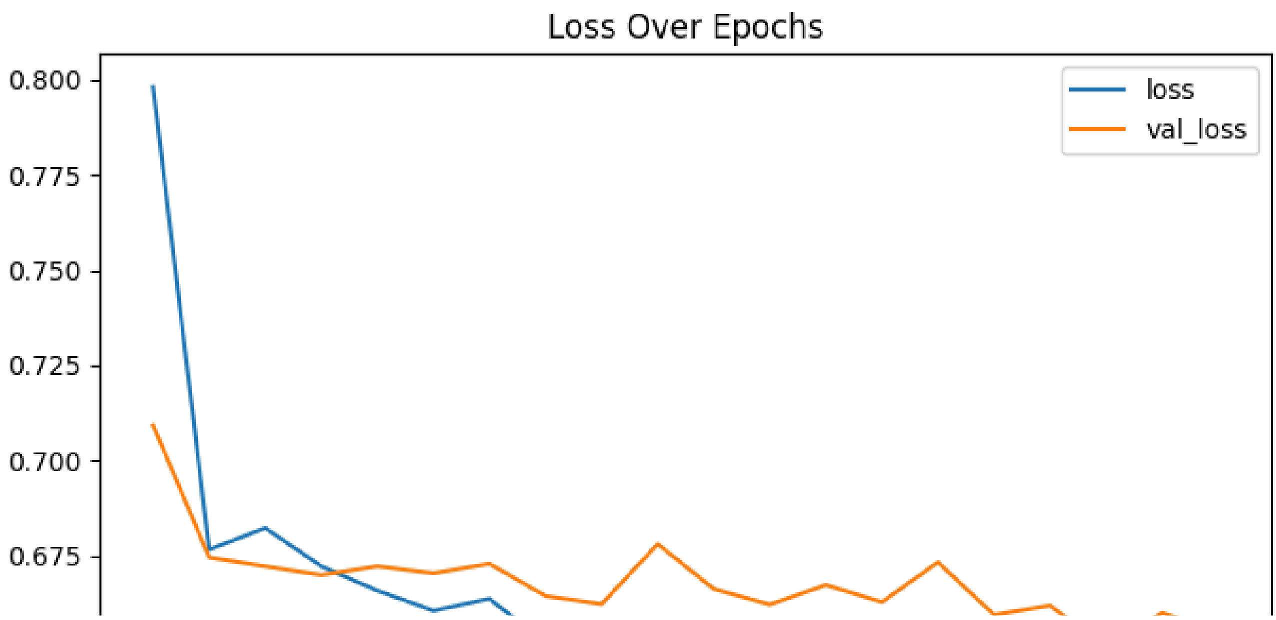
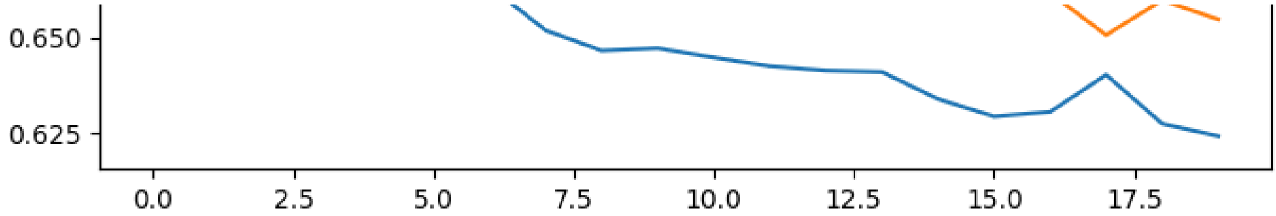
A feed-forward neural network

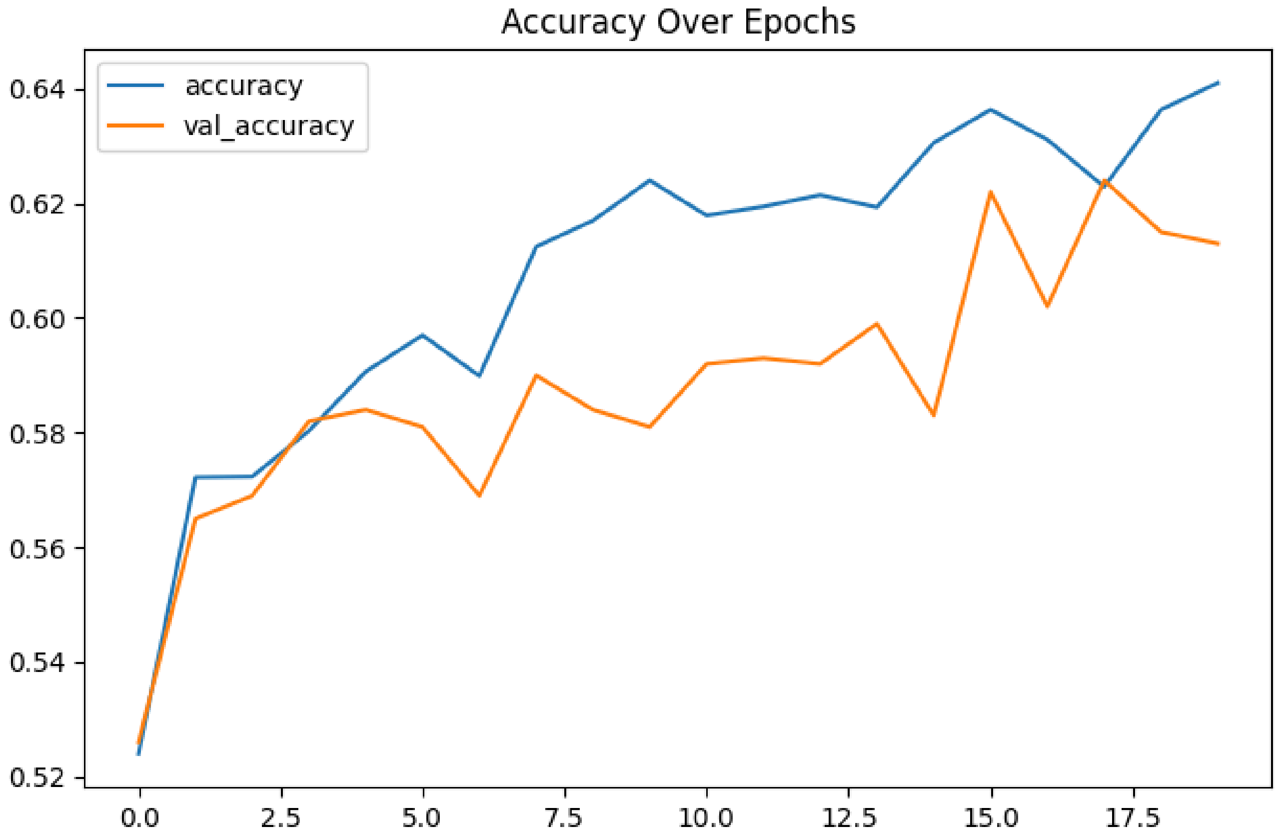
```
import tensorflow as tf
from tensorflow.keras import layers, models
import numpy as np

# 1. Load CIFAR-10 and filter for cats (3) and dogs (5)
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
y_train, y_test = y_train.flatten(), y_test.flatten()

mask_train = np.isin(y_train, [3, 5])
mask_test  = np.isin(y_test, [3, 5])
x_train, y_train = x_train[mask_train], y_train[mask_train]
x_test, y_test   = x_test[mask_test],   y_test[mask_test]

# Map labels: cat → 0, dog → 1
y_train = (y_train == 5).astype('int32')
y_test  = (y_test  == 5).astype('int32')

# 2. Preprocess: Normalize and flatten images
x_train = x_train.astype('float32') / 255.0
x_test  = x_test.astype('float32')  / 255.0
x_train = x_train.reshape(-1, 32*32*3)
x_test  = x_test.reshape(-1, 32*32*3)

# 3. Build feed-forward model
model = models.Sequential([
    layers.Input(shape=(32*32*3,)),         # Flattened input
    layers.Dense(512, activation='relu'),
    layers.Dense(128, activation='relu'),
    layers.Dense(2)                         # Two outputs: cat vs. dog
])

model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])

# 4. Train the model
history = model.fit(x_train, y_train, epochs=20, batch_size=128, validation_split=0.1)

# 5. Evaluate on test set
test_loss, test_acc = model.evaluate(x_test, y_test)
print(f"Test accuracy: {test_acc:.4f}")

# 7.1. Plot training history
import pandas as pd, matplotlib.pyplot as plt
hist_df = pd.DataFrame(history.history)
hist_df[['loss','val_loss']].plot(title='Loss Over Epochs', figsize=(8,5)); plt.show()
hist_df[['accuracy','val_accuracy']].plot(title='Accuracy Over Epochs', figsize=(8,5)); p

# 7.2. Confusion matrix
```

```
from sklearn.metrics import ConfusionMatrixDisplay
# Reshape x_test to match the expected input shape of the model
x_test_reshaped = x_test.reshape(-1, 32*32*3)
y_pred = np.argmax(model.predict(x_test_reshaped), axis=1)
ConfusionMatrixDisplay.from_predictions(y_test, y_pred, display_labels=['Cat','Dog'], cma
plt.title('Confusion Matrix - Cats vs Dogs'); plt.show()
```

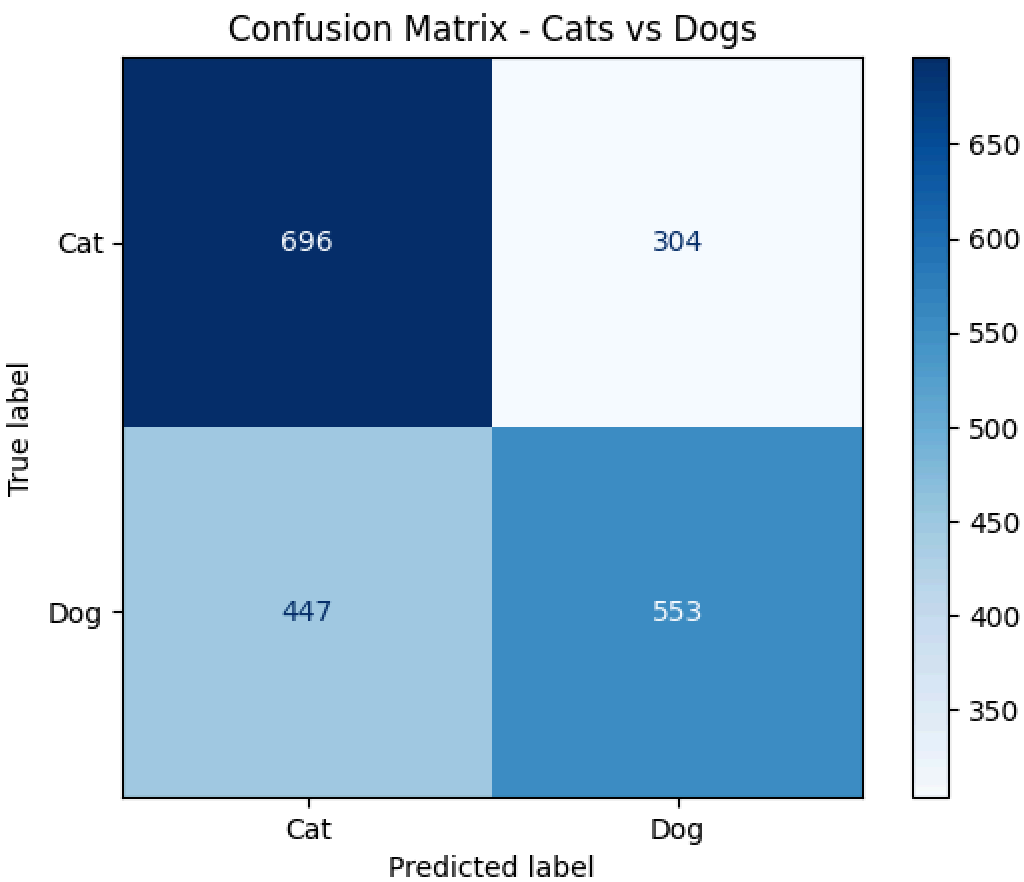
```
Epoch 1/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 4s 36ms/step - accuracy: 0.5140 - loss: 1.0076 - val_accur
Epoch 2/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 6s 48ms/step - accuracy: 0.5635 - loss: 0.6762 - val_accur
Epoch 3/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 4s 33ms/step - accuracy: 0.5859 - loss: 0.6712 - val_accur
Epoch 4/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 39ms/step - accuracy: 0.5778 - loss: 0.6731 - val_accur
Epoch 5/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 6s 49ms/step - accuracy: 0.5819 - loss: 0.6717 - val_accur
Epoch 6/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 32ms/step - accuracy: 0.6049 - loss: 0.6549 - val_accur
Epoch 7/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.5918 - loss: 0.6618 - val_accur
Epoch 8/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.6119 - loss: 0.6539 - val_accur
Epoch 9/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 32ms/step - accuracy: 0.6190 - loss: 0.6460 - val_accur
Epoch 10/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 4s 48ms/step - accuracy: 0.6224 - loss: 0.6475 - val_accur
Epoch 11/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 4s 32ms/step - accuracy: 0.6157 - loss: 0.6476 - val_accur
Epoch 12/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 33ms/step - accuracy: 0.6211 - loss: 0.6395 - val_accur
Epoch 13/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.6227 - loss: 0.6412 - val_accur
Epoch 14/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 43ms/step - accuracy: 0.6197 - loss: 0.6409 - val_accur
Epoch 15/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 4s 32ms/step - accuracy: 0.6305 - loss: 0.6348 - val_accur
Epoch 16/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 33ms/step - accuracy: 0.6310 - loss: 0.6313 - val_accur
Epoch 17/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 32ms/step - accuracy: 0.6385 - loss: 0.6282 - val_accur
Epoch 18/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 4s 49ms/step - accuracy: 0.6273 - loss: 0.6358 - val_accur
Epoch 19/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 4s 33ms/step - accuracy: 0.6472 - loss: 0.6199 - val_accur
Epoch 20/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 34ms/step - accuracy: 0.6432 - loss: 0.6225 - val_accur
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.6245 - loss: 0.6645
Test accuracy: 0.6245
```








```
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
```



A back propagation neural network

```
import numpy as np
import tensorflow as tf
from tensorflow.keras import layers, models
# 1. Load CIFAR-10 and filter cats vs. dogs
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()  # :contentR
y_train, y_test = y_train.flatten(), y_test.flatten()
mask_train = np.isin(y_train, [3,5]); mask_test = np.isin(y_test, [3,5])
x_train, y_train = x_train[mask_train], y_train[mask_train]
x_test, y_test   = x_test[mask_test],   y_test[mask_test]
y_train = (y_train == 5).astype('int32'); y_test = (y_test == 5).astype('int32')
# 2. Preprocess: Normalize & flatten
x_train = x_train.astype('float32')/255.0; x_test = x_test.astype('float32')/255.0  # :cc
x_train = x_train.reshape(-1, 32*32*3); x_test = x_test.reshape(-1, 32*32*3)
# 3. Build the model
model = models.Sequential([
    layers.Input(shape=(32*32*3,)),
    layers.Dense(512, activation='relu'),
    layers.Dense(128, activation='relu'),
    layers.Dense(2)       # logits
])  # :contentReference[oaicite:7]{index=7}
# 4. Compile
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
# 5. Train
model.fit(x_train, y_train, epochs=20, batch_size=128, validation_split=0.1)
# 6. Evaluate
test_loss, test_acc = model.evaluate(x_test, y_test)
print(f"Test accuracy: {test_acc:.4f}")
```

```
Epoch 1/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 4s 37ms/step - accuracy: 0.5168 - loss: 1.0989 - val_accur
Epoch 2/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 32ms/step - accuracy: 0.5864 - loss: 0.6698 - val_accur
Epoch 3/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 47ms/step - accuracy: 0.5636 - loss: 0.6921 - val_accur
Epoch 4/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 32ms/step - accuracy: 0.5814 - loss: 0.6817 - val_accur
Epoch 5/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 32ms/step - accuracy: 0.6035 - loss: 0.6580 - val_accur
Epoch 6/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.5922 - loss: 0.6591 - val_accur
Epoch 7/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 32ms/step - accuracy: 0.6132 - loss: 0.6471 - val_accur
Epoch 8/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 46ms/step - accuracy: 0.6008 - loss: 0.6570 - val_accur
Epoch 9/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 32ms/step - accuracy: 0.6215 - loss: 0.6436 - val_accur
Epoch 10/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 32ms/step - accuracy: 0.6282 - loss: 0.6402 - val_accur
Epoch 11/20
```

```
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 32ms/step - accuracy: 0.6267 - loss: 0.6398 - val_accur
Epoch 12/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 33ms/step - accuracy: 0.6269 - loss: 0.6362 - val_accur
Epoch 13/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 47ms/step - accuracy: 0.6368 - loss: 0.6332 - val_accur
Epoch 14/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.6298 - loss: 0.6347 - val_accur
Epoch 15/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 31ms/step - accuracy: 0.6297 - loss: 0.6326 - val_accur
Epoch 16/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 35ms/step - accuracy: 0.6391 - loss: 0.6287 - val_accur
Epoch 17/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 34ms/step - accuracy: 0.6373 - loss: 0.6233 - val_accur
Epoch 18/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 48ms/step - accuracy: 0.6533 - loss: 0.6153 - val_accur
Epoch 19/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 32ms/step - accuracy: 0.6527 - loss: 0.6147 - val_accur
Epoch 20/20
71/71 ━━━━━━━━━━━━━━━━━━━━ 3s 32ms/step - accuracy: 0.6552 - loss: 0.6122 - val_accur
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.5923 - loss: 0.6872
Test accuracy: 0.5950
```

```
import tensorflow as tf
from tensorflow.keras import layers, models, callbacks
import numpy as np

# 1. Load & Filter CIFAR-10
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
y_train, y_test = y_train.flatten(), y_test.flatten()
mask_train = np.isin(y_train, [3,5]); mask_test = np.isin(y_test, [3,5])
x_train, y_train = x_train[mask_train], (y_train[mask_train]==5).astype('int32')
x_test,  y_test  = x_test[mask_test],  (y_test[mask_test]==5).astype('int32')

# 2. Data Augmentation
data_augment = tf.keras.Sequential([
    layers.RandomFlip("horizontal"),
    layers.RandomRotation(0.1),
    layers.RandomZoom(0.1),
])

# 3. Preprocess: normalize & flatten
def preprocess(x, y):
    x = tf.cast(x, tf.float32)/255.0
    x = tf.reshape(x, (-1, 32*32*3))
    return x, y

train_ds = tf.data.Dataset.from_tensor_slices((x_train, y_train)).shuffle(5000).batch(128
train_ds = train_ds.map(lambda x,y: (data_augment(x), y)).map(preprocess).prefetch(1)
test_ds  = tf.data.Dataset.from_tensor_slices((x_test, y_test)).batch(128).map(preprocess

# 4. Model with Dropout & BatchNorm
model = models.Sequential([
    layers.Input(shape=(32*32*3,)),
    layers.Dense(1024, activation=None),
    layers.BatchNormalization(),
```

```
    layers.ReLU(),
    layers.Dropout(0.3),

    layers.Dense(512, activation=None),
    layers.BatchNormalization(),
    layers.ReLU(),
    layers.Dropout(0.3),

    layers.Dense(256, activation=None),
    layers.BatchNormalization(),
    layers.ReLU(),
    layers.Dropout(0.2),

    layers.Dense(2)  # logits
])

# 5. Compile with LR Scheduler
# Remove the learning rate schedule from the optimizer definition
model.compile(
    optimizer=tf.keras.optimizers.Adam(),  # Remove learning_rate=lr_schedule
    loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
    metrics=['accuracy']
)

# 6. Callbacks
def lr_schedule(epoch):
  """Learning Rate Schedule

  Learning rate is scheduled to be reduced after 80, 120, 160, 180 epochs.
  Called automatically every epoch as part of callbacks during training.

  # Arguments
      epoch (int): The number of epochs

  # Returns
      lr (float32): learning rate
  """
  lr = 1e-3
  if epoch > 180:
    lr *= 0.5e-3
  elif epoch > 160:
    lr *= 1e-3
  elif epoch > 120:
    lr *= 1e-2
  elif epoch > 80:
    lr *= 1e-1
  print('Learning rate: ', lr)
  return lr
# Add LearningRateScheduler callback to manage the learning rate
cb = [
    callbacks.EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True),
    callbacks.ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=2),
    callbacks.LearningRateScheduler(lr_schedule)  # Add this line
]
```

```
# 7. Train & Evaluate
history = model.fit(train_ds, epochs=30, validation_data=test_ds, callbacks=cb)

# 7.1. Plot training history
import pandas as pd, matplotlib.pyplot as plt
hist_df = pd.DataFrame(history.history)
hist_df[['loss','val_loss']].plot(title='Loss Over Epochs', figsize=(8,5)); plt.show()
hist_df[['accuracy','val_accuracy']].plot(title='Accuracy Over Epochs', figsize=(8,5)); p

test_loss, test_acc = model.evaluate(test_ds)
print(f"Test accuracy: {test_acc:.4f}")
```

```
Learning rate:  0.001
Epoch 1/30
79/79 ━━━━━━━━━━━━━━━━━━━━ 12s 111ms/step - accuracy: 0.5482 - loss: 0.8246 - val_acc
Learning rate:  0.001
Epoch 2/30
79/79 ━━━━━━━━━━━━━━━━━━━━ 10s 109ms/step - accuracy: 0.5608 - loss: 0.7139 - val_acc
Learning rate:  0.001
Epoch 3/30
79/79 ━━━━━━━━━━━━━━━━━━━━ 10s 114ms/step - accuracy: 0.5761 - loss: 0.6996 - val_acc
Learning rate:  0.001
Epoch 4/30
79/79 ━━━━━━━━━━━━━━━━━━━━ 11s 118ms/step - accuracy: 0.5995 - loss: 0.6775 - val_acc
Learning rate:  0.001
Epoch 5/30
79/79 ━━━━━━━━━━━━━━━━━━━━ 9s 106ms/step - accuracy: 0.5937 - loss: 0.6768 - val_accu
Learning rate:  0.001
Epoch 6/30
79/79 ━━━━━━━━━━━━━━━━━━━━ 10s 105ms/step - accuracy: 0.6007 - loss: 0.6599 - val_acc
Learning rate:  0.001
Epoch 7/30
79/79 ━━━━━━━━━━━━━━━━━━━━ 9s 117ms/step - accuracy: 0.6135 - loss: 0.6571 - val_accu
Learning rate:  0.001
Epoch 8/30
79/79 ━━━━━━━━━━━━━━━━━━━━ 9s 118ms/step - accuracy: 0.6135 - loss: 0.6516 - val_accu
Learning rate:  0.001
Epoch 9/30
79/79 ━━━━━━━━━━━━━━━━━━━━ 8s 103ms/step - accuracy: 0.6100 - loss: 0.6536 - val_accu
```