

NNDL: ICP5

Jyothi Kiran Boddeda
700769023

GITHUB LINK : <https://github.com/jyothikiranboddeda/Neural-Network-Deep-Learning.git>

VIDEO LINK :

https://drive.google.com/file/d/1s_pxOAKn0qqNZCUdmbp-3NHuZ3iB4zCj/view?usp=drive_link

1. Follow the instruction below and then report how the performance changed. (apply all at once)

- Convolutional input layer, 32 feature maps with a size of 3×3 and a rectifier activation function.
- Dropout layer at 20%.
- Convolutional layer, 32 feature maps with a size of 3×3 and a rectifier activation function.
- Max Pool layer with size 2×2 .
- Convolutional layer, 64 feature maps with a size of 3×3 and a rectifier activation function.
- Dropout layer at 20%.
- Convolutional layer, 64 feature maps with a size of 3×3 and a rectifier activation function.
- Max Pool layer with size 2×2 .
- Convolutional layer, 128 feature maps with a size of 3×3 and a rectifier activation function.
- Dropout layer at 20%.
- Convolutional layer, 128 feature maps with a size of 3×3 and a rectifier activation function.
- Max Pool layer with size 2×2 .
- Flatten layer.
- Dropout layer at 20%.
- Fully connected layer with 1024 units and a rectifier activation function.
- Dropout layer at 20%.
- Fully connected layer with 512 units and a rectifier activation function.
- Dropout layer at 20%.
- Fully connected output layer with 10 units and a Softmax activation function

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ICP5.ipynb

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```
import tensorflow as tf
from tensorflow.keras import layers, models

# Build the model
model = models.Sequential([
    # Convolutional Block 1
    layers.Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=(32, 32, 3)), # 32x32 input
    layers.Dropout(0.2),
    layers.Conv2D(32, (3, 3), activation='relu', padding='same'),
    layers.MaxPooling2D((2, 2)), # Reduces to 16x16

    # Convolutional Block 2
    layers.Conv2D(64, (3, 3), activation='relu', padding='same'),
    layers.Dropout(0.2),
    layers.Conv2D(64, (3, 3), activation='relu', padding='same'),
    layers.MaxPooling2D((2, 2)), # Reduces to 8x8

    # Convolutional Block 3
    layers.Conv2D(128, (3, 3), activation='relu', padding='same'),
    layers.Dropout(0.2),
    layers.Conv2D(128, (3, 3), activation='relu', padding='same'),
    layers.MaxPooling2D((2, 2)), # Reduces to 4x4

    # Flattening and Dense Layers
    layers.Flatten(),
    layers.Dropout(0.2),
    layers.Dense(1024, activation='relu'),
    layers.Dropout(0.2),
    layers.Dense(512, activation='relu'),
    layers.Dense(10, activation='softmax') # Assuming 10 classes
])

# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Print the model summary
model.summary()

# Train the model (example using placeholder dataset)
# Replace (x_train, y_train) with actual data
model.fit(x_train, y_train, epochs=3, batch_size=64, validation_split=0.2)
```

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```
layers.Dense(1024, activation='relu'),
layers.Dropout(0.2),
layers.Dense(512, activation='relu'),
layers.Dropout(0.2),

# Output Layer
layers.Dense(10, activation='softmax') # Assuming 10 classes
])

# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Print the model summary
model.summary()

# Train the model (example using placeholder dataset)
# Replace (x_train, y_train) with actual data
model.fit(x_train, y_train, epochs=3, batch_size=64, validation_split=0.2)
```

Model: "sequential_7"

Layer (type)	Output Shape	Param #
conv2d_42 (Conv2D)	(None, 32, 32, 32)	896
dropout_42 (Dropout)	(None, 32, 32, 32)	0

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Model: "sequential_7"

Layer (type)	Output Shape	Param #
conv2d_42 (Conv2D)	(None, 32, 32, 32)	896
dropout_42 (Dropout)	(None, 32, 32, 32)	0
conv2d_43 (Conv2D)	(None, 32, 32, 32)	9,248
max_pooling2d_21 (MaxPooling2D)	(None, 16, 16, 32)	0
conv2d_44 (Conv2D)	(None, 16, 16, 64)	18,496
dropout_43 (Dropout)	(None, 16, 16, 64)	0
conv2d_45 (Conv2D)	(None, 16, 16, 64)	36,928
max_pooling2d_22 (MaxPooling2D)	(None, 8, 8, 64)	0
conv2d_46 (Conv2D)	(None, 8, 8, 128)	73,856
dropout_44 (Dropout)	(None, 8, 8, 128)	0
conv2d_47 (Conv2D)	(None, 8, 8, 128)	147,584
max_pooling2d_23 (MaxPooling2D)	(None, 4, 4, 128)	0
flatten_7 (Flatten)	(None, 2048)	0
dropout_45 (Dropout)	(None, 2048)	0
dense_21 (Dense)	(None, 1024)	2,098,176
dropout_46 (Dropout)	(None, 1024)	0

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conv2d_46 (Conv2D)	(None, 8, 8, 128)	73,856
dropout_44 (Dropout)	(None, 8, 8, 128)	0
conv2d_47 (Conv2D)	(None, 8, 8, 128)	147,584
max_pooling2d_23 (MaxPooling2D)	(None, 4, 4, 128)	0
flatten_7 (Flatten)	(None, 2048)	0
dropout_45 (Dropout)	(None, 2048)	0
dense_21 (Dense)	(None, 1024)	2,098,176
dropout_46 (Dropout)	(None, 1024)	0
dense_22 (Dense)	(None, 512)	524,800
dropout_47 (Dropout)	(None, 512)	0
dense_23 (Dense)	(None, 10)	5,130

Total params: 2,915,114 (11.12 MB)

Trainable params: 2,915,114 (11.12 MB)

Non-trainable params: 0 (0.00 B)

Epoch 1/3

625/625 310s 491ms/step - accuracy: 0.2326 - loss: 2.8958 - val_accuracy: 0.4346 - val_loss: 1.5915

Epoch 2/3

625/625 306s 489ms/step - accuracy: 0.4507 - loss: 1.5028 - val_accuracy: 0.5282 - val_loss: 1.3173

Epoch 3/3

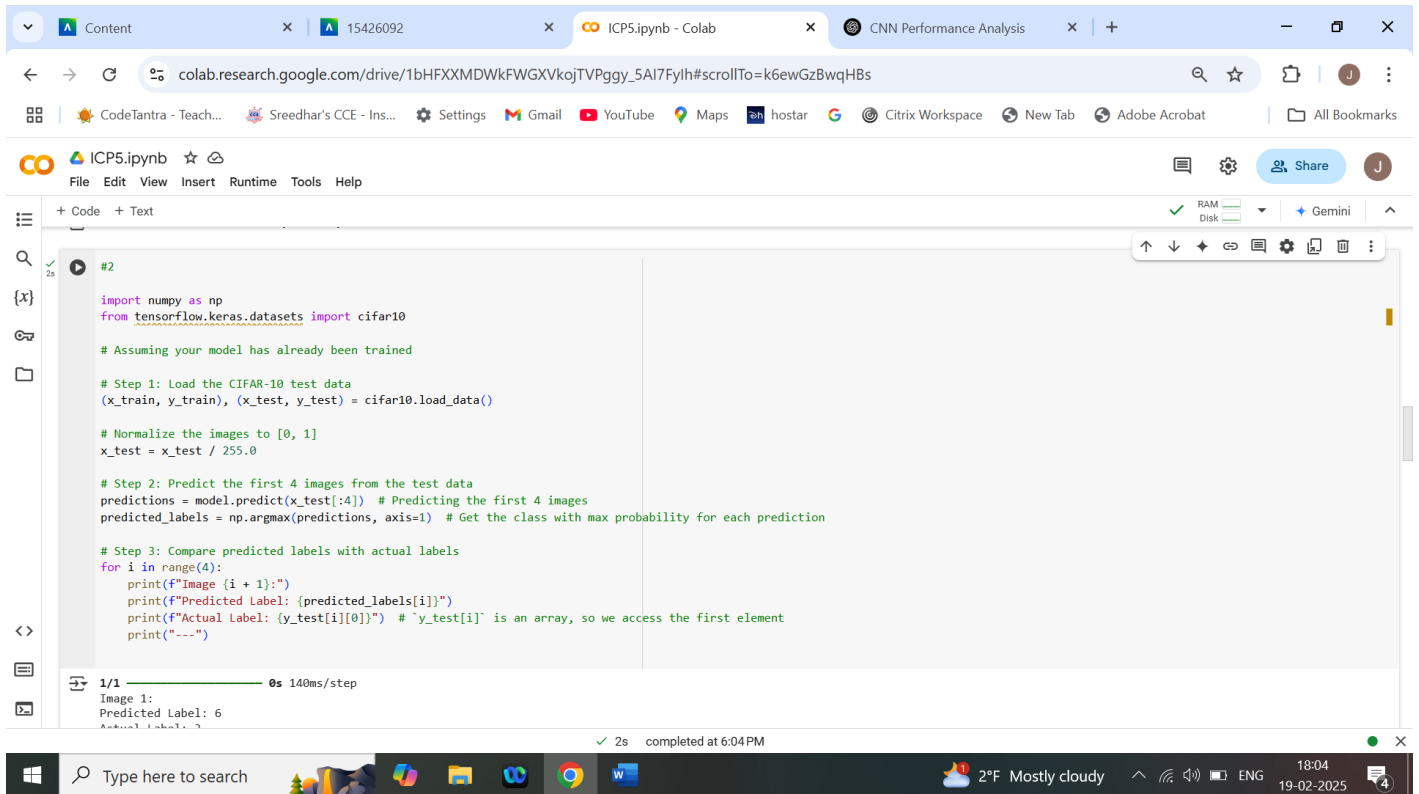
625/625 322s 490ms/step - accuracy: 0.5452 - loss: 1.2761 - val_accuracy: 0.6152 - val_loss: 1.1401

<keras.src.callbacks.history.History at 0x7e2fe3c00350>

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2. Predict the first 4 images of the test data using the above model. Then, compare with the actual label for those 4 images to check whether or not the model has predicted correctly.



```
#2

import numpy as np
from tensorflow.keras.datasets import cifar10

# Assuming your model has already been trained

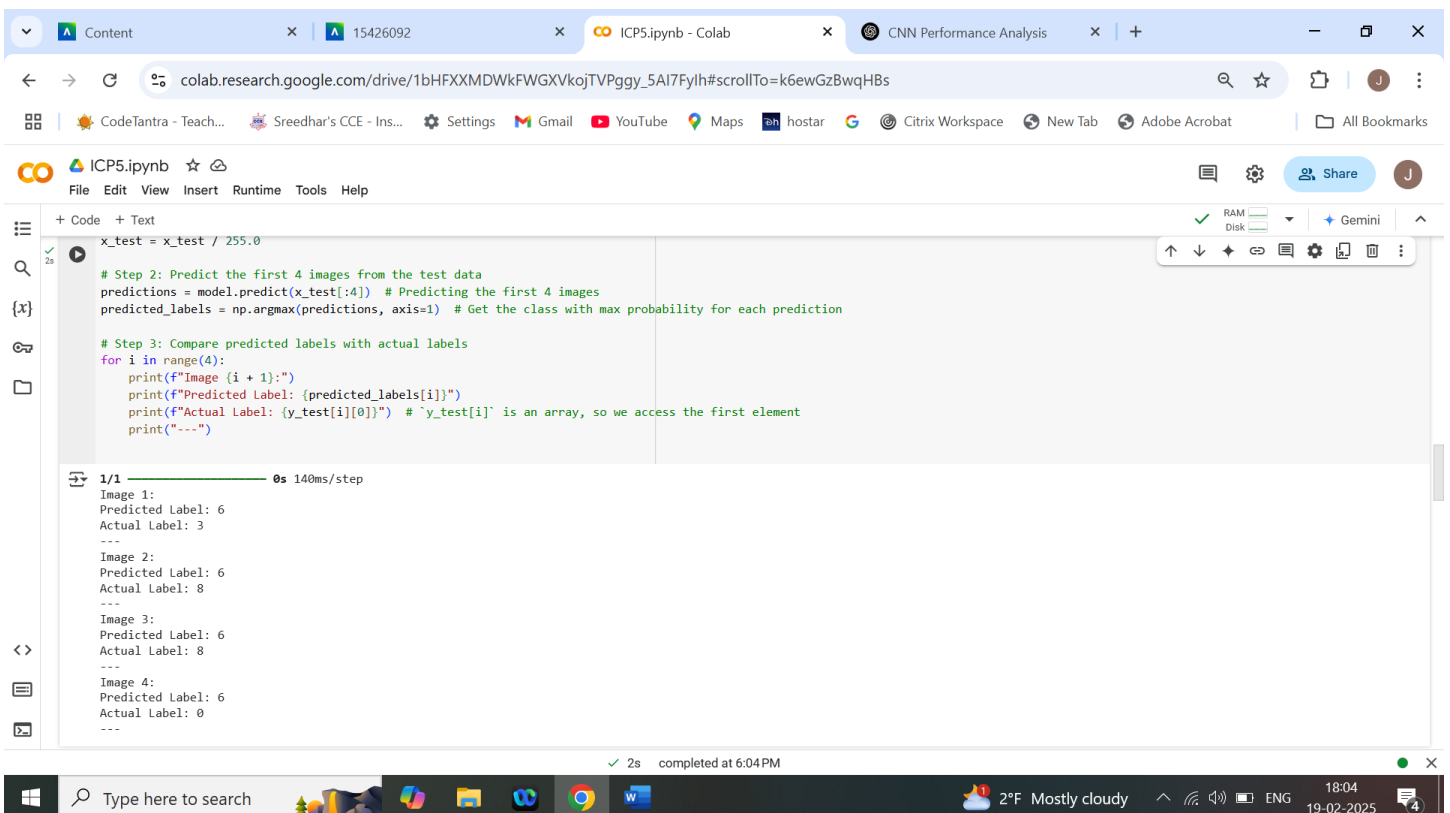
# Step 1: Load the CIFAR-10 test data
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Normalize the images to [0, 1]
x_test = x_test / 255.0

# Step 2: Predict the first 4 images from the test data
predictions = model.predict(x_test[:4]) # Predicting the first 4 images
predicted_labels = np.argmax(predictions, axis=1) # Get the class with max probability for each prediction

# Step 3: Compare predicted labels with actual labels
for i in range(4):
    print(f"Image {i + 1}:")
    print(f"Predicted Label: {predicted_labels[i]}")
    print(f"Actual Label: {y_test[i][0]}") # 'y_test[i]' is an array, so we access the first element
    print("----")

1/1 ----- 0s 140ms/step
Image 1:
Predicted Label: 6
Actual Label: 3
```



```
x_test = x_test / 255.0

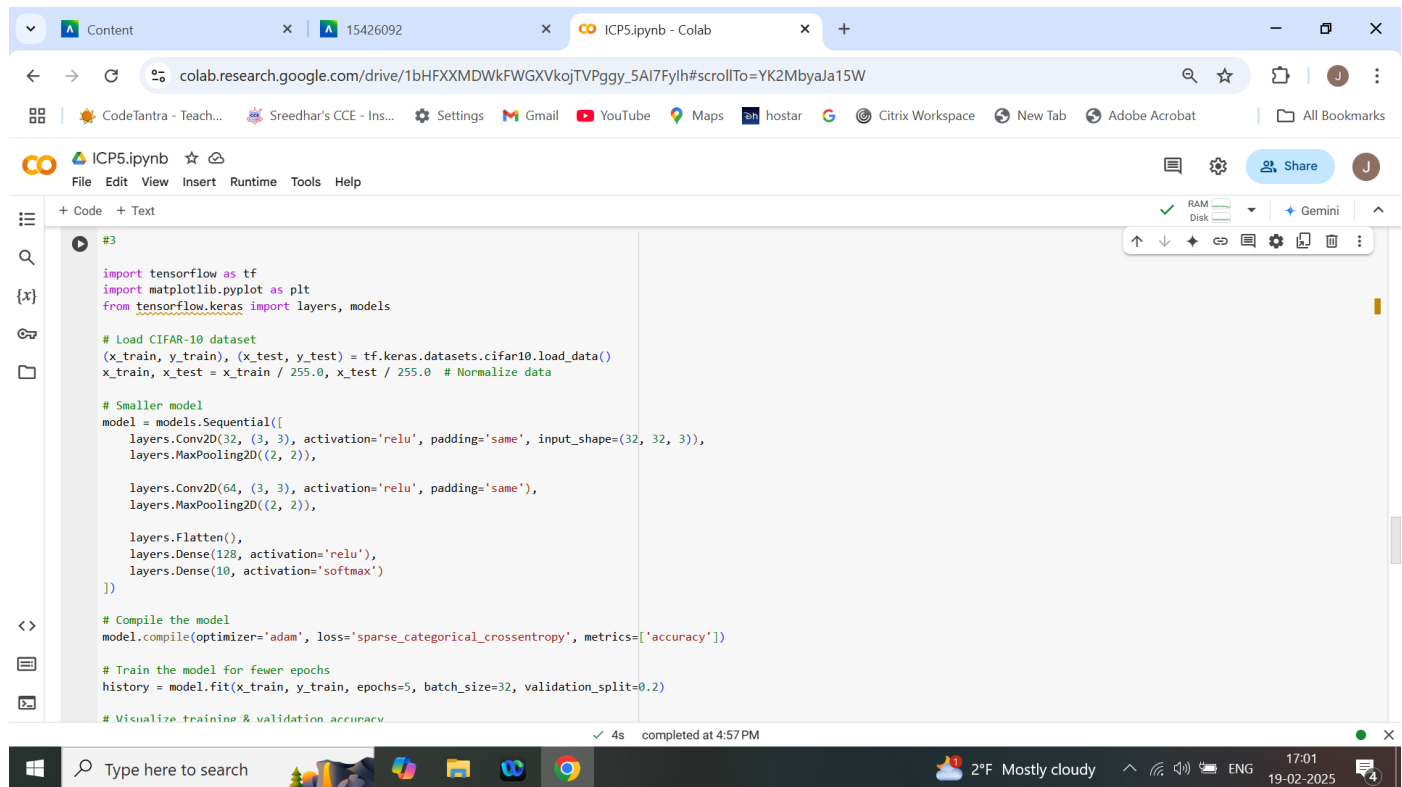
# Step 2: Predict the first 4 images from the test data
predictions = model.predict(x_test[:4]) # Predicting the first 4 images
predicted_labels = np.argmax(predictions, axis=1) # Get the class with max probability for each prediction

# Step 3: Compare predicted labels with actual labels
for i in range(4):
    print(f"Image {i + 1}:")
    print(f"Predicted Label: {predicted_labels[i]}")
    print(f"Actual Label: {y_test[i][0]}") # 'y_test[i]' is an array, so we access the first element
    print("----")

1/1 ----- 0s 140ms/step
Image 1:
Predicted Label: 6
Actual Label: 3

Image 2:
Predicted Label: 6
Actual Label: 8
---
Image 3:
Predicted Label: 6
Actual Label: 8
---
Image 4:
Predicted Label: 6
Actual Label: 0
---
```

3. Visualize Loss and Accuracy using the history object\



The first screenshot shows a Google Colab notebook with the following code:

```
#3

import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras import layers, models

# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0 # Normalize data

# Smaller model
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=(32, 32, 3)),
    layers.MaxPooling2D((2, 2)),

    layers.Conv2D(64, (3, 3), activation='relu', padding='same'),
    layers.MaxPooling2D((2, 2)),

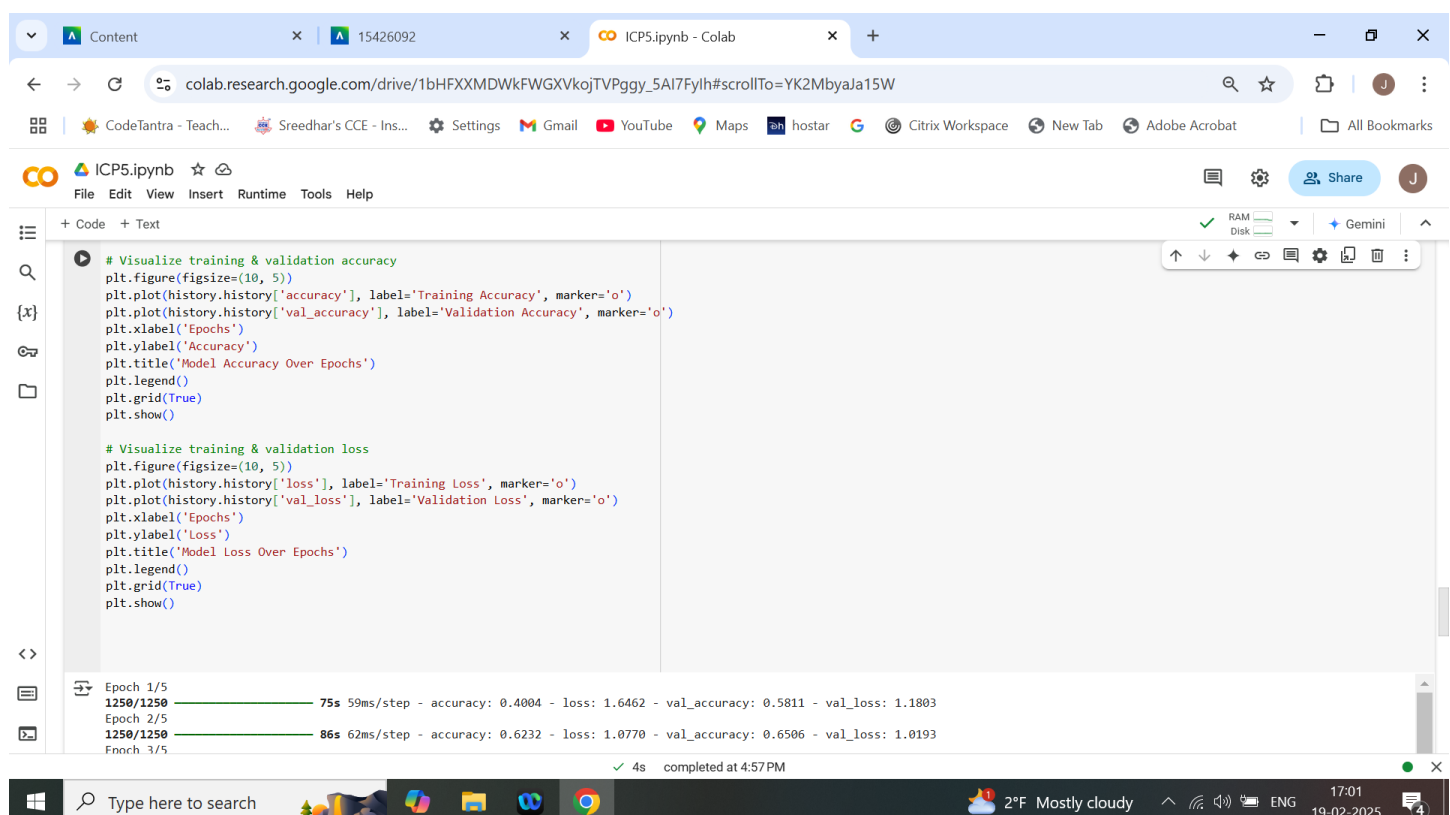
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(10, activation='softmax')
])

# Compile the model
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Train the model for fewer epochs
history = model.fit(x_train, y_train, epochs=5, batch_size=32, validation_split=0.2)

# Visualize training & validation accuracy
```

The notebook interface shows the code is completed at 4:57 PM. The Windows taskbar at the bottom indicates the date is 19-02-2025 and the time is 17:01.



The second screenshot shows the same Colab notebook with additional code for visualizing the training history:

```
# Visualize training & validation accuracy
plt.figure(figsize=(10, 5))
plt.plot(history.history['accuracy'], label='Training Accuracy', markers='o')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', marker='o')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Model Accuracy Over Epochs')
plt.legend()
plt.grid(True)
plt.show()

# Visualize training & validation loss
plt.figure(figsize=(10, 5))
plt.plot(history.history['loss'], label='Training Loss', marker='o')
plt.plot(history.history['val_loss'], label='Validation Loss', marker='o')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Model Loss Over Epochs')
plt.legend()
plt.grid(True)
plt.show()
```

Below the code, the training progress is displayed:

Epoch	1/5	2/5	3/5
Time	1250/1250	1250/1250	1250/1250
Step	75s	86s	86s
Time/step	59ms/step	62ms/step	62ms/step
Accuracy	accuracy: 0.4004	accuracy: 0.6232	accuracy: 0.6506
Loss	loss: 1.6462	loss: 1.0770	loss: 1.0193
Val Accuracy	val_accuracy: 0.5811	val_accuracy: 0.6506	val_accuracy: 0.6506
Val Loss	val_loss: 1.1803	val_loss: 1.0193	val_loss: 1.0193

The notebook is completed at 4:57 PM. The Windows taskbar at the bottom shows the same date and time as the first screenshot.

