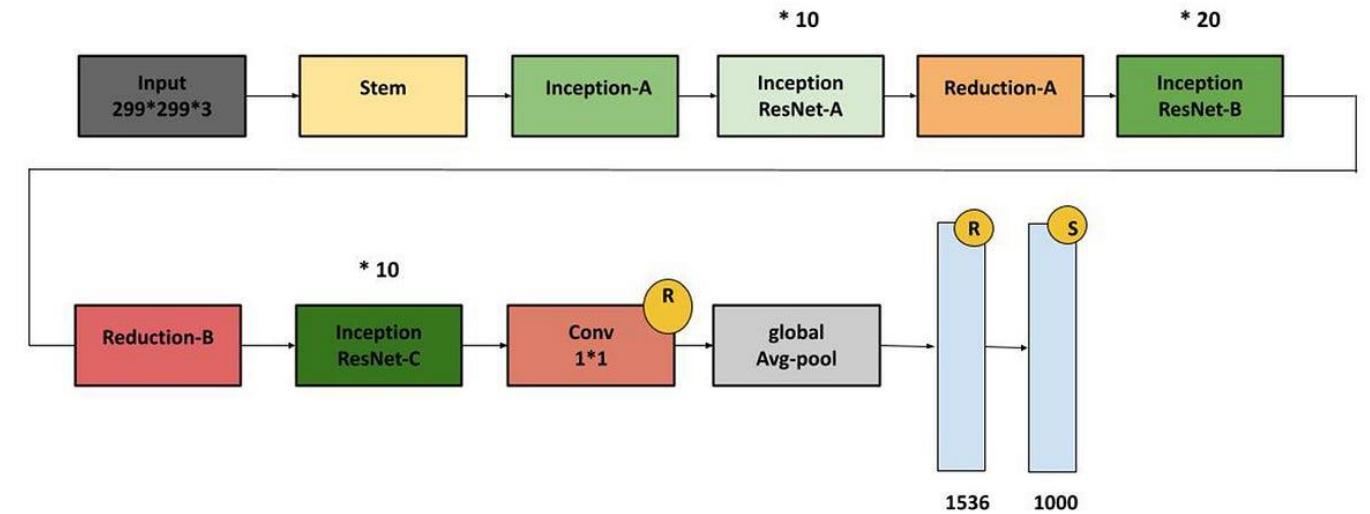
InceptionResNetV2 is a deep convolutional neural network that combines:

- Inception modules
- Residual connections

Number of Layers: Approximately **572 layers**, making it one of the **deepest** CNNs available.

Input Size: Typically **299 × 299 pixels**.

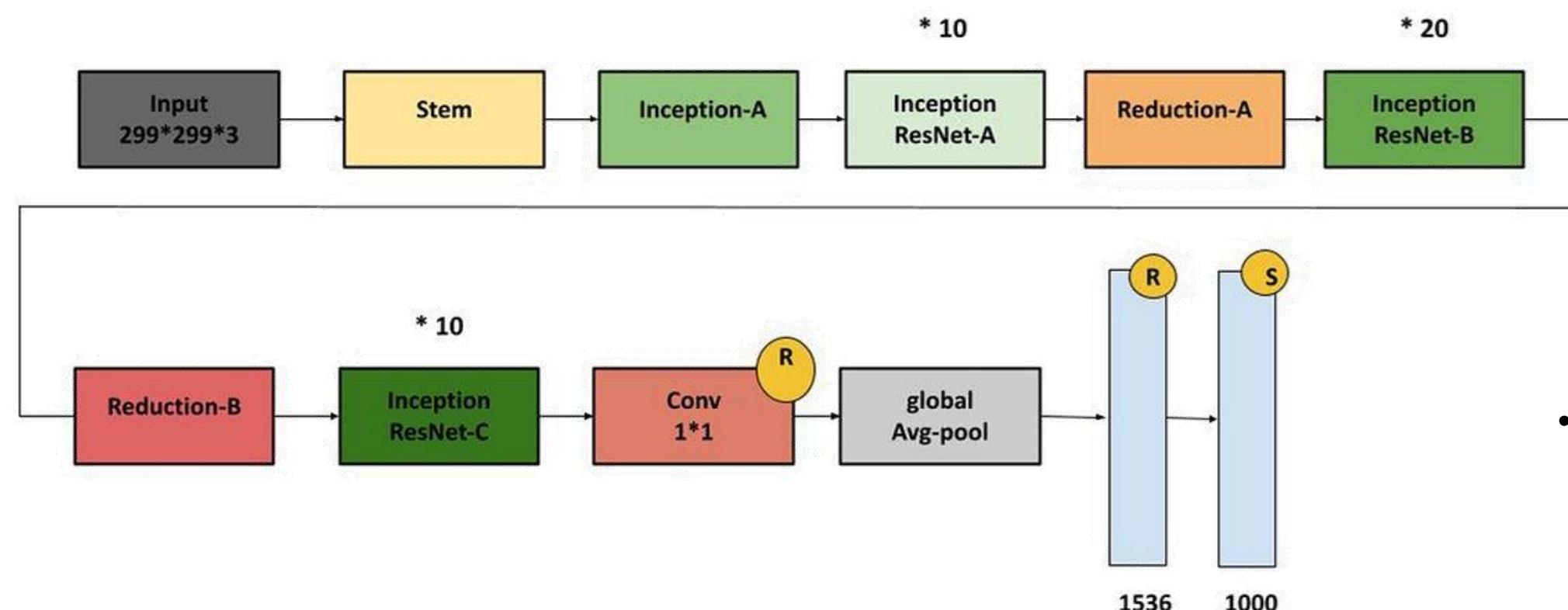
Inception-V2





Deep learning models for image classification

Inception-V2



- **Inception Modules:**

- Use **parallel convolutional branches** with different filter sizes (e.g., 1×1, 3×3, 5×5) to capture features at multiple scales.
- Example: A single Inception block might combine:
 - **1×1 convolutions** (for **dimensionality reduction**),
 - **3×3 convolutions** (extract local information),
 - **5×5 convolutions** (extract broader information),
 - **3×3 max pooling** (to retain spatial information).

- **Goal:** Efficiently learn both local and global patterns.

$$\text{InceptionBlock}(x) \cdot \alpha + x = \text{Output}$$

- **Residual Connections (Shortcuts):**

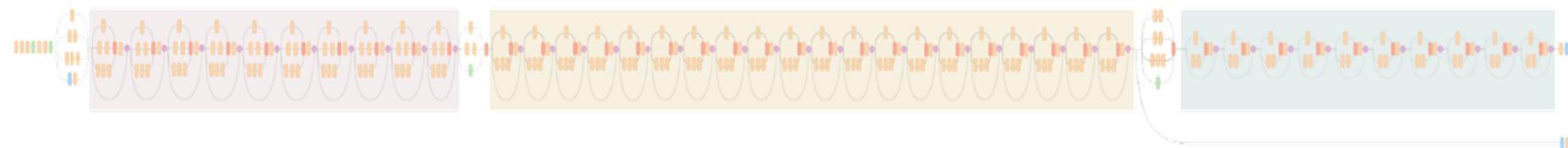
- Borrowed from **ResNet** architectures.
- Add the input of a block to its output:

$$\text{Output} = F(x) + x$$

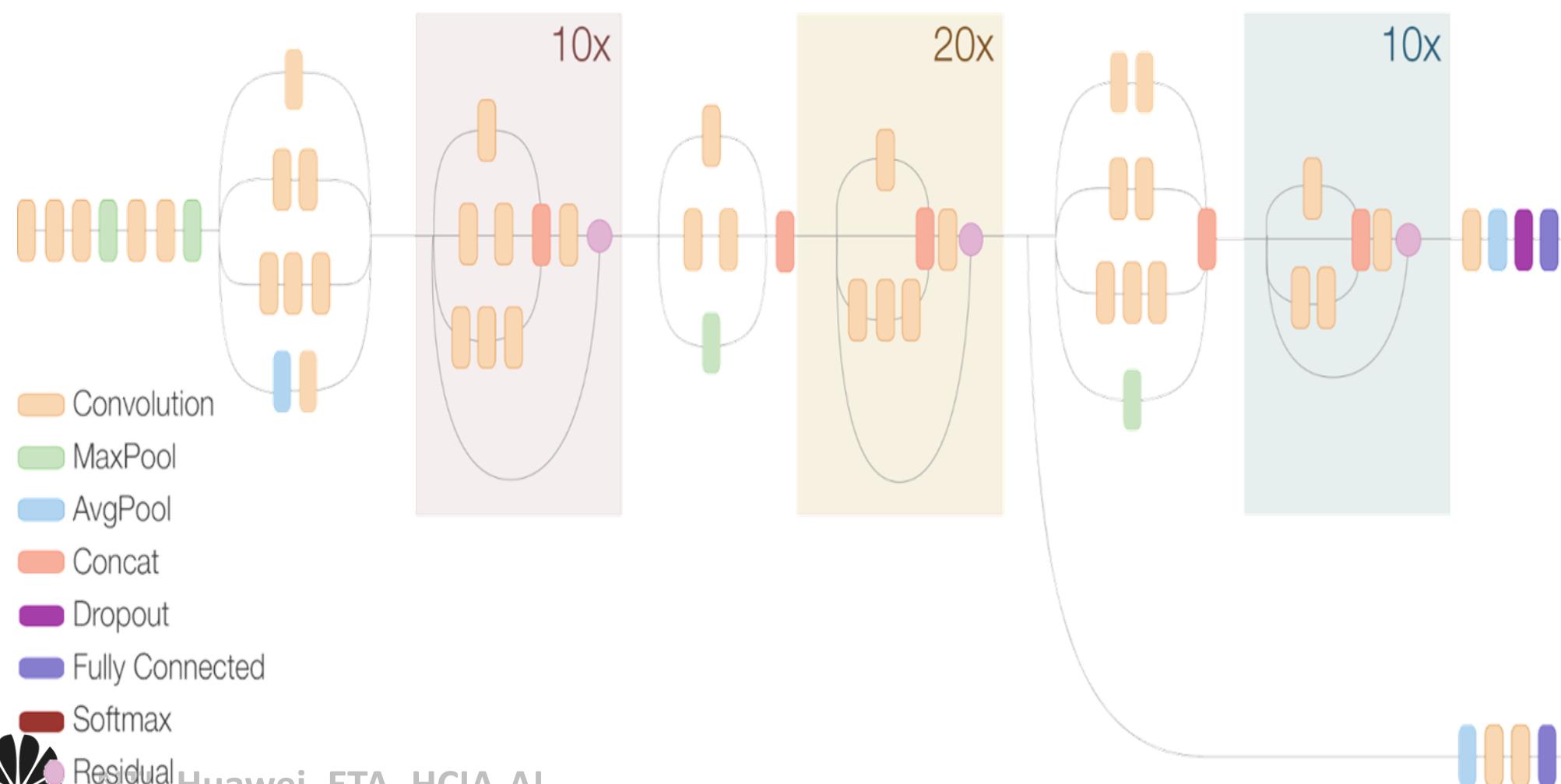


Deep learning models for image classification

Inception Resnet V2 Network



Compressed View



Layer Count:

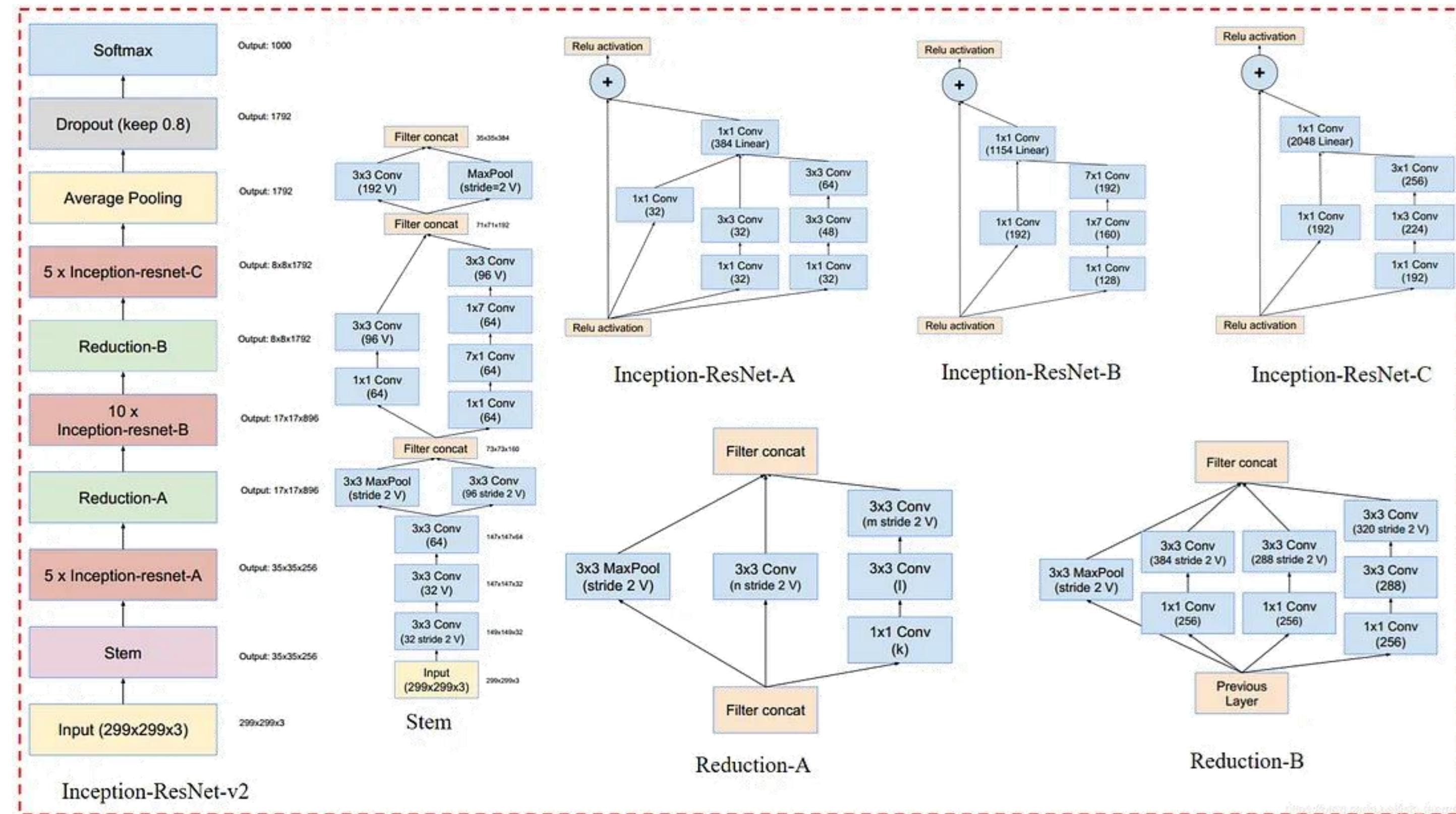
- **Total Layers:** ~572 layers (including convolutional, pooling, batch norm, and fully connected layers).

Breakdown:

- 164 convolutional layers (with varying filter sizes),
- 12 Inception-ResNet modules (complex multi-branch blocks),
- 2 stem blocks (initial feature extractors),
- Auxiliary classifiers (for training stabilization).



Deep learning models for image classification





Deep learning models for image classification

InceptionResNetV2 Architecture

Strengths

Learns both **fine-grained and high-level features**.

Faster convergence during training **due to residual paths**.

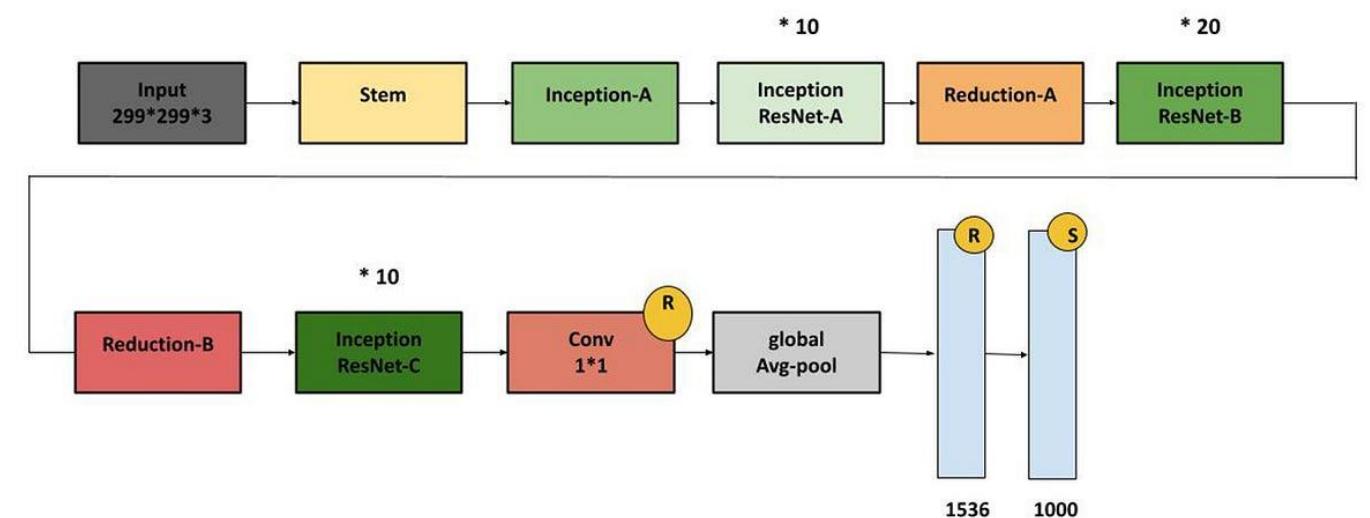
High accuracy in complex classification tasks.

Limitations

High computational cost and **memory usage**.

Requires **large datasets** and **powerful GPUs** for effective training.

Inception-V2



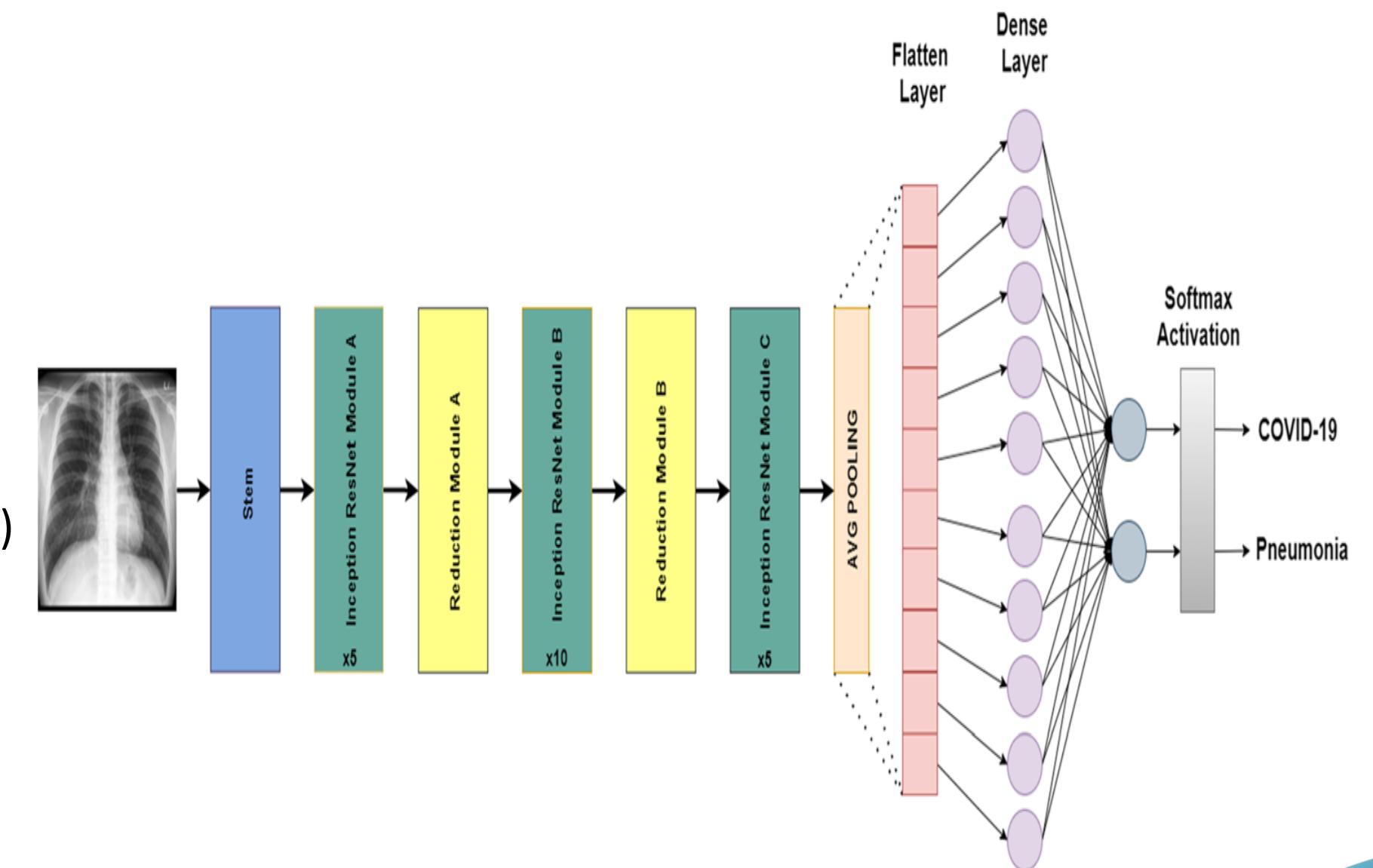


Deep learning models for image classification

InceptionResNetV2 Architecture

Common Use Cases

- **Medical image** analysis (e.g., **COVID-19 detection**)
- **Fine-grained classification** tasks (e.g., **plant disease detection**)
- **Industrial inspection** and **defect detection**.





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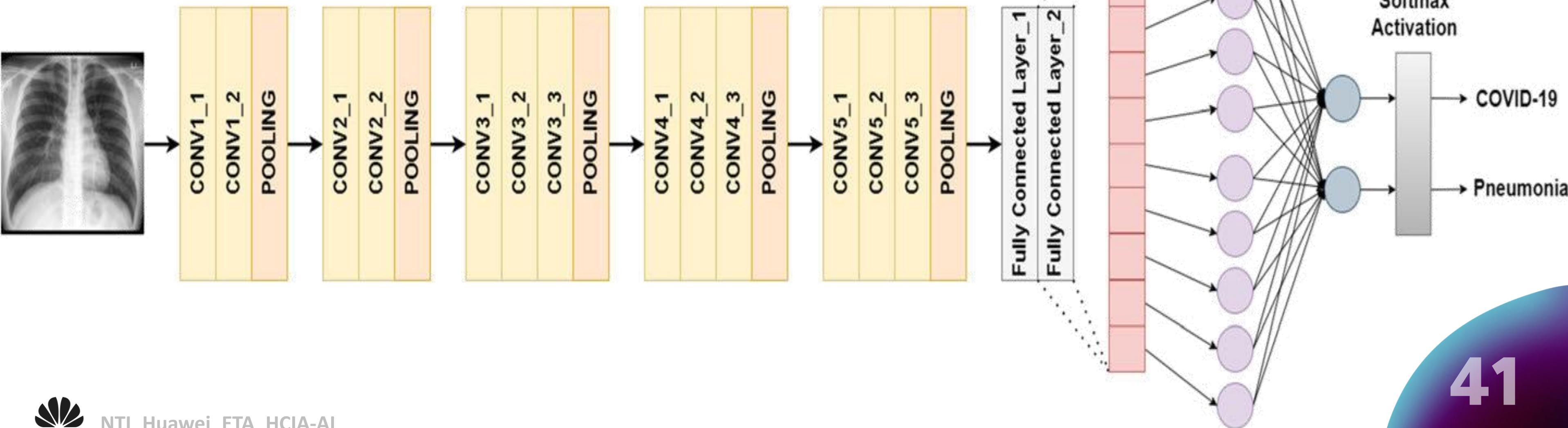
A QUICK COMPARISON OF THE MODELS THAT WERE USED





A quick comparison of the models that were used

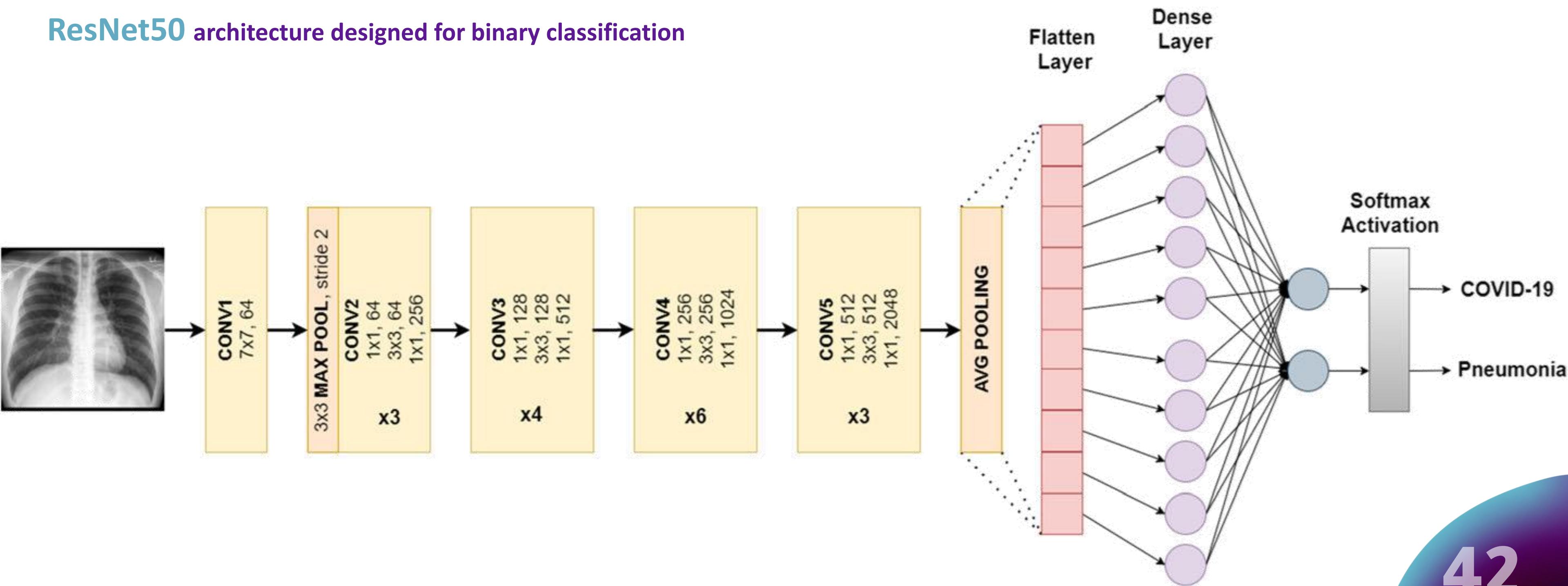
VGG16 architecture designed for binary classification





A quick comparison of the models that were used

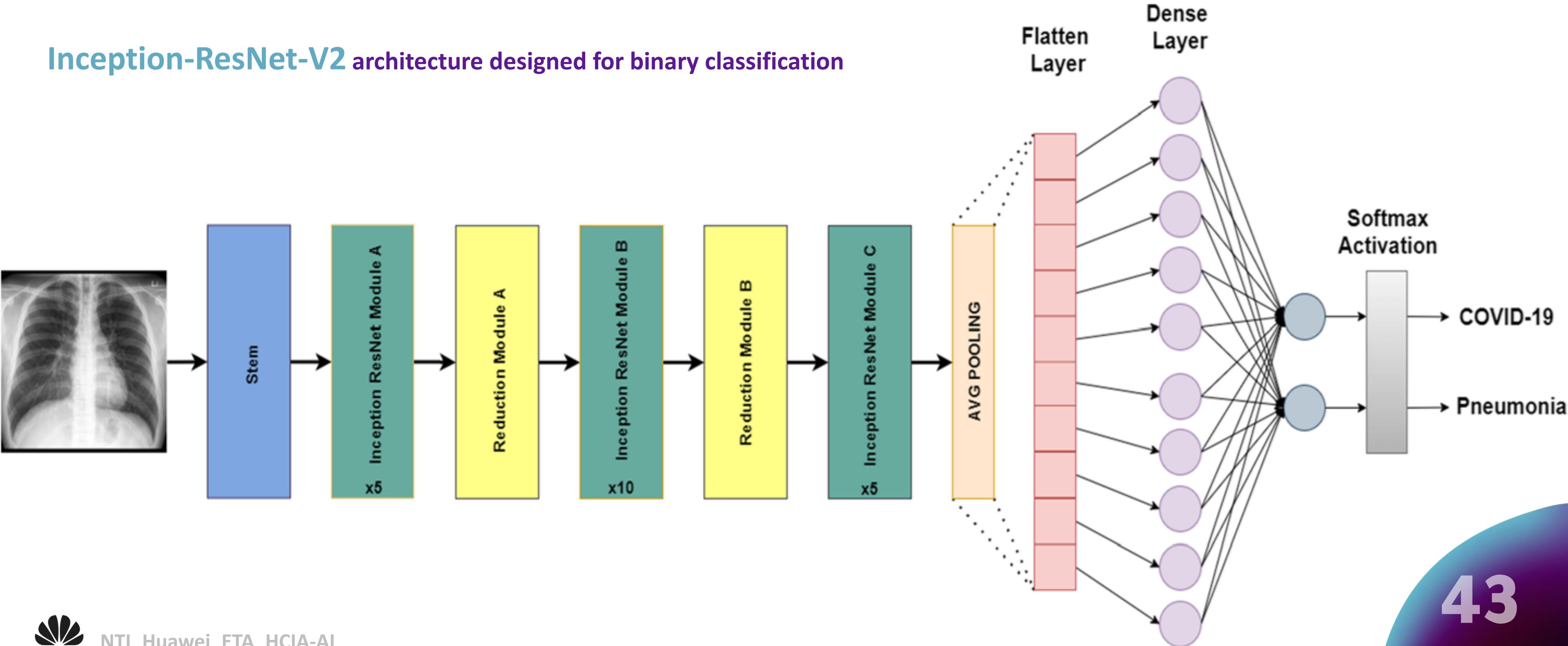
ResNet50 architecture designed for binary classification





A quick comparison of the models that were used

Inception-ResNet-V2 architecture designed for binary classification





A quick comparison of the models that were used

Model	Number of Layers	Strengths	Limitations	Common Use Cases
InceptionResNetV2	~572	<ul style="list-style-type: none"> - Captures multi-scale and abstract features- Residual connections improve training stability - High classification accuracy 	<ul style="list-style-type: none"> - Very high computational and memory cost - Requires large datasets and powerful GPUs 	<ul style="list-style-type: none"> Medical image analysis, plant disease detection
ResNet50	50	<ul style="list-style-type: none"> - Efficient depth with residual connections - Good performance on moderate hardware 	<ul style="list-style-type: none"> - May miss very fine-grained features - Not ideal for highly detailed textures 	<ul style="list-style-type: none"> General image classification, diagnostics
VGG16	16	<ul style="list-style-type: none"> - Easy to understand and implement - Solid baseline for model comparison 	<ul style="list-style-type: none"> - Large number of parameters (~138M) - Prone to overfitting - Slow training 	<ul style="list-style-type: none"> Academic demos, basic visual recognition tasks
Custom CNN	5–15 (typical)	<ul style="list-style-type: none"> - Lightweight and fast - Fully adaptable to specific tasks and limited hardware 	<ul style="list-style-type: none"> - Lower accuracy in complex domains - Limited generalization capabilities 	<ul style="list-style-type: none"> Mobile apps, embedded systems, real-time detection



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PRACTICAL APPLICATION





Practical application

```
import numpy as np
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.applications import ResNet50, InceptionResNetV2
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import os

# -----
# 2. Basic Settings and Data Paths
# -----
dataset_path = "/kaggle/input/new-plant-diseases-dataset/New Plant Diseases Dataset(Augmented)/New Plant Diseases Dataset(Augmented)"
train_dir = os.path.join(dataset_path, "train")
test_dir = os.path.join(dataset_path, "valid")
batch_size = 32
img_size = 224
epochs = 3 # Increased for ResNet
```



Practical application

```
# -----
# 3. Data Preparation and Generation
# -----
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=45,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.3,
    horizontal_flip=True,
    vertical_flip=True,
    fill_mode='nearest')

test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(img_size, img_size),
    batch_size=batch_size,
    class_mode='categorical')

test_generator = test_datagen.flow_from_directory(
    test_dir,
    target_size=(img_size, img_size),
    batch_size=batch_size,
    class_mode='categorical',
    shuffle=False)
```

Output

Found 70295 images belonging to 38 classes.
Found 17572 images belonging to 38 classes.





Practical application

```
# -----
# 4. Build CNN Model
# -----
def build_cnn_model():
    model = models.Sequential([
        layers.Conv2D(32, (3,3), activation='relu', input_shape=(img_size, img_size, 3)),
        layers.MaxPooling2D((2, 2)),
        layers.Conv2D(64, (3,3), activation='relu'),
        layers.MaxPooling2D((2, 2)),
        layers.Conv2D(128, (3,3), activation='relu'),
        layers.MaxPooling2D((2, 2)),
        layers.Flatten(),
        layers.Dense(512, activation='relu'),
        layers.Dropout(0.5),
        layers.Dense(train_generator.num_classes, activation='softmax')
    ])

    model.compile(optimizer='adam',
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model
```



Practical application

```
# -----
# 5. Build ResNet Model with Improvements
# -----
def build_resnet_model():
    base_model = ResNet50(
        weights='imagenet',
        include_top=False,
        input_shape=(img_size, img_size, 3)
    )

    model = models.Sequential([
        base_model,
        layers.GlobalAveragePooling2D(),
        layers.Dense(1024, activation='relu'), # Increased units
        layers.BatchNormalization(),
        layers.Dropout(0.4), # Adjusted dropout
        layers.Dense(512, activation='relu'),
        layers.BatchNormalization(),
        layers.Dropout(0.3),
        layers.Dense(train_generator.num_classes, activation='softmax')
    ])

    model.compile(
        optimizer=tf.keras.optimizers.Adam(learning_rate=1e-4),
        loss='categorical_crossentropy',
        metrics=['accuracy']
    )
    return model
```



Practical application

```
# -----
# 6. Build Inception-ResNet-V2 Model
# -----
def build_inception_model():
    base_model = InceptionResNetV2(
        weights='imagenet',
        include_top=False,
        input_shape=(img_size, img_size, 3)
    )

    model = models.Sequential([
        base_model,
        layers.GlobalAveragePooling2D(),
        layers.Dense(512, activation='relu'),
        layers.BatchNormalization(),
        layers.Dropout(0.5),
        layers.Dense(train_generator.num_classes, activation='softmax')
    ])

    model.compile(
        optimizer=tf.keras.optimizers.Adam(learning_rate=1e-4),
        loss='categorical_crossentropy',
        metrics=['accuracy']
    )
    return model
```



Practical application

```
# -----
# 7. Train Models
# -----
# Callbacks for ResNet
early_stopping = EarlyStopping(monitor='val_loss', patience=2, restore_best_weights=True)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, min_lr=1e-6)

# Train Inception-ResNet-V2
inception_model = build_inception_model()
print("\n--- Training Inception-ResNet-V2 Model ---")
history_inception = inception_model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // batch_size,
    epochs=1, # Keep 1 epoch for Inception
    validation_data=test_generator,
    validation_steps=test_generator.samples // batch_size)

--- Training Inception-ResNet-V2 Model ---
2196/2196 [=====] 1480s 591ms/step - accuracy: 0.7989 - loss: 0.7580 - val_accuracy: 0.984
3 - val_loss: 0.0522
```



Practical application

```
# Train CNN
cnn_model = build_cnn_model()
print("\n--- Training CNN Model ---")
history_cnn = cnn_model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // batch_size,
    epochs=1, # Keep 1 epoch for CNN
    validation_data=test_generator,
    validation_steps=test_generator.samples // batch_size)

/usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning:
Do not pass an `input_shape`/'input_dim' argument to a layer. When using Sequential models, prefer us
ing an `Input(shape)` object as the first layer in the model instead.
    super().__init__(activity_regularizer=activity_regularizer, **kwargs)

--- Training CNN Model ---
2196/2196 ━━━━━━━━━━ 913s 413ms/step - accuracy: 0.3179 - loss: 2.4007 - val_accuracy: 0.7086
- val_loss: 0.8975
```



Practical application

```
# Train ResNet
resnet_model = build_resnet_model()
print("\n--- Training ResNet Model ---")
history_resnet = resnet_model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // batch_size,
    epochs=1,
    validation_data=test_generator,
    validation_steps=test_generator.samples // batch_size,
    callbacks=[early_stopping, reduce_lr])
```

```
2196/2196 [=====] 1396s 601ms/step - accuracy: 0.7648 - loss: 0.8864 - val_accuracy: 0.977
2 - val_loss: 0.0680 - learning_rate: 1.0000e-04
```



Practical application

```
# -----
# 8. Evaluation Functions
# -----

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import classification_report, confusion_matrix

# List to store evaluation results
results = []

def evaluate_model(model, history, model_name, test_generator):
    # Evaluate the model
    test_loss, test_acc = model.evaluate(test_generator)
    print(f'\nModel {model_name} Test Accuracy: {test_acc:.4f}, Test Loss: {test_loss:.4f}')

    # Store results
    results.append({
        'Model': model_name,
        'Test Accuracy': test_acc,
        'Test Loss': test_loss
    })

    # Predictions and classification report
    y_pred = model.predict(test_generator)
    y_pred_classes = np.argmax(y_pred, axis=1)

    print(f"\nDetailed Classification Report for {model_name}:")
    print(classification_report(test_generator.classes, y_pred_classes,
                                target_names=list(test_generator.class_indices.keys())))

    # Confusion matrix
    plt.figure(figsize=(10, 8))
    sns.heatmap(confusion_matrix(test_generator.classes, y_pred_classes),
                annot=True, fmt='d', cmap='Blues')
    plt.title(f'Confusion Matrix - {model_name}')
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.savefig(f'{model_name}_confusion_matrix.png')
    plt.show() # Display the plot
    plt.close()

    return history, test_acc, test_loss

# -----
# 9. Execute Evaluation
# -----

print("\n==== Evaluating Models ====")

# Lists to store histories
histories = []
model_names = ["CNN", "ResNet", "InceptionResNetV2"]
```



Practical application

```
Evaluating CNN Model...
550/550 ━━━━━━━━ 34s 63ms/step - accuracy: 0.7062 - loss: 0.9118

# -----
# 9. Execute Evaluation
# -----
print("\n== Evaluating Models ==")

# Lists to store histories
histories = []
model_names = ["CNN", "ResNet", "InceptionResNetV2"]

# Evaluate CNN
print("\nEvaluating CNN Model...")
history_cnn, cnn_acc, cnn_loss = evaluate_model(cnn_model, history_cnn, "CNN", test_generator)
histories.append(history_cnn)

# Evaluate ResNet
print("\nEvaluating ResNet Model...")
history_resnet, resnet_acc, resnet_loss = evaluate_model(resnet_model, history_resnet, "ResNet", test_generator)
histories.append(history_resnet)

# Evaluate Inception-ResNet-V2
print("\nEvaluating Inception-ResNet-V2 Model...")
history_inception, inception_acc, inception_loss = evaluate_model(inception_model, history_inception, "InceptionResNetV2", test_generator)
histories.append(history_inception)

# Plot comparative metrics
plot_comparative_metrics(histories, model_names)

# Save comparison table
save_comparison_table(results)

Model CNN Test Accuracy: 0.7086, Test Loss: 0.8973
550/550 ━━━━━━━━ 32s 58ms/step

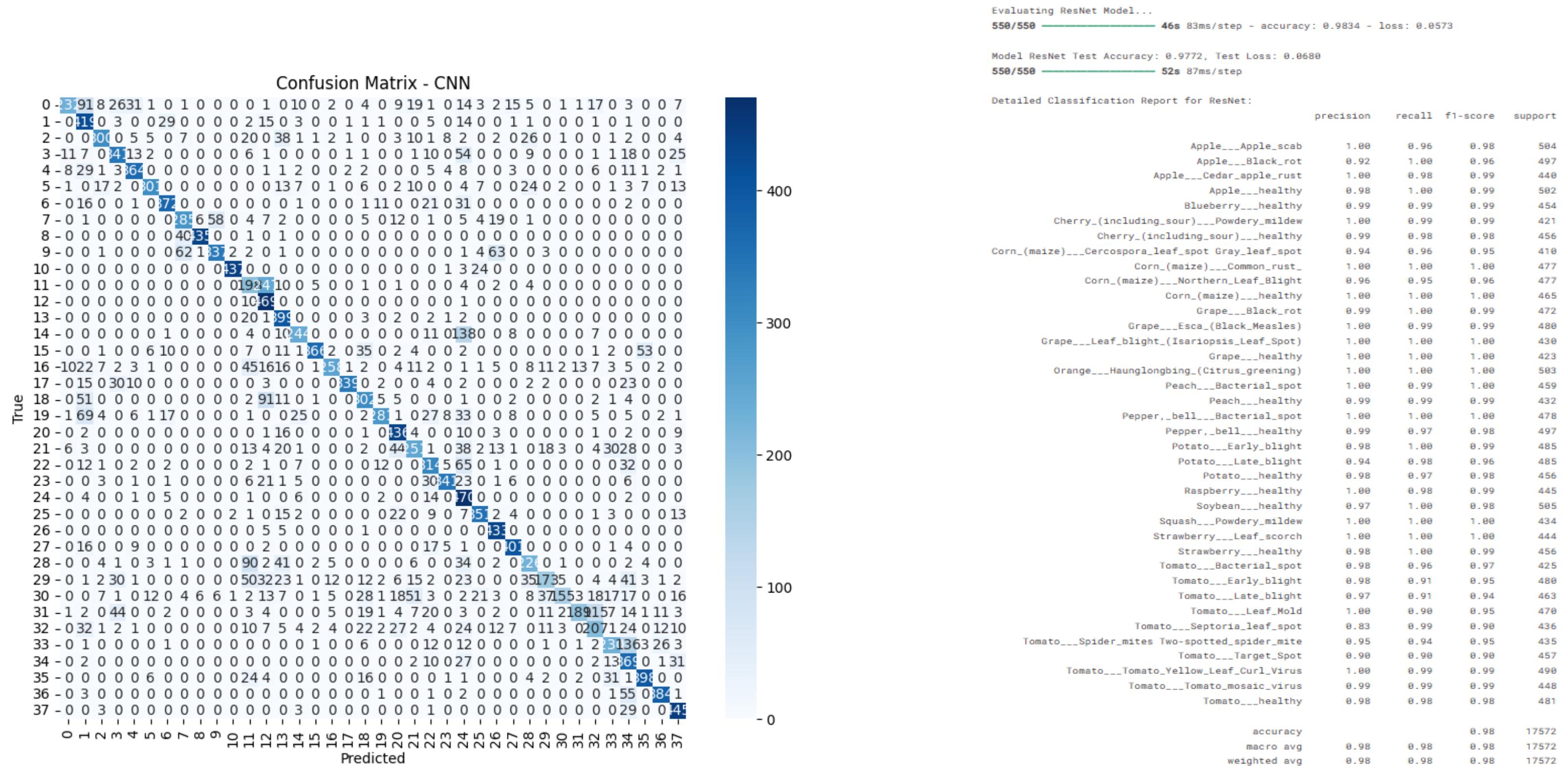
Detailed Classification Report for CNN:

          precision    recall   f1-score   support
Apple__Apple_scab      0.86     0.46     0.60      584
Apple__Black_rot       0.53     0.84     0.65      497
Apple__Cedar_apple_rust 0.83     0.68     0.75      448
Apple__healthy          0.70     0.68     0.69      502
Blueberry__healthy      0.81     0.80     0.81      454
Cherry_(including_sour)_Powdery_mildew 0.89     0.71     0.79      421
Cherry_(including_sour)_healthy          0.84     0.82     0.83      456
Corn_(maize)_Cercospora_leaf_spot_Gray_leaf_spot 0.71     0.70     0.70      418
Corn_(maize)_Common_rust_               0.97     0.91     0.94      477
Corn_(maize)_Northern_Leaf_Blight      0.84     0.71     0.77      477
Corn_(maize)_healthy                  0.99     0.94     0.96      465
Grape__Black_rot                   0.38     0.42     0.40      472
Grape__Esca_(Black_Measles)           0.49     0.98     0.66      488
Grape__Leaf_blight_(Isariopsis_Leaf_Spot) 0.62     0.93     0.74      430
Grape__healthy                      0.76     0.58     0.65      423
Orange__Haunglongbing_(Citrus_greening) 0.96     0.73     0.83      583
Peach__Bacterial_spot                0.87     0.56     0.68      459
Peach__healthy                      0.98     0.78     0.87      432
Pepper,_bell__Bacterial_spot        0.64     0.63     0.64      478
Pepper,_bell__healthy                0.88     0.57     0.69      497
Potato__Early_blight                 0.73     0.90     0.81      485
Potato__Late_blight                  0.64     0.52     0.57      485
Potato__healthy                      0.59     0.69     0.64      456
Raspberry__healthy                  0.91     0.77     0.83      445
Soybean__healthy                     0.44     0.93     0.60      585
Squash__Powdery_mildew              0.84     0.81     0.82      434
Strawberry__Leaf_scorch              0.77     0.98     0.86      444
Strawberry__healthy                  0.88     0.88     0.88      456
Tomato__Bacterial_spot               0.64     0.53     0.58      425
Tomato__Early_blight                 0.64     0.36     0.46      488
Tomato__Late_blight                  0.89     0.33     0.49      463
Tomato__Leaf_Mold                    0.90     0.40     0.56      478
Tomato__Septoria_leaf_spot           0.52     0.47     0.49      436
Tomato__Spider_mites_Two-spotted_spider_mite 0.66     0.53     0.59      435
Tomato__Target_Spot                  0.44     0.81     0.57      457
Tomato__Tomato_Yellow_Leaf_Curl_Virus 0.85     0.81     0.83      498
Tomato__Tomato_mosaic_virus          0.87     0.86     0.86      448
Tomato__healthy                      0.76     0.93     0.83      481

accuracy          0.71      17572
macro avg         0.75      0.71      0.71      17572
weighted avg      0.75      0.71      0.71      17572
```

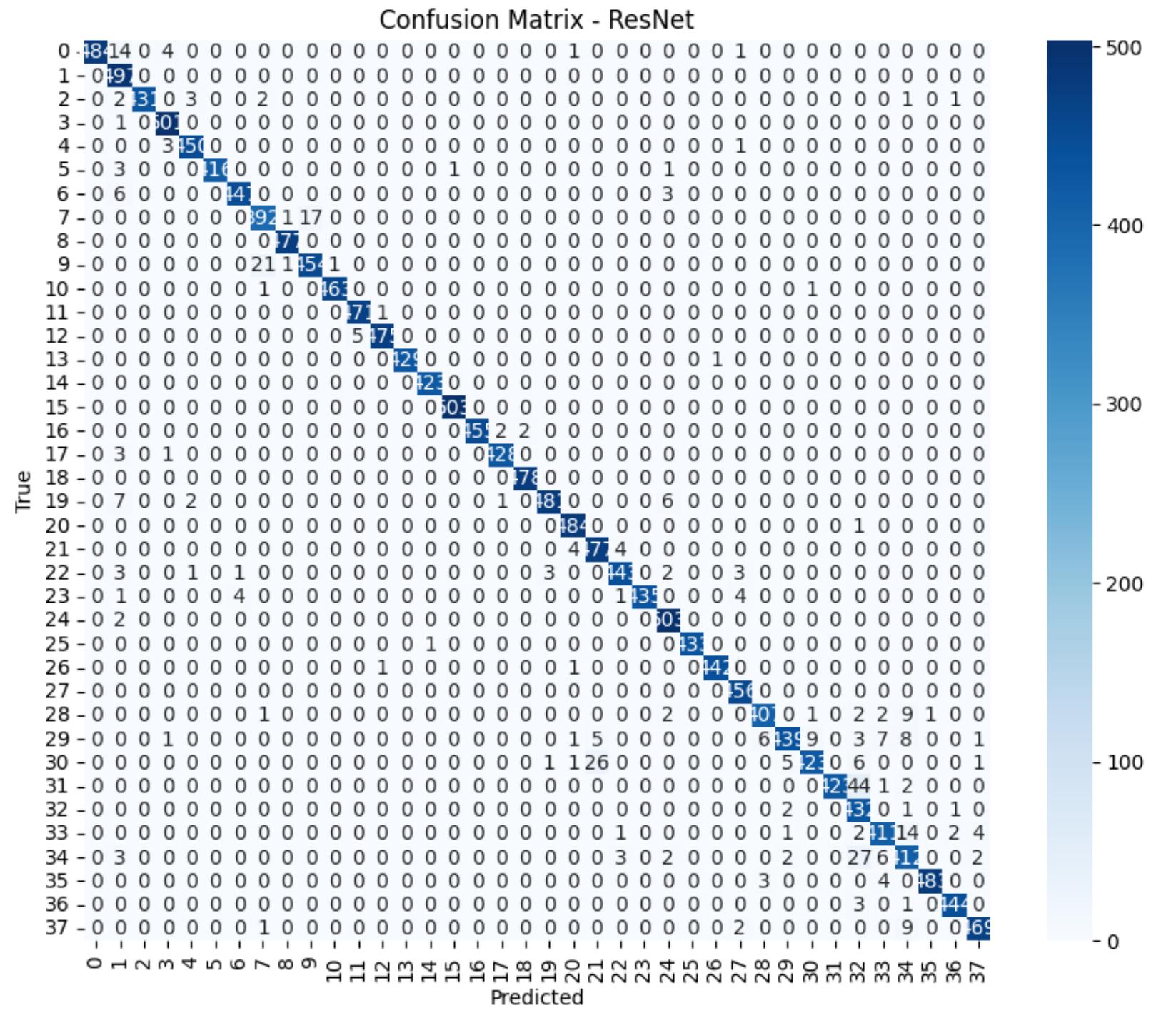


Practical application





Practical application



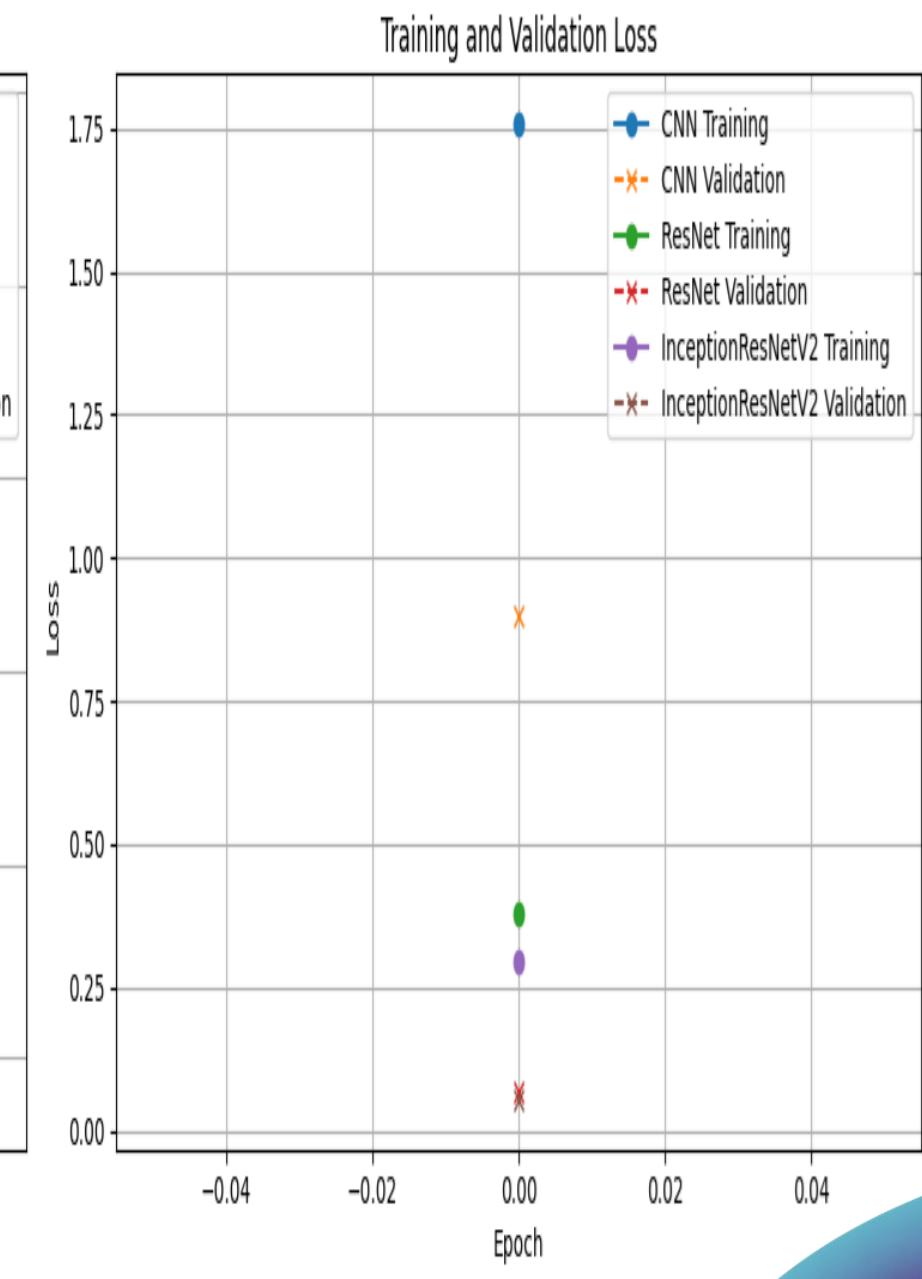
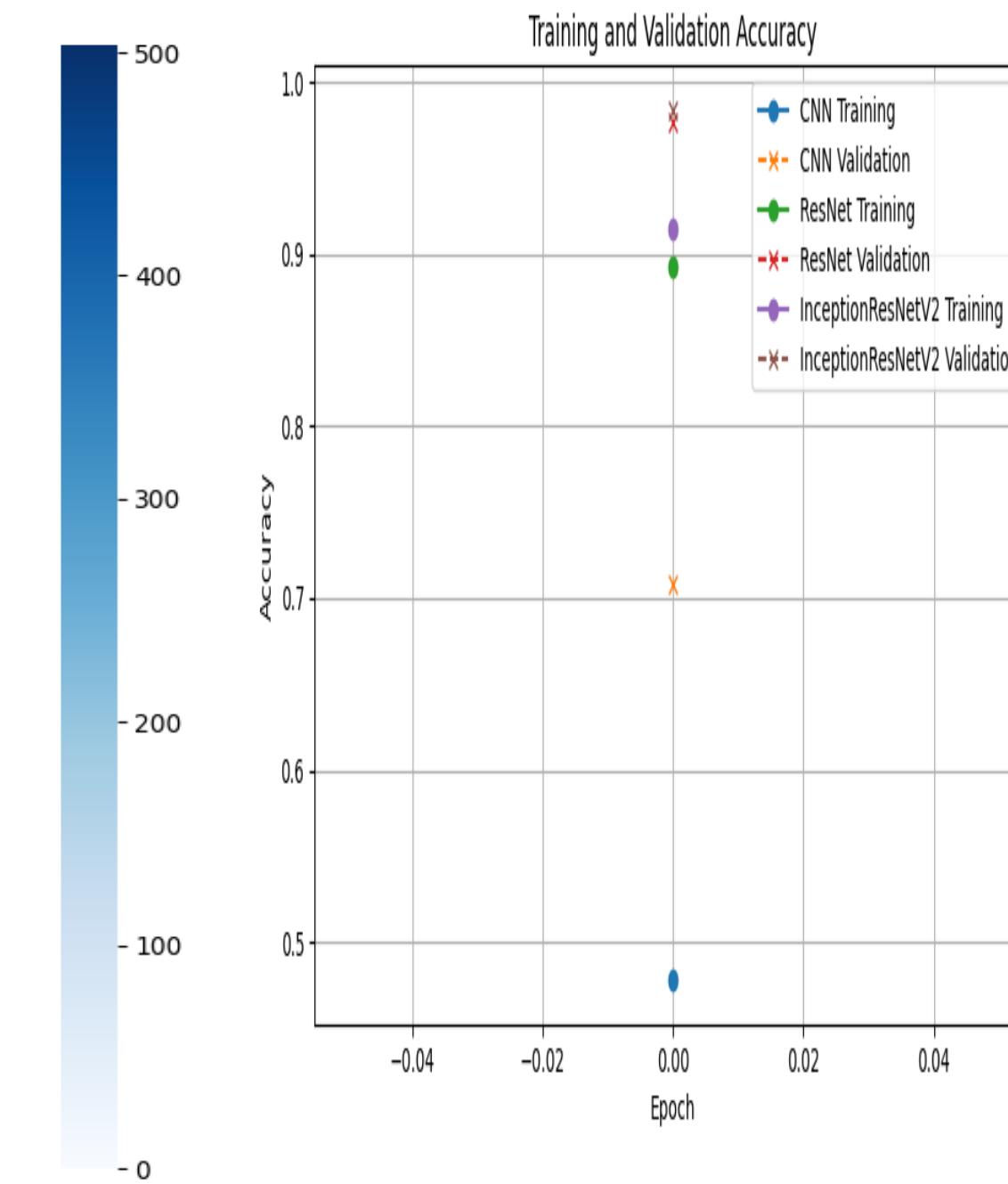
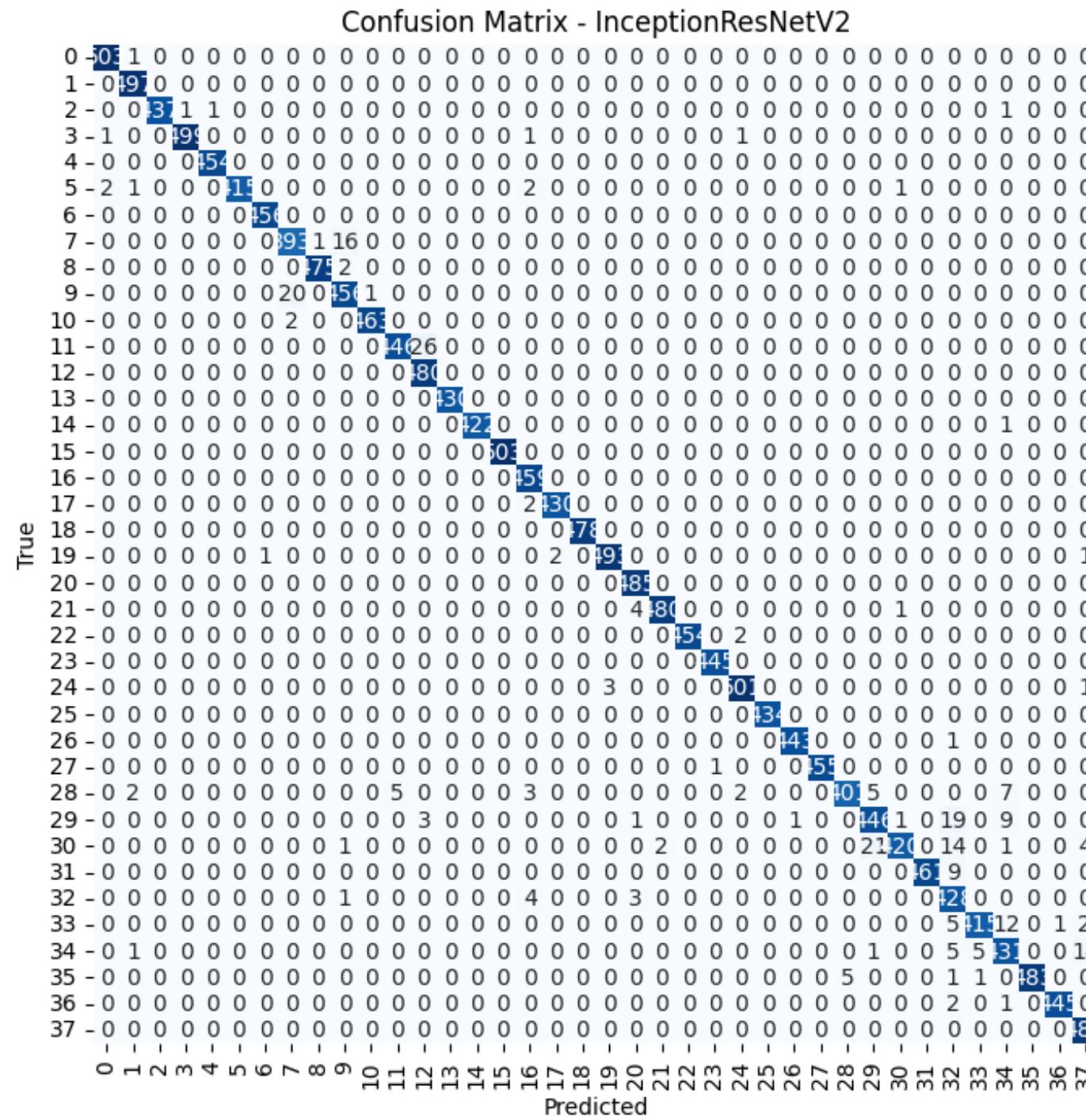
```
Evaluating Inception-ResNet-V2 Model...
550/550 - 84s 152ms/step - accuracy: 0.9904 - loss: 0.0346
```

Model InceptionResNetV2 Test Accuracy: 0.9844, Test Loss: 0.0522
550/550 ————— 105s 169ms/step

Detailed Classification Report for InceptionResNetV2:					
		precision	recall	f1-score	support
	Apple___Apple_scab	0.99	1.00	1.00	504
	Apple___Black_rot	0.99	1.00	0.99	497
	Apple___Cedar_apple_rust	1.00	0.99	1.00	448
	Apple___healthy	1.00	0.99	1.00	502
	Blueberry___healthy	1.00	1.00	1.00	454
Cherry_(including_sour)	___Powdery_mildew	1.00	0.99	0.99	421
	Cherry_(including_sour)___healthy	1.00	1.00	1.00	456
Corn_(maize)	___Cercospora_leaf_spot_Gray_leaf_spot	0.95	0.96	0.95	410
	Corn_(maize)___Common_rust_	1.00	1.00	1.00	477
	Corn_(maize)___Northern_Leaf_Blight	0.96	0.96	0.96	477
	Corn_(maize)___healthy	1.00	1.00	1.00	465
	Grape___Black_rot	0.99	0.94	0.97	472
	Grape___Esca_(Black_Measles)	0.94	1.00	0.97	480
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)		1.00	1.00	1.00	430
	Grape___healthy	1.00	1.00	1.00	423
Orange___Haunglongbing_(Citrus_greening)		1.00	1.00	1.00	503
	Peach___Bacterial_spot	0.97	1.00	0.99	459
	Peach___healthy	1.00	1.00	1.00	432
Pepper,_bell	___Bacterial_spot	1.00	1.00	1.00	478
	Pepper,_bell___healthy	0.99	0.99	0.99	497
Potato___Early_blight		0.98	1.00	0.99	485
	Potato___Late_blight	1.00	0.99	0.99	485
	Potato___healthy	1.00	1.00	1.00	456
Raspberry___healthy		1.00	1.00	1.00	445
Soybean___healthy		0.99	0.99	0.99	505
Squash___Powdery_mildew		1.00	1.00	1.00	434
Strawberry___Leaf_scorch		1.00	1.00	1.00	444
	Strawberry___healthy	1.00	1.00	1.00	456
Tomato___Bacterial_spot		0.99	0.94	0.97	425
	Tomato___Early_blight	0.94	0.93	0.94	480
	Tomato___Late_blight	0.99	0.91	0.95	463
	Tomato___Leaf_Mold	1.00	0.98	0.99	470
Tomato___Septoria_leaf_spot		0.88	0.98	0.93	436
Tomato___Spider_mites Two-spotted_spider_mite		0.99	0.95	0.97	435
	Tomato___Target_Spot	0.93	0.94	0.94	457
Tomato___Tomato_Yellow_Leaf_Curl_Virus		1.00	0.99	0.99	490
	Tomato___Tomato_mosaic_virus	1.00	0.99	1.00	448
	Tomato___healthy	0.96	1.00	0.98	481
	accuracy			0.98	17572
	macro avg	0.98	0.98	0.98	17572
	weighted avg	0.98	0.98	0.98	17572

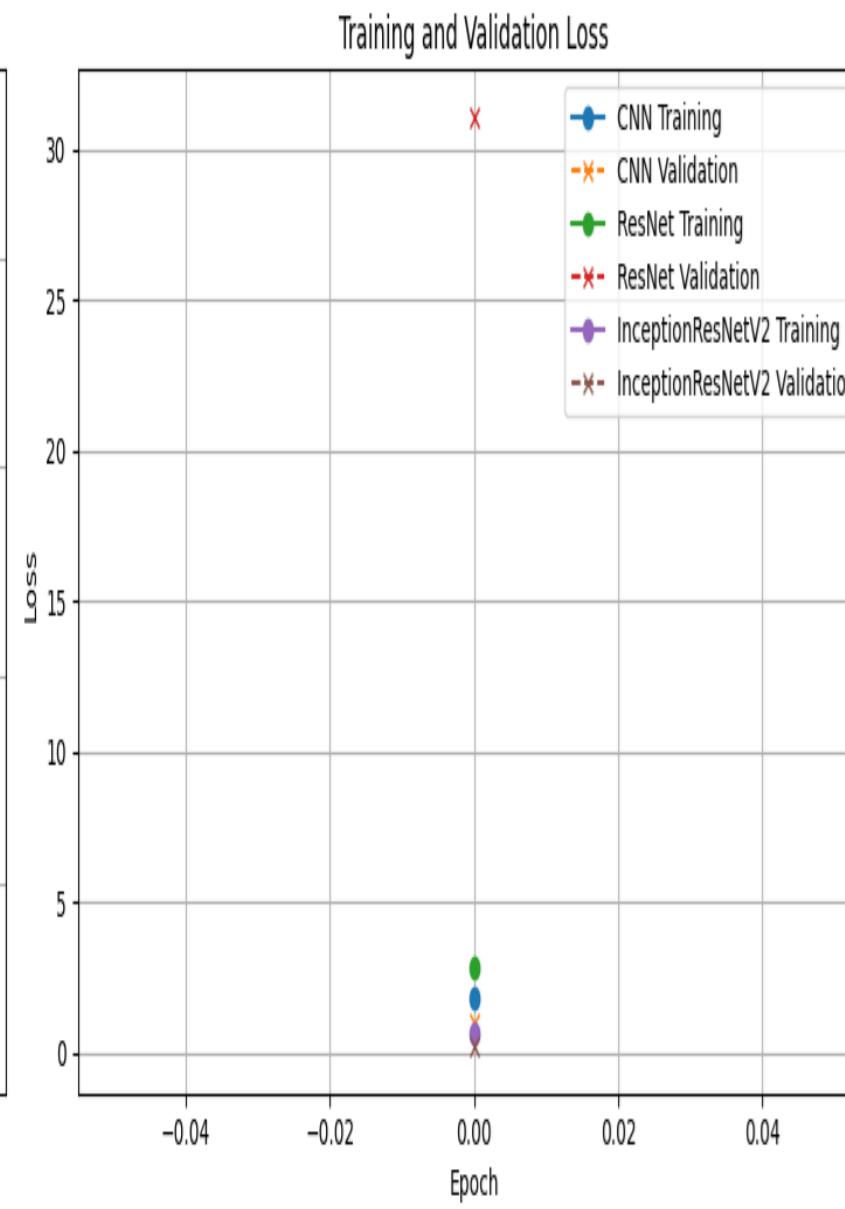
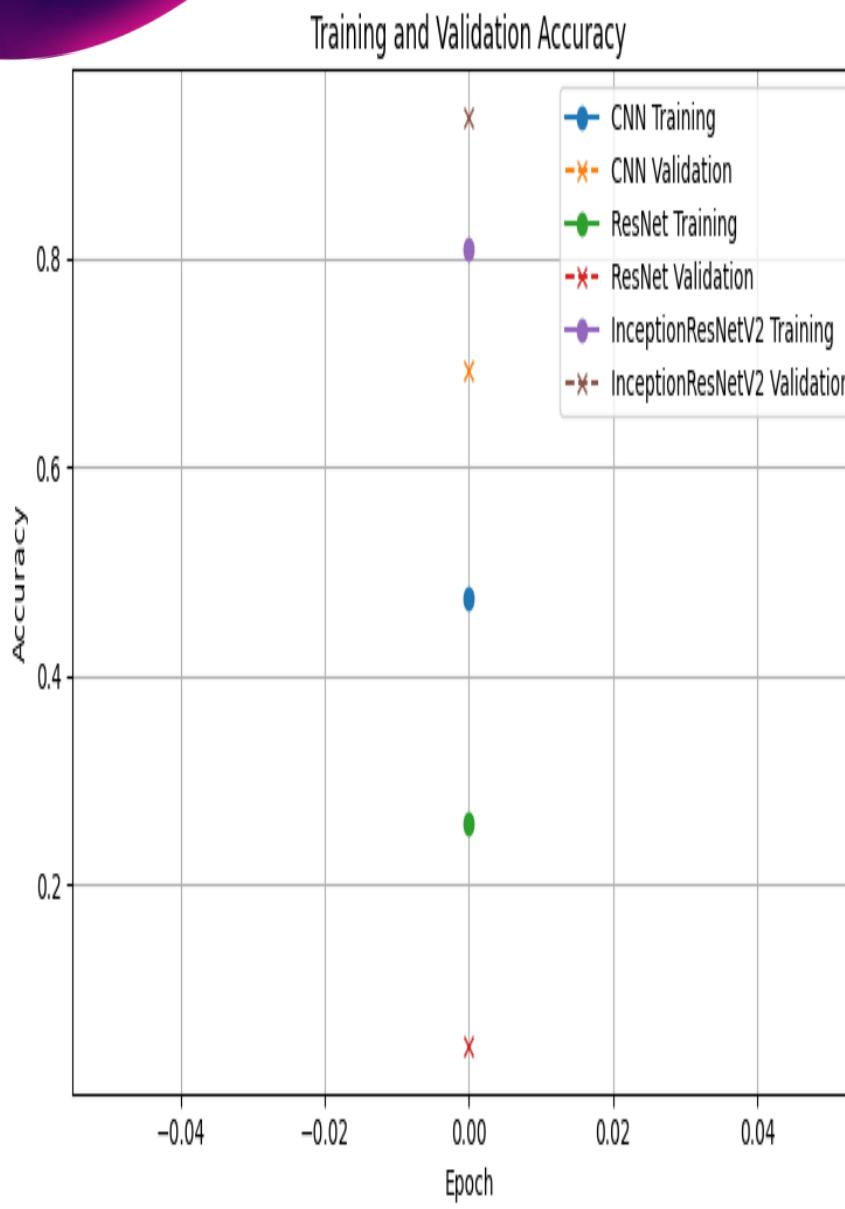


Practical application





Practical application



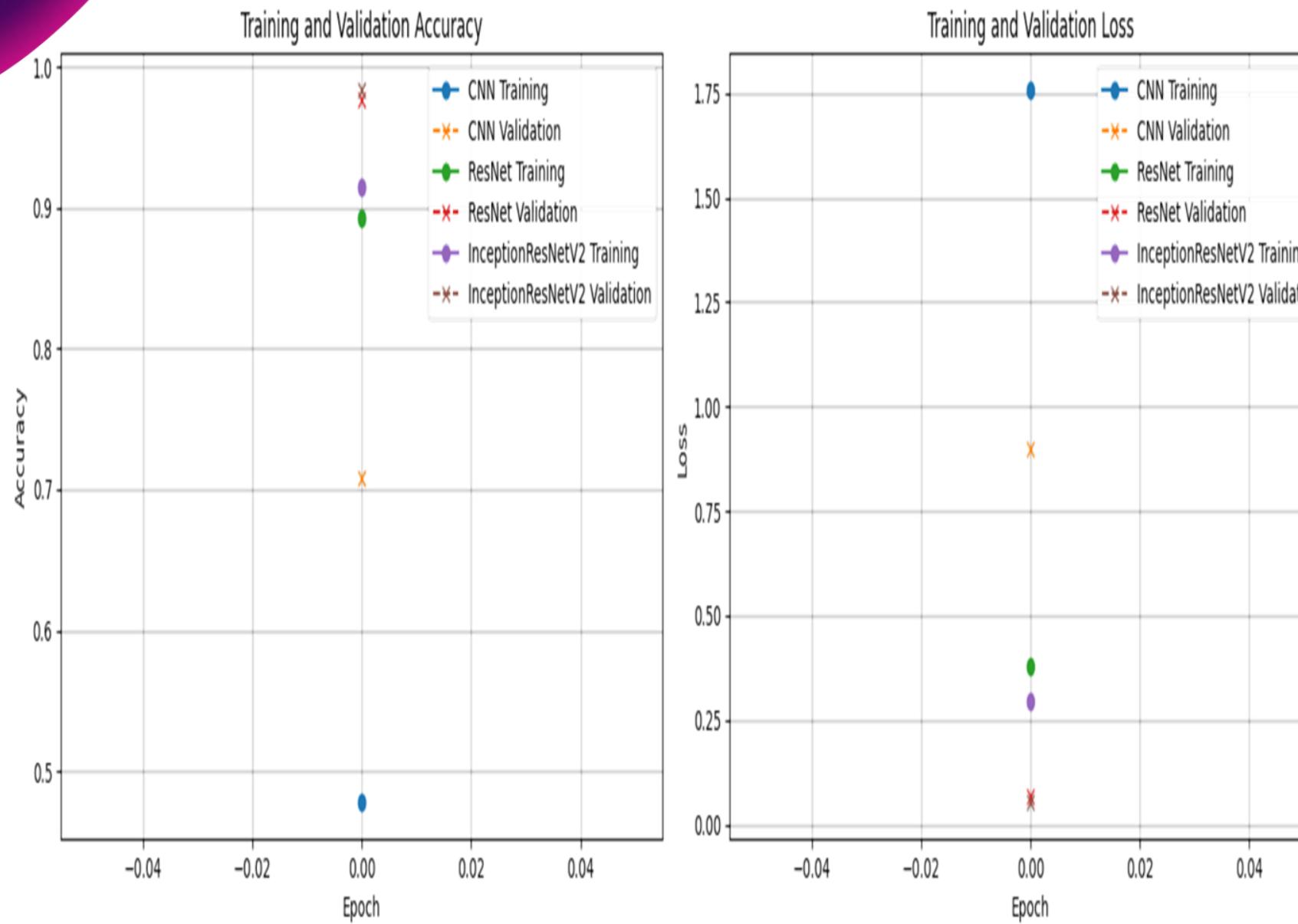
Model Comparison Table:

	Model	Test Accuracy	Test Loss
0	CNN	0.693547	0.980185
1	ResNet	0.844787	31.103748
2	InceptionResNetV2	0.936433	0.194551

Comparison table saved as "model_comparison.csv"



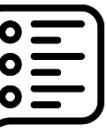
Practical application



Model Comparison Table:

	Model	Test Accuracy	Test Loss
0	CNN	0.708627	0.897286
1	ResNet	0.977180	0.067971
2	InceptionResNetV2	0.984350	0.052198

Comparison table saved as 'model_comparison.csv'



Practical application

Inception-ResNet-V2 (Epoch=3)

```
# -----
# 4. Build Inception-ResNet-V2 Model
# -----
def build_inception_model():
    base_model = InceptionResNetV2(
        weights='imagenet',
        include_top=False,
        input_shape=(img_size, img_size, 3)
    )

    for layer in base_model.layers[-30:]:
        layer.trainable = True
    for layer in base_model.layers[:-30]:
        layer.trainable = False

    model = models.Sequential([
        base_model,
        layers.GlobalAveragePooling2D(),
        layers.Dense(512, activation='relu'),
        layers.BatchNormalization(),
        layers.Dropout(0.5),
        layers.Dense(train_generator.num_classes, activation='softmax')
    ])

    model.compile(
        optimizer=tf.keras.optimizers.Adam(learning_rate=1e-4),
        loss='categorical_crossentropy',
        metrics=['accuracy']
    )
    return model

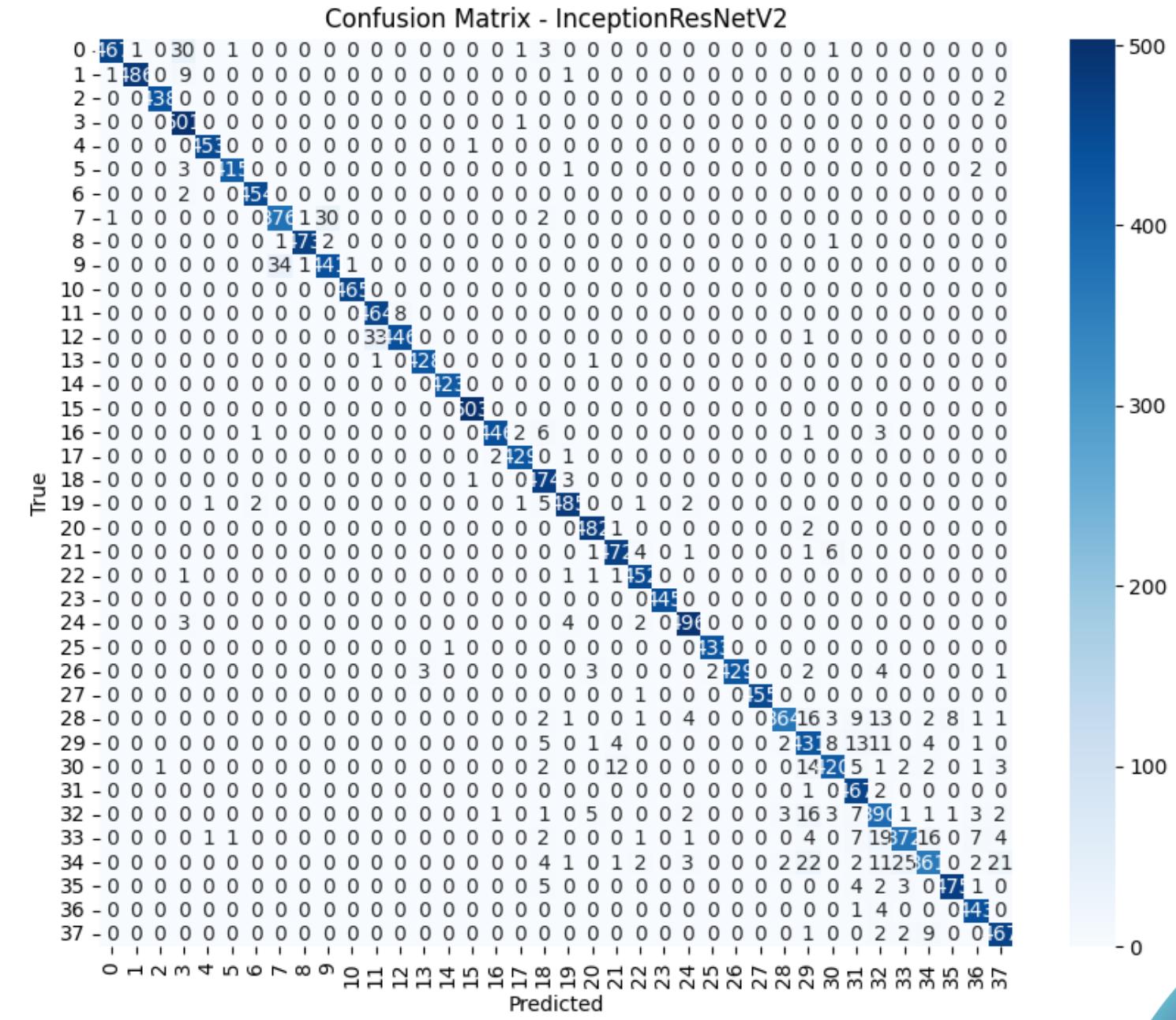
# Train Inception-ResNet-V2
inception_model = build_inception_model()
print("\n--- Training Inception-ResNet-V2 Model ---")
history_inception = inception_model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // batch_size,
    epochs=3,
    validation_data=test_generator,
    validation_steps=test_generator.samples // batch_size)

--- Training Inception-ResNet-V2 Model ---
Epoch 1/3
2196/2196 [=====] 1040s 455ms/step - accuracy: 0.6668 - loss: 1.2330 - val_accuracy: 0.9445 - val_loss: 0.1658
Epoch 2/3
2196/2196 [=====] 79s 36ms/step - accuracy: 0.8750 - loss: 0.2283 - val_accuracy: 0.9443 - val_loss: 0.1650
Epoch 3/3
2196/2196 [=====] 1016s 463ms/step - accuracy: 0.9251 - loss: 0.2385 - val_accuracy: 0.9629 - val_loss: 0.1092
```



Practical application

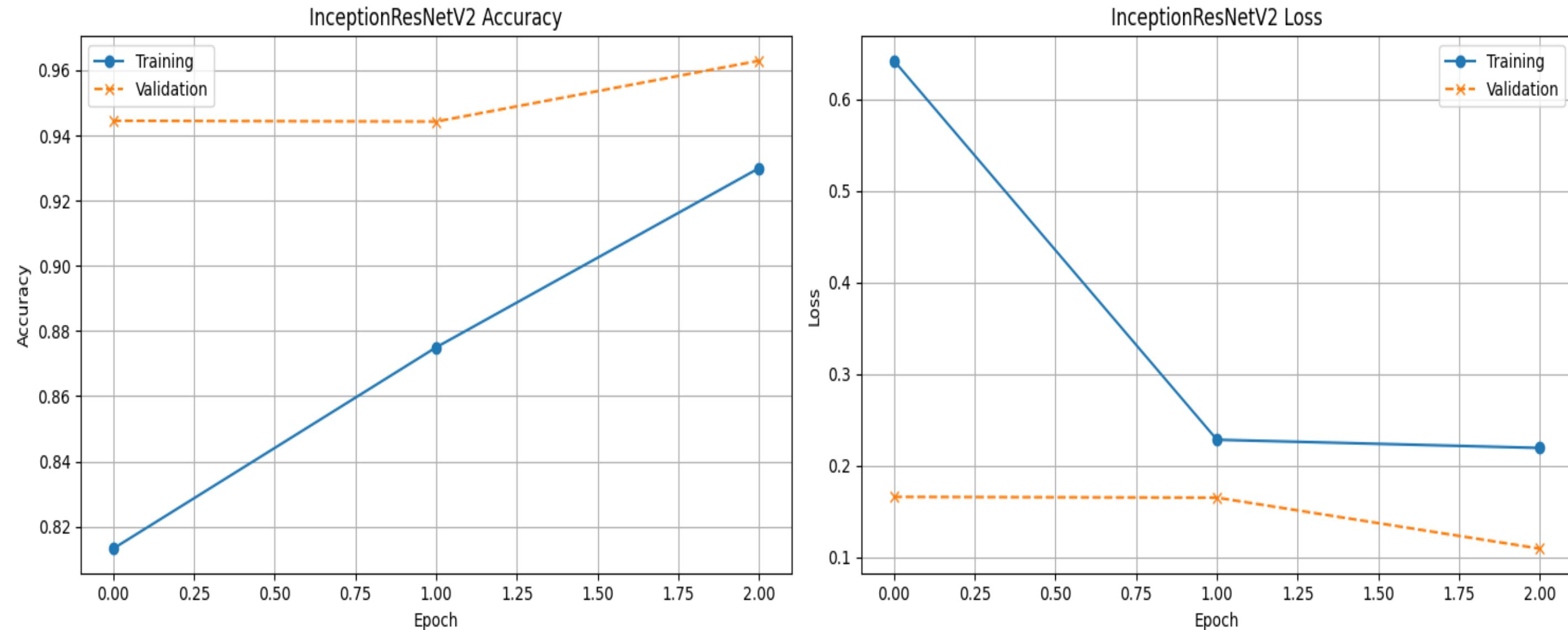
Inception-ResNet-V2 (Epoch=3)





Practical application

Inception-ResNet-V2 (Epoch=3)



Model Results:

```
Model Test Accuracy Test Loss
0 InceptionResNetv2 0.962952 0.109196
Results saved as 'model_results.csv'
```



Practical application

Inception-ResNet-V2 (Epoch=5)

```
# -----
# 4. Build Inception-ResNet-V2 Model
# -----
def build_inception_model():
    base_model = InceptionResNetV2(
        weights='imagenet',
        include_top=False,
        input_shape=(img_size, img_size, 3)
    )

    model = models.Sequential([
        base_model,
        layers.GlobalAveragePooling2D(),
        layers.Dense(512, activation='relu'),
        layers.BatchNormalization(),
        layers.Dropout(0.5),
        layers.Dense(train_generator.num_classes, activation='softmax')
    ])

    model.compile(
        optimizer=tf.keras.optimizers.Adam(learning_rate=1e-4),
        loss='categorical_crossentropy',
        metrics=['accuracy']
    )
    return model

# Train Inception-ResNet-V2
inception_model = build_inception_model()
print("\n--- Training Inception-ResNet-V2 Model ---")
history_inception = inception_model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // batch_size,
    epochs=5,
    validation_data=test_generator,
    validation_steps=test_generator.samples // batch_size)

Epoch 1/5
2196/2196 [=====] 1560s 622ms/step - accuracy: 0.8059 - loss: 0.7408 - val_accuracy: 0.970
3 - val_loss: 0.1317
Epoch 2/5
1/2196 [=====] 21:59 601ms/step - accuracy: 1.0000 - loss: 0.0144
2196/2196 [=====] 82s 37ms/step - accuracy: 1.0000 - loss: 0.0144 - val_accuracy: 0.9689 -
val_loss: 0.1316
Epoch 3/5
2196/2196 [=====] 1289s 587ms/step - accuracy: 0.9766 - loss: 0.0769 - val_accuracy: 0.981
4 - val_loss: 0.0861
Epoch 4/5
2196/2196 [=====] 82s 37ms/step - accuracy: 0.9688 - loss: 0.1458 - val_accuracy: 0.9817 -
val_loss: 0.0858
Epoch 5/5
2196/2196 [=====] 1289s 587ms/step - accuracy: 0.9838 - loss: 0.0544 - val_accuracy: 0.989
2 - val_loss: 0.0371
```





Practical application

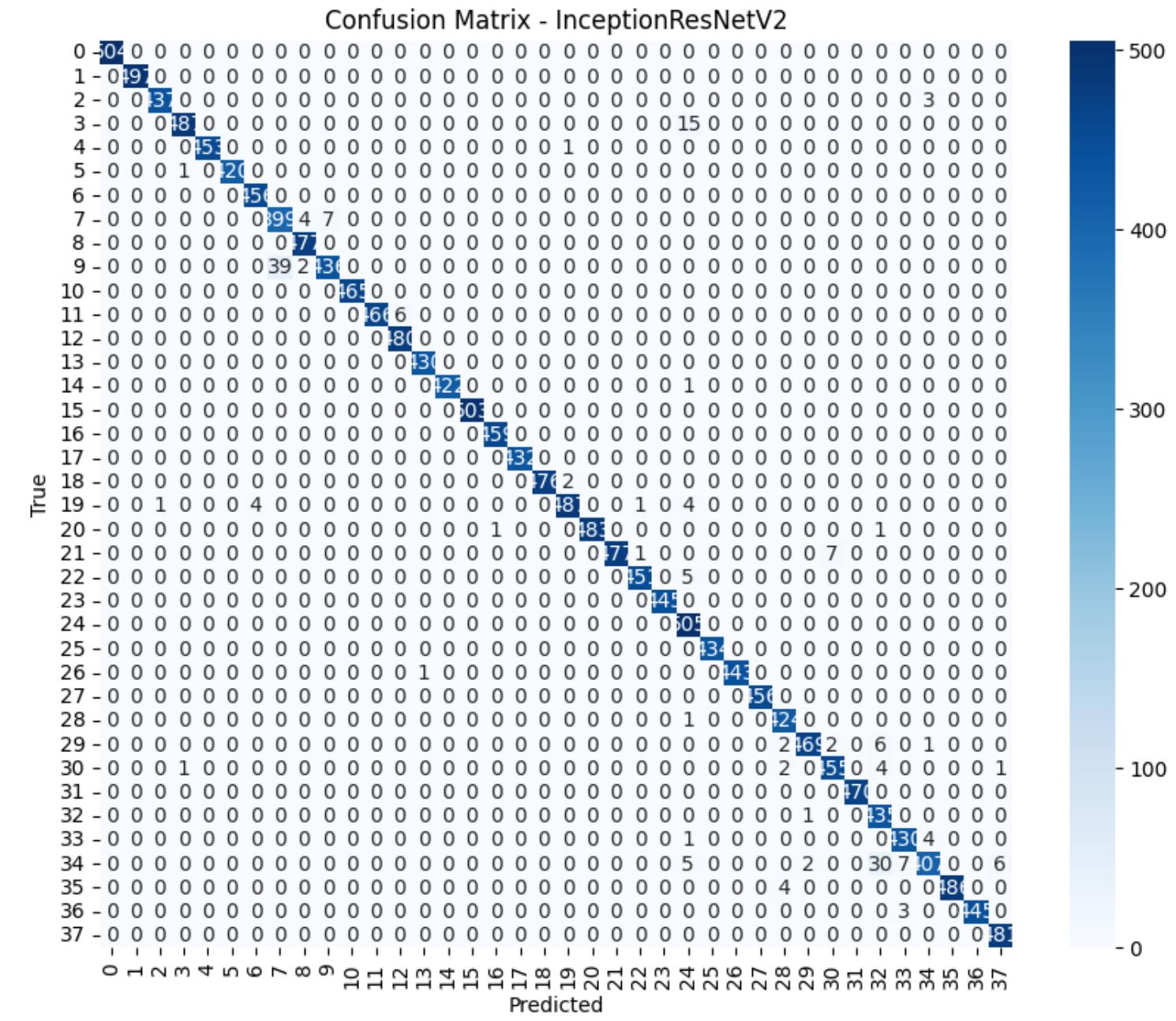
Inception-ResNet-V2 (Epoch=5)

Evaluating Inception-ResNet-V2 Model...
F10 / F50 20s 161ms/step - accuracy: 0.9919 - loss: 0

```
550/550 [██████████] 89s 161ms/step - accuracy: 0.9910 -  
  
Model InceptionResNetV2 Test Accuracy: 0.9892, Test Loss: 0.037  
550/550 [██████████] 108s 172ms/step
```

Detailed Classification Report for InceptionResNetV1

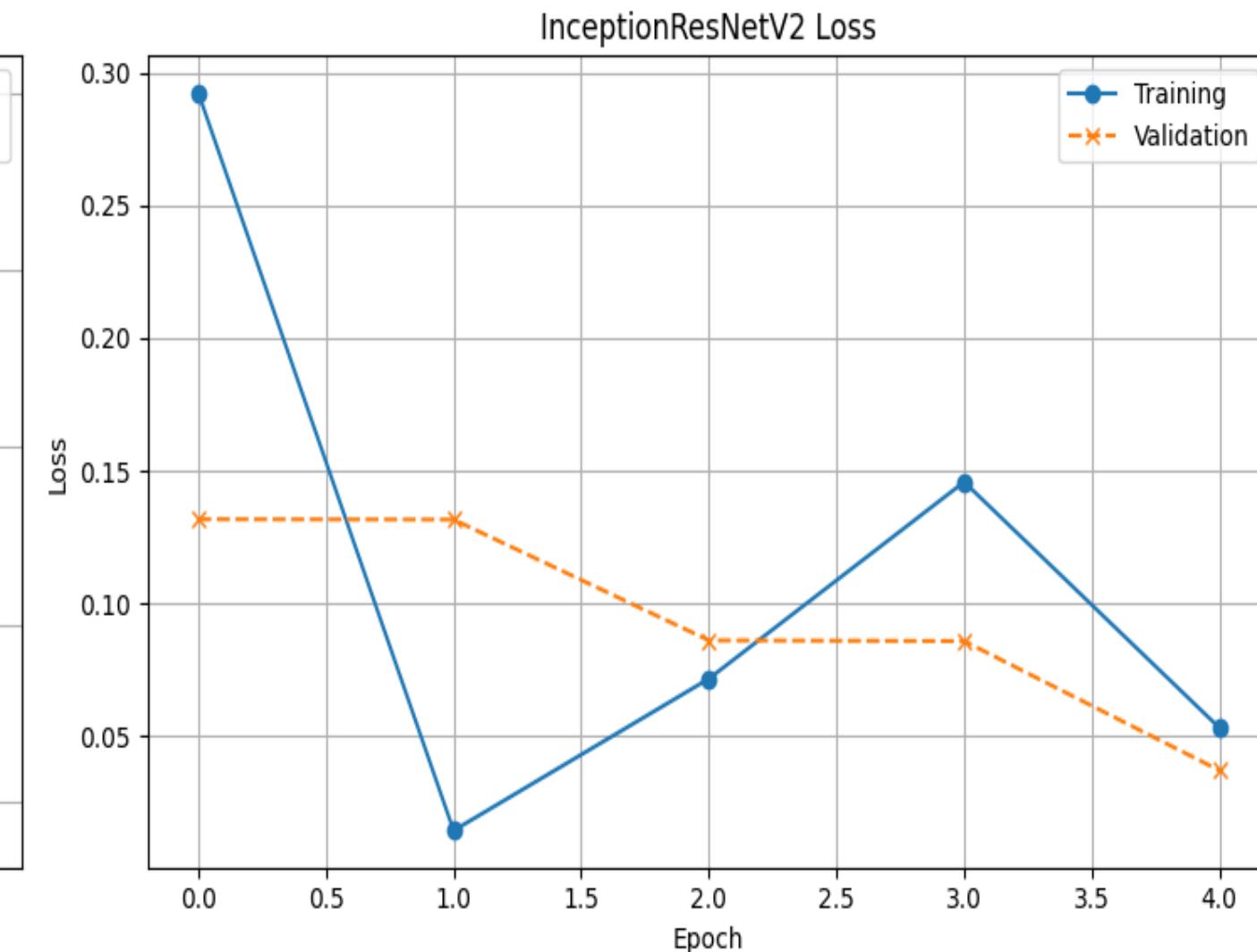
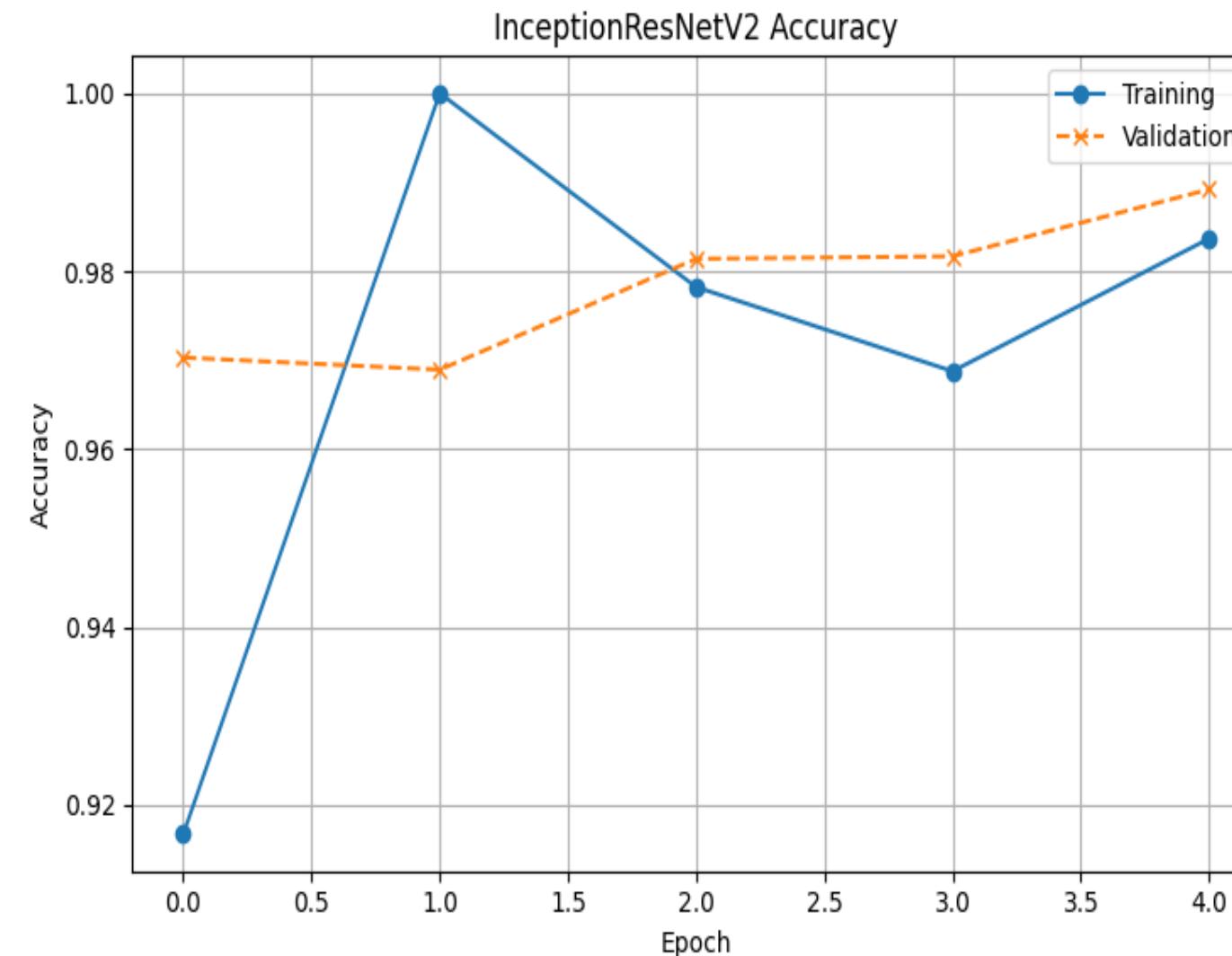
		precision	recall	f1-score	support
	Apple___Apple_scab	1.00	1.00	1.00	50
	Apple___Black_rot	1.00	1.00	1.00	40
	Apple___Cedar_apple_rust	1.00	0.99	1.00	40
	Apple___healthy	1.00	0.97	0.98	50
	Blueberry___healthy	1.00	1.00	1.00	40
Cherry_(including_sour)___Powdery_mildew		1.00	1.00	1.00	40
Cherry_(including_sour)___healthy		0.99	1.00	1.00	40
Corn_(maize)___Cercospora_leaf_spot_Gray_leaf_spot		0.91	0.97	0.94	40
Corn_(maize)___Common_rust_		0.99	1.00	0.99	40
Corn_(maize)___Northern_Leaf_Blight		0.98	0.91	0.95	40
Corn_(maize)___healthy		1.00	1.00	1.00	40
Grape___Black_rot		1.00	0.99	0.99	40
Grape___Esca_(Black_Measles)		0.99	1.00	0.99	40
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)		1.00	1.00	1.00	40
Grape___healthy		1.00	1.00	1.00	40
Orange___Haunglongbing_(Citrus_greening)		1.00	1.00	1.00	50
Peach___Bacterial_spot		1.00	1.00	1.00	40
Peach___healthy		1.00	1.00	1.00	40
Pepper,_bell___Bacterial_spot		1.00	1.00	1.00	40
Pepper,_bell___healthy		0.99	0.98	0.99	40
Potato___Early_blight		1.00	1.00	1.00	40
Potato___Late_blight		1.00	0.98	0.99	40
Potato___healthy		1.00	0.99	0.99	40
Raspberry___healthy		1.00	1.00	1.00	40
Soybean___healthy		0.94	1.00	0.97	50
Squash___Powdery_mildew		1.00	1.00	1.00	40
Strawberry___Leaf_scorch		1.00	1.00	1.00	40
Strawberry___healthy		1.00	1.00	1.00	40
Tomato___Bacterial_spot		0.98	1.00	0.99	40
Tomato___Early_blight		0.99	0.98	0.99	40
Tomato___Late_blight		0.98	0.98	0.98	40
Tomato___Leaf_Mold		1.00	1.00	1.00	40
Tomato___Septoria_leaf_spot		0.91	1.00	0.95	40
Tomato___Spider_mites_Two-spotted_spider_mite		0.98	0.99	0.98	40
Tomato___Target_Spot		0.98	0.89	0.93	40
Tomato___Tomato_Yellow_Leaf_Curl_Virus		1.00	0.99	1.00	40
Tomato___Tomato_mosaic_virus		1.00	0.99	1.00	40
Tomato___healthy		0.99	1.00	0.99	40
accuracy					
macro avg					
weighted avg					





Practical application

Inception-ResNet-V2 (Epoch=5)



Model Results:

	Model	Test Accuracy	Test Loss
0	InceptionResNetV2	0.989187	0.037079
Results saved as 'model_results.csv'			



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CONCLUSION



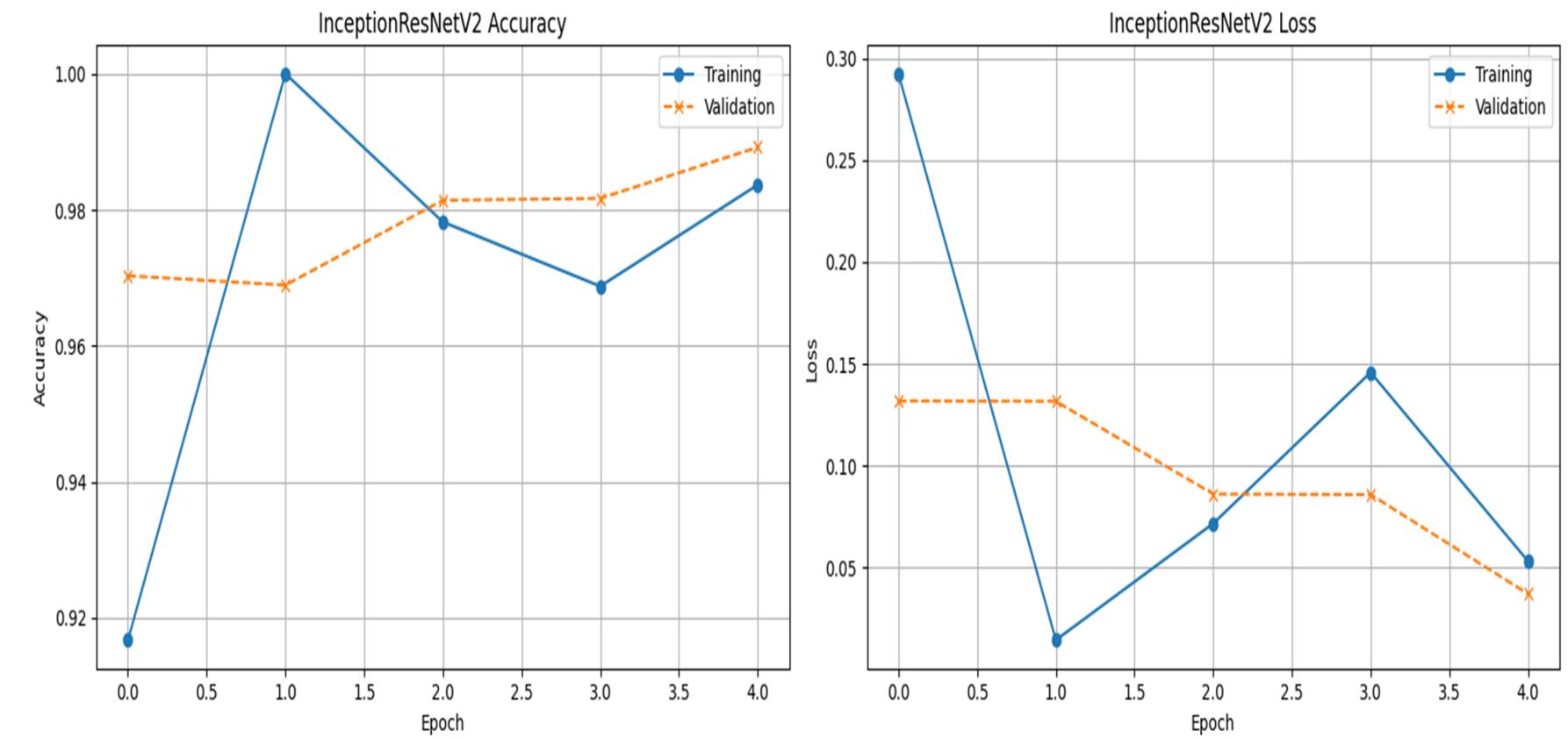


Conclusion

- "This study showed deep learning (InceptionResNetV2) effectively detects plant diseases from leaf images, achieving high accuracy rapidly using a diverse dataset and data augmentation."

Key Points Retained:

- Disease detection via inceptionresnetv2.
- Critical methods (dataset diversity + augmentation).
- Efficiency high accuracy with minimal training.



Model Results:

Model	Test Accuracy	Test Loss
InceptionResNetV2	0.989187	0.037079

Results saved as 'model_results.csv'



Conclusion

Importance

The integration of **AI** into agriculture opens new doors for **early**

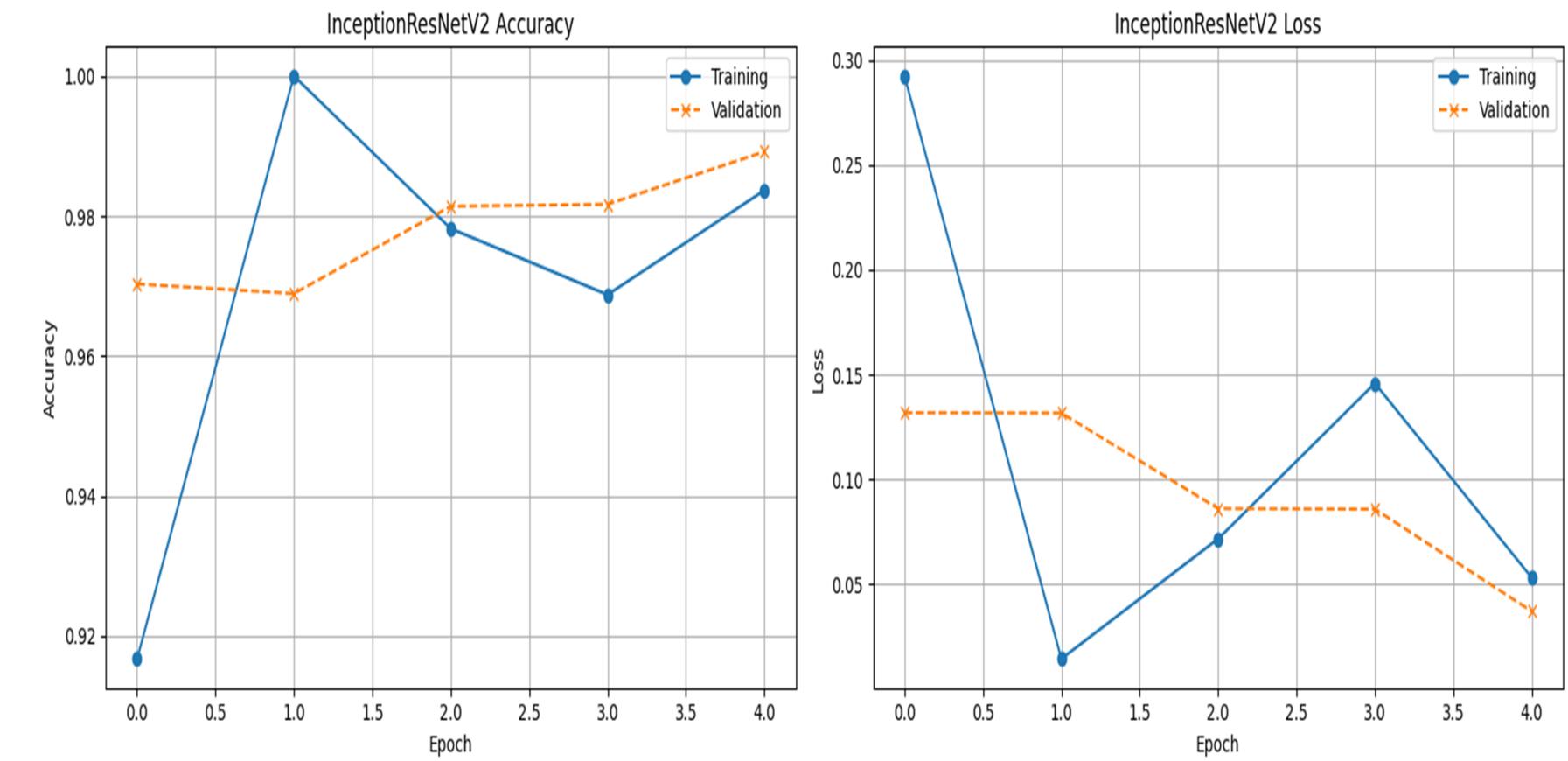
disease detection, leading to:

- Increased **crop productivity**
- Reduced **economic losses**
- Improved **food security**

Deep learning models like InceptionResNetV2 have the potential to

revolutionize plant health monitoring, making agriculture more

intelligent, scalable, and sustainable.



Model Results:

Model	Test Accuracy	Test Loss
InceptionResNetV2	0.989187	0.037079

Results saved as 'model_results.csv'

Thank You

