Section 1: ANN vs. Classical Models for CIFAR-10

Loading Data

The data will be loaded and preprocessed based on pipelines from the previous project.

```
# Import custom scikit-learn transformers
from Pipelines.custom_transformers import *

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

# Load data
(X_train, y_train), (X_test, y_test) = cifar10.load_data()

import joblib

# Load preprocessing pipeline
preprocessing = joblib.load('Pipelines/preprocessing.pkl')
preprocessing
```

```
Pipeline(steps=[('dataset_combiner', DatasetCombiner()),
                ('reshaper', Reshaper()), ('splitter', Splitter()),
                ('scaler', Scaler())])
```

```
# Apply preprocessing pipeline
X_train, X_test, y_train, y_test =
preprocessing.fit_transform((X_train, X_test, y_train, y_test))
```

Building ANN and Tuning

We will first build the architecture of the ANN model, allowing for flexibility in terms of the activation function and number of neurons in each layer.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Input,
BatchNormalization
from tensorflow.keras.optimizers import Adam, SGD
from keras_tuner import HyperModel
from tensorflow.keras.callbacks import EarlyStopping

class HyperANN(HyperModel):

    def __init__(self, *args, epochs=5, num_features=3072, **kwargs):
        super().__init__(*args, **kwargs)
```

```
        self.epochs = epochs
        self.num_features = num_features

    def build(self, hp):

        # Hyperparameters
        num_neurons = [16, 32, 64, 128, 256, 512]
        activations = ['relu', 'selu', 'leaky_relu']
        dropouts = [0.0, 0.1, 0.2, 0.3, 0.4, 0.5]
        num_hidden = [2, 3, 4, 5, 6]
        optimizers = ['adam', 'sgd']
        learning_rates = [1e-5, 1e-4, 1e-3]

        # Input layer (dense with dropout)
        model = Sequential()
        activation = hp.Choice('input_activation', activations)

        if activation == 'selu':
            initializer='lecun_normal'
        else:
            initializer='he_normal'

        model.add(Input(shape=(self.num_features,)))
        model.add(Dense(hp.Choice('input_neurons', num_neurons),
activation=activation, kernel_initializer=initializer))
        model.add(BatchNormalization())
        model.add(Dropout(hp.Choice('input_dropout', dropouts)))

        # Dense hidden layers
        num_hidden_layers = hp.Choice('num_hidden_layers', num_hidden)

        for i in range(num_hidden_layers):

            activation = hp.Choice(f'hidden_activation{i}',
activations)

            if activation == 'selu':
                initializer='lecun_normal'
            else:
                initializer='he_normal'

            model.add(Dense(hp.Choice(f'hidden_neurons{i}',
num_neurons), activation=activation, kernel_initializer=initializer))
            model.add(BatchNormalization())
            model.add(Dropout(hp.Choice(f'hidden_dropout{i}',
dropouts)))

        # Dense output layer
        model.add(Dense(10, activation='softmax'))
```

```
        # Determine batch size for the future fitting
        batch_size=hp.Choice('batch_size', [16, 32, 64, 128, 256])
        self.batch_size = batch_size

        # Compiling model
        learning_rate = hp.Choice('learning_rate', learning_rates)
        optimizer = hp.Choice('optimizer', optimizers)
        if optimizer == 'adam':
            optimizer = Adam(learning_rate=learning_rate)
        elif optimizer == 'sgd':
            optimizer = SGD(learning_rate=learning_rate)
        else:
            raise NameError('Optimizer name has not been dealt with 
properly!')

        model.compile(optimizer=optimizer,
loss='sparse_categorical_crossentropy', metrics=['accuracy'])
        return model

    def fit(self, hp, model, *args, **kwargs):

        early_stopping = EarlyStopping(
        monitor='val_loss',
        patience=5,
        restore_best_weights=True
)

        return model.fit(
            *args,
            batch_size=self.batch_size,
            epochs=self.epochs,
            callbacks=[early_stopping]
            **kwargs,
        )
```

Now, we can tune the ANN using 10 epochs and early stopping with a patience of 5.

```
from keras_tuner import RandomSearch
import time

# Tune and track time
tuner = RandomSearch(HyperANN(epochs=10,
num_features=X_train.shape[1]).build, objective='val_accuracy',
max_trials=200, directory='ANN_Results')

start_time = time.time()
tuner.search(X_train, y_train, validation_split=0.2)
end_time = time.time()

tuning_time_secs = end_time-start_time
```

```
tuning_time_mins = tuning_time_secs/60
print('-----------------------------------------------------------------------')
print(f'Time to Tune: {tuning_time_mins} mins')
print('-----------------------------------------------------------------------')
```

```
Trial 200 Complete [00h 00m 09s]
val_accuracy: 0.17114582657814026

Best val_accuracy So Far: 0.40666666626930237
Total elapsed time: 00h 25m 51s
-------------------------------------------------------------------
Time to Tune: 25.85037029981613 mins
-------------------------------------------------------------------
```

The ANN will be trained with more epochs.

```
# Get best tuned model
best_model = tuner.get_best_models(num_models=1)[0]
best_trial = tuner.oracle.get_best_trials(num_trials=1)[0]
best_params = best_trial.hyperparameters.values

# Show best parameters
print('-----------------------------------------------------------------------')
print(f'Best Parameters: {best_params}')
print('-----------------------------------------------------------------------')

early_stopping = EarlyStopping(
    monitor='val_loss',
    patience=10,
    restore_best_weights=True
)

# Train with more epochs
start_time = time.time()
best_model.fit(X_train, y_train, epochs=200, validation_split=0.2,
batch_size=best_params['batch_size'], callbacks=[early_stopping])
end_time = time.time()

# Show time to train with more epochs
tuning_time_secs = end_time-start_time
tuning_time_mins = tuning_time_secs/60
print('-----------------------------------------------------------------------')
print(f'Time to Train with More Epochs: {tuning_time_mins} mins')
print('-----------------------------------------------------------------------')
```

```python
# Save model
best_model.save('Models/ANN.keras')
```

```
c:\Users\ethan\anaconda3\envs\ML_env\Lib\site-packages\keras\src\
saving\saving_lib.py:757: UserWarning: Skipping variable loading for
optimizer 'adam', because it has 2 variables whereas the saved
optimizer has 30 variables.
  saveable.load_own_variables(weights_store.get(inner_path))

------------------------------------------------------------------
Best Parameters: {'input_activation': 'leaky_relu', 'input_neurons':
512, 'input_dropout': 0.0, 'num_hidden_layers': 2,
'hidden_activation0': 'leaky_relu', 'hidden_neurons0': 512,
'hidden_dropout0': 0.2, 'hidden_activation1': 'leaky_relu',
'hidden_neurons1': 64, 'hidden_dropout1': 0.3, 'batch_size': 16,
'learning_rate': 0.0001, 'optimizer': 'adam', 'hidden_activation2':
'selu', 'hidden_neurons2': 16, 'hidden_dropout2': 0.2,
'hidden_activation3': 'relu', 'hidden_neurons3': 256,
'hidden_dropout3': 0.5, 'hidden_activation4': 'relu',
'hidden_neurons4': 128, 'hidden_dropout4': 0.1, 'hidden_activation5':
'selu', 'hidden_neurons5': 512, 'hidden_dropout5': 0.5}
------------------------------------------------------------------
Epoch 1/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 18s 7ms/step - accuracy: 0.3288 - loss:
1.9484 - val_accuracy: 0.4349 - val_loss: 1.6076
Epoch 2/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.3629 - loss:
1.8150 - val_accuracy: 0.4352 - val_loss: 1.6005
Epoch 3/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 506s 211ms/step - accuracy: 0.3857 -
loss: 1.7442 - val_accuracy: 0.4400 - val_loss: 1.6081
Epoch 4/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 20s 8ms/step - accuracy: 0.4078 - loss:
1.6687 - val_accuracy: 0.4659 - val_loss: 1.5376
Epoch 5/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 18s 7ms/step - accuracy: 0.4212 - loss:
1.6403 - val_accuracy: 0.4673 - val_loss: 1.5134
Epoch 6/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.4379 - loss:
1.6066 - val_accuracy: 0.4670 - val_loss: 1.5038
Epoch 7/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.4448 - loss:
1.5746 - val_accuracy: 0.4903 - val_loss: 1.4550
Epoch 8/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.4573 - loss:
1.5396 - val_accuracy: 0.4935 - val_loss: 1.4412
Epoch 9/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.4564 - loss:
1.5327 - val_accuracy: 0.4840 - val_loss: 1.4549
```

```
Epoch 10/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.4716 - loss:
1.5013 - val_accuracy: 0.5005 - val_loss: 1.4173
Epoch 11/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.4776 - loss:
1.4850 - val_accuracy: 0.4864 - val_loss: 1.4517
Epoch 12/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.4795 - loss:
1.4728 - val_accuracy: 0.4622 - val_loss: 1.4975
Epoch 13/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 18s 7ms/step - accuracy: 0.4826 - loss:
1.4665 - val_accuracy: 0.4811 - val_loss: 1.4402
Epoch 14/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 18s 7ms/step - accuracy: 0.4832 - loss:
1.4565 - val_accuracy: 0.4796 - val_loss: 1.4696
Epoch 15/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 18s 7ms/step - accuracy: 0.4970 - loss:
1.4344 - val_accuracy: 0.5027 - val_loss: 1.4072
Epoch 16/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.4967 - loss:
1.4210 - val_accuracy: 0.5131 - val_loss: 1.3820
Epoch 17/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 18s 7ms/step - accuracy: 0.5053 - loss:
1.4018 - val_accuracy: 0.4866 - val_loss: 1.4377
Epoch 18/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5107 - loss:
1.3967 - val_accuracy: 0.5048 - val_loss: 1.4004
Epoch 19/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 18s 7ms/step - accuracy: 0.5098 - loss:
1.3871 - val_accuracy: 0.5107 - val_loss: 1.3836
Epoch 20/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 18s 7ms/step - accuracy: 0.5153 - loss:
1.3804 - val_accuracy: 0.5015 - val_loss: 1.3915
Epoch 21/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 18s 7ms/step - accuracy: 0.5153 - loss:
1.3744 - val_accuracy: 0.5100 - val_loss: 1.3663
Epoch 22/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5233 - loss:
1.3520 - val_accuracy: 0.5150 - val_loss: 1.3760
Epoch 23/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5247 - loss:
1.3536 - val_accuracy: 0.5135 - val_loss: 1.3721
Epoch 24/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5243 - loss:
1.3481 - val_accuracy: 0.5197 - val_loss: 1.3552
Epoch 25/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5358 - loss:
1.3370 - val_accuracy: 0.5221 - val_loss: 1.3532
Epoch 26/200
```

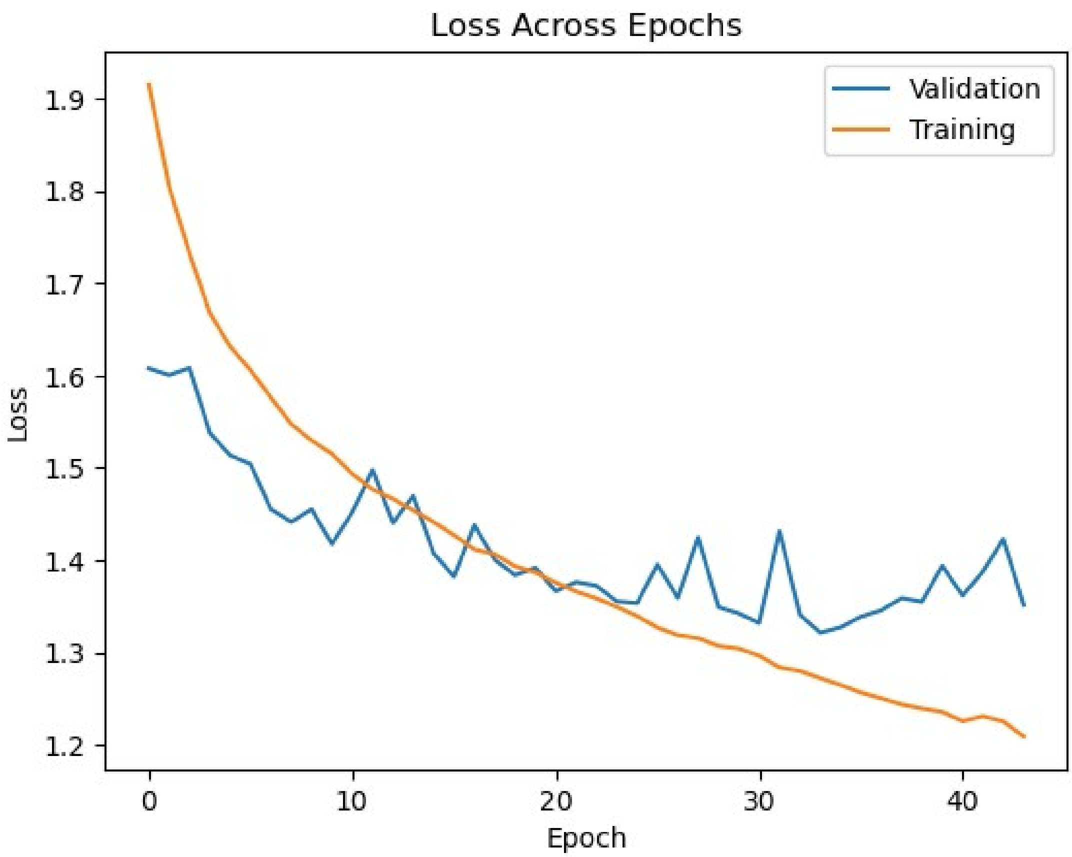
```
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5288 - loss:
1.3312 - val_accuracy: 0.4989 - val_loss: 1.3952
Epoch 27/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5361 - loss:
1.3170 - val_accuracy: 0.5267 - val_loss: 1.3589
Epoch 28/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5434 - loss:
1.3049 - val_accuracy: 0.4943 - val_loss: 1.4245
Epoch 29/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5376 - loss:
1.3118 - val_accuracy: 0.5203 - val_loss: 1.3489
Epoch 30/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5421 - loss:
1.2943 - val_accuracy: 0.5205 - val_loss: 1.3420
Epoch 31/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5466 - loss:
1.2948 - val_accuracy: 0.5299 - val_loss: 1.3316
Epoch 32/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5529 - loss:
1.2744 - val_accuracy: 0.4984 - val_loss: 1.4313
Epoch 33/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5514 - loss:
1.2642 - val_accuracy: 0.5266 - val_loss: 1.3406
Epoch 34/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5577 - loss:
1.2538 - val_accuracy: 0.5294 - val_loss: 1.3212
Epoch 35/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5553 - loss:
1.2583 - val_accuracy: 0.5295 - val_loss: 1.3270
Epoch 36/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5626 - loss:
1.2439 - val_accuracy: 0.5236 - val_loss: 1.3385
Epoch 37/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5580 - loss:
1.2472 - val_accuracy: 0.5224 - val_loss: 1.3454
Epoch 38/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5638 - loss:
1.2373 - val_accuracy: 0.5201 - val_loss: 1.3587
Epoch 39/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5704 - loss:
1.2323 - val_accuracy: 0.5259 - val_loss: 1.3548
Epoch 40/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5623 - loss:
1.2386 - val_accuracy: 0.5146 - val_loss: 1.3936
Epoch 41/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5737 - loss:
1.2211 - val_accuracy: 0.5191 - val_loss: 1.3614
Epoch 42/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5690 - loss:
```

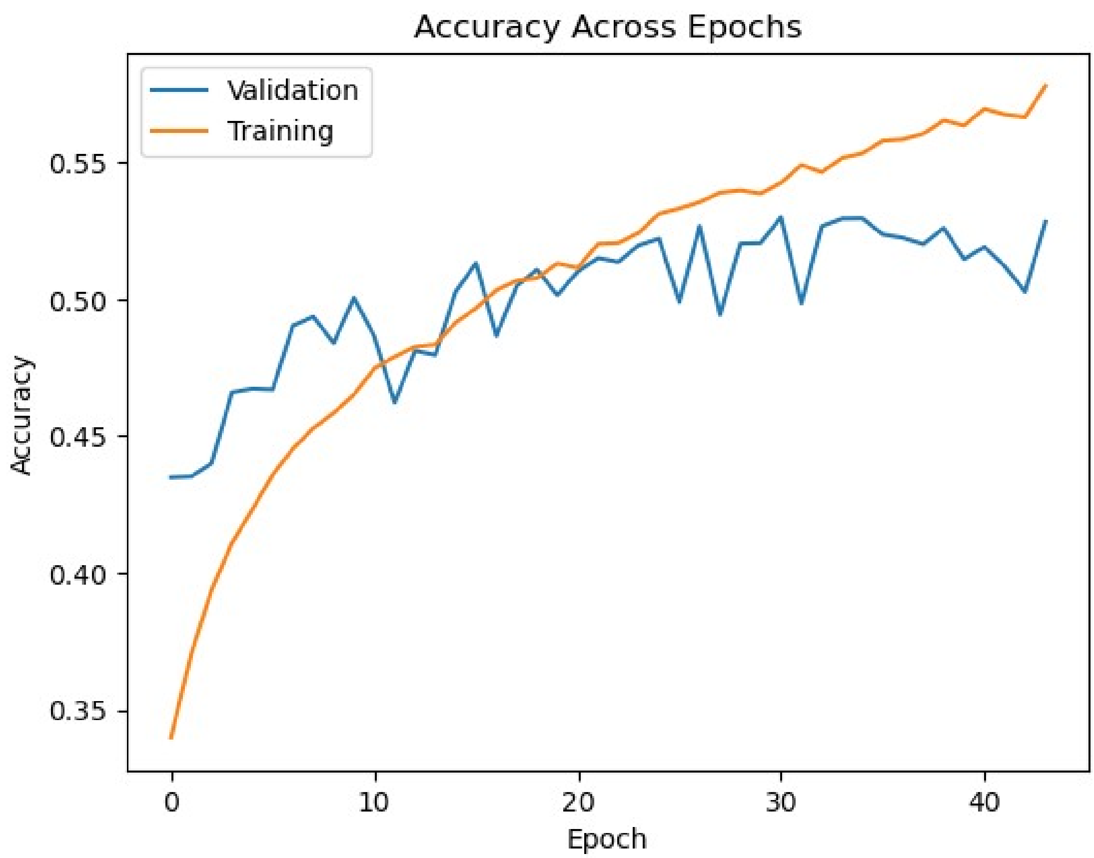
```
1.2235 - val_accuracy: 0.5120 - val_loss: 1.3875
Epoch 43/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5647 - loss:
1.2199 - val_accuracy: 0.5027 - val_loss: 1.4227
Epoch 44/200
2400/2400 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.5784 - loss:
1.2037 - val_accuracy: 0.5282 - val_loss: 1.3514
------------------------------------------------------------------
Time to Train with More Epochs: 20.87196930249532 mins
------------------------------------------------------------------
```

Note that if the number of hidden layers chosen is 2 for example, in the chosen hyperparameters you might see parameters like "hidden_neurons3" which would be the number of hidden neurons in the 4th layer (index 3). This seems contradictory but it is because the tuning would assign values to old parameters even if they were not needed for the current trial. Regardless, the "num_hidden_layers" parameter indicates how many layers were chosen and the extra parameters can be ignored. Next, we will show loss and validation across the epochs.

```
import matplotlib.pyplot as plt

# Print accuracy of saved state
print(f"Validation Accuracy:
{best_model.history.history['val_accuracy'][-1]}")
print(f"Training Accuracy: {best_model.history.history['accuracy'][-
1]}")

# Plot loss
val_loss = best_model.history.history['val_loss']
plt.plot(range(len(val_loss)), val_loss, label='Validation')
train_loss = best_model.history.history['loss']
plt.plot(range(len(train_loss)), train_loss, label='Training')
plt.title('Loss Across Epochs')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend()
plt.show()

# Plot accuracy
val_accuracy = best_model.history.history['val_accuracy']
plt.plot(range(len(val_accuracy)), val_accuracy, label='Validation')
train_accuracy = best_model.history.history['accuracy']
plt.plot(range(len(train_accuracy)), train_accuracy, label='Training')
plt.title('Accuracy Across Epochs')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()
```

```
Validation Accuracy: 0.5282291769981384
Training Accuracy: 0.5778385400772095
```





Compare to Classical Models

The previously found best classical model with dimensionality reduction and the best classical model without dimensionality reduction will be compared to the ANN on the training set.

```
from sklearn.metrics import classification_report, confusion_matrix,
ConfusionMatrixDisplay

def evaluate(model, X_true, y_true, is_ANN=False):

    """ Evaluate Model Performance """

    # List class names in order
    class_names = [
    "airplane", "automobile", "bird", "cat", "deer",
    "dog", "frog", "horse", "ship", "truck"]

    # Make predictions
    start_time = time.time()
    y_pred = model.predict(X_true)
    if is_ANN:
        y_pred = np.argmax(y_pred, axis=-1)
    end_time = time.time()
```

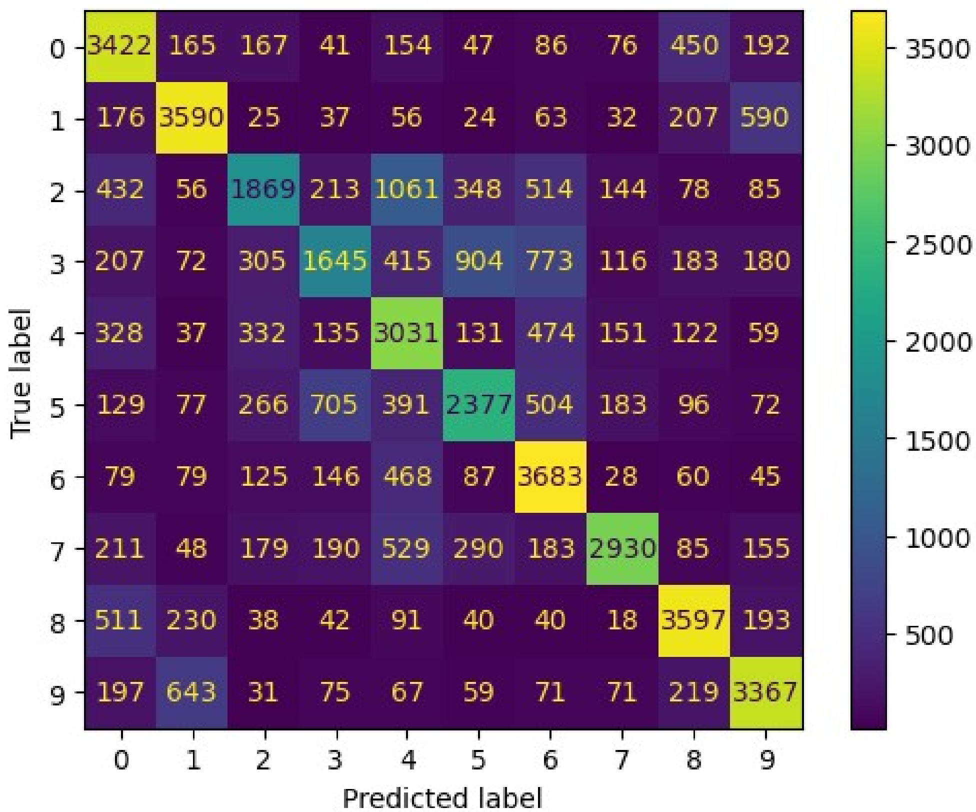
```
    # Show prediction time
    pred_time_secs = end_time - start_time
    print(f'Time Taken to Make Prediction: {pred_time_secs} secs')
    print()

    # Precision, Recall, F1-score
    print('Classification Report')
    print(classification_report(y_true, y_pred))
    print()

    # Confusion Matrix
    cm = confusion_matrix(y_true, y_pred)
    print('Confusion Matrix')
    disp = ConfusionMatrixDisplay(confusion_matrix=cm)
    disp.plot()
    plt.show()

import zipfile
import os

# Extract models from zip if it's not already unzipped
if not os.path.exists('Models'):

    file_path = 'Models.zip'

    with zipfile.ZipFile(file_path, 'r') as zip_ref:
        zip_ref.extractall()
```

Now we can evaluate the models on the training set ...

```
# Evaluate ANN
ann_model = best_model
evaluate(ann_model, X_train, y_train, is_ANN=True)
```

```
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 2s 1ms/step
Time Taken to Make Prediction: 2.4192731380462646 secs

Classification Report
              precision    recall  f1-score   support

           0       0.60      0.71      0.65      4800
           1       0.72      0.75      0.73      4800
           2       0.56      0.39      0.46      4800
           3       0.51      0.34      0.41      4800
           4       0.48      0.63      0.55      4800
           5       0.55      0.50      0.52      4800
           6       0.58      0.77      0.66      4800
           7       0.78      0.61      0.69      4800
           8       0.71      0.75      0.73      4800
```

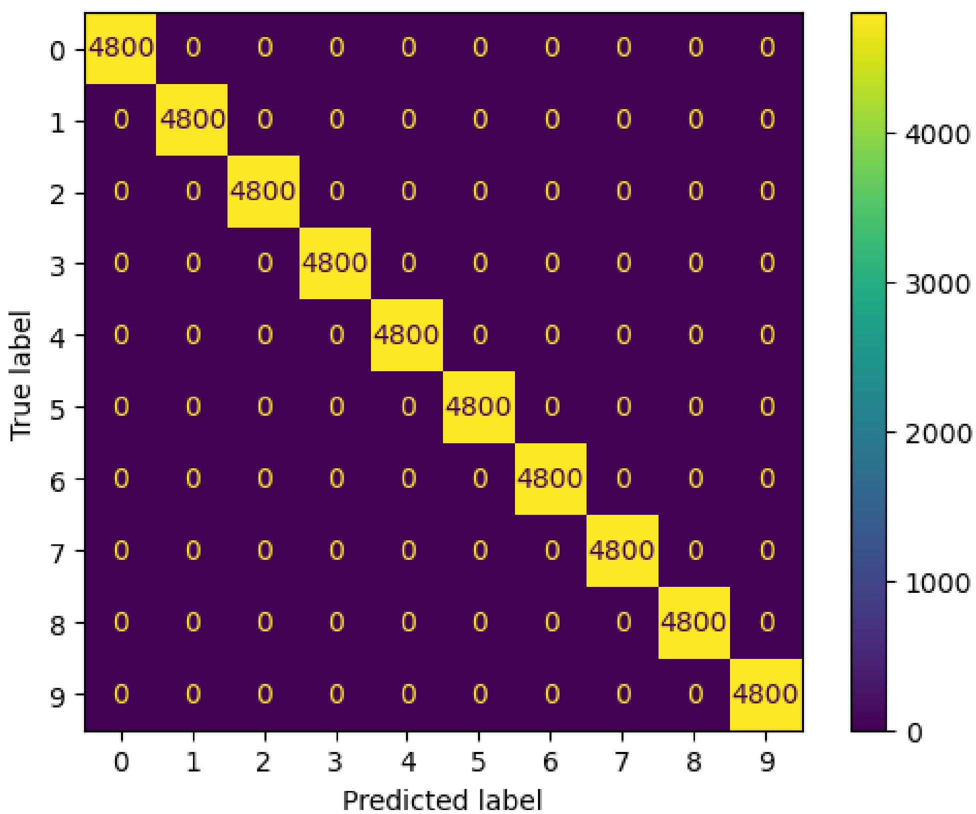
```
           9       0.68      0.70      0.69      4800

    accuracy                           0.61     48000
   macro avg       0.62      0.61      0.61     48000
weighted avg       0.62      0.61      0.61     48000


Confusion Matrix
```




```python
import joblib

# Evaluate best classical model without dimensionality reduction
(random forest)
rf_raw = joblib.load('Models/random_forest_raw.pkl')
evaluate(rf_raw, X_train, y_train, is_ANN=False)
```

```
Time Taken to Make Prediction: 5.8763439655303955 secs

Classification Report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      4800
           1       1.00      1.00      1.00      4800
           2       1.00      1.00      1.00      4800
```

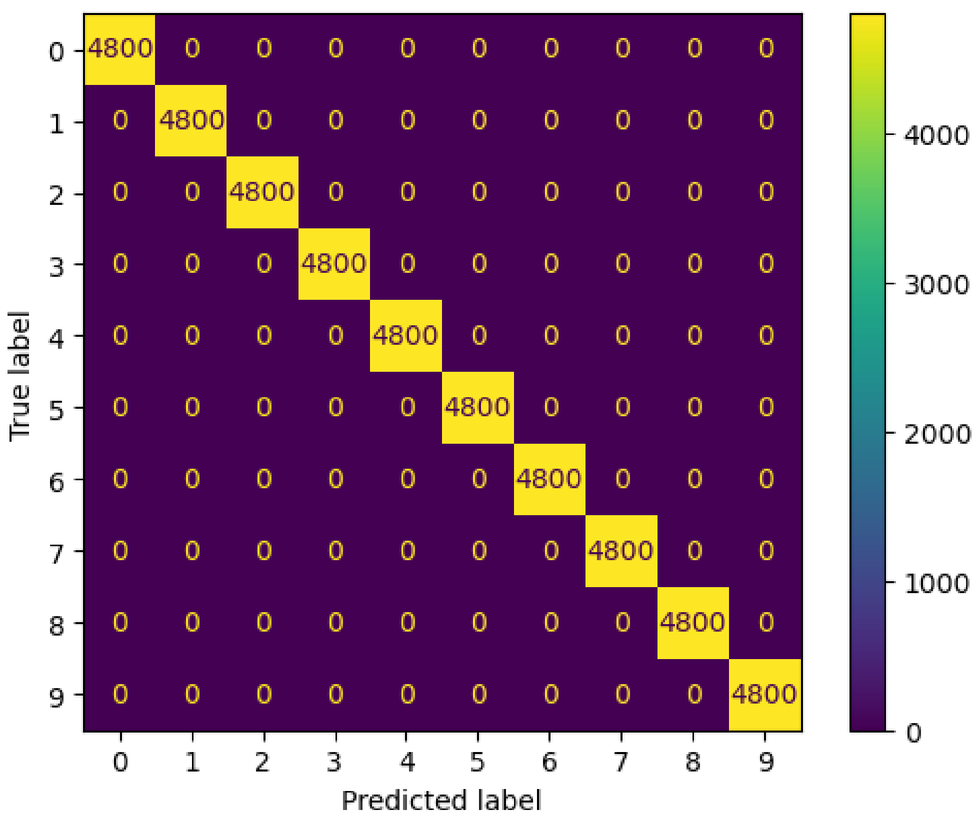
```
           3       1.00      1.00      1.00      4800
           4       1.00      1.00      1.00      4800
           5       1.00      1.00      1.00      4800
           6       1.00      1.00      1.00      4800
           7       1.00      1.00      1.00      4800
           8       1.00      1.00      1.00      4800
           9       1.00      1.00      1.00      4800

    accuracy                           1.00     48000
   macro avg       1.00      1.00      1.00     48000
weighted avg       1.00      1.00      1.00     48000


Confusion Matrix
```




```
# Evaluate best classical model with dimensionality reduction (random forest PCA)
rf_pca = joblib.load('Models/random_forest_pca.pkl')
evaluate(rf_pca, X_train, y_train, is_ANN=False)
```

```
Time Taken to Make Prediction: 3.1078684329986572 secs

Classification Report
              precision    recall  f1-score   support
```

```
           0       1.00      1.00      1.00      4800
           1       1.00      1.00      1.00      4800
           2       1.00      1.00      1.00      4800
           3       1.00      1.00      1.00      4800
           4       1.00      1.00      1.00      4800
           5       1.00      1.00      1.00      4800
           6       1.00      1.00      1.00      4800
           7       1.00      1.00      1.00      4800
           8       1.00      1.00      1.00      4800
           9       1.00      1.00      1.00      4800

    accuracy                           1.00     48000
   macro avg       1.00      1.00      1.00     48000
weighted avg       1.00      1.00      1.00     48000


Confusion Matrix
```



Gradio UI

Gradio will be used so that users can upload their own images and get a classification from the ANN.

```
import gradio as gr
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
import numpy as np

# Load trained ANN
ANN_model = load_model('Models/ANN.keras')

# Function called during gradio interaction (preprocesses image and
makes prediction)
def predict(img):

    try:
        # Resize image to 32x32
        new_size = (32, 32)
        img = img['composite'][:, :, :3]
        img = image.smart_resize(img, new_size)

        # Flatten
        img = np.array(img).flatten()

        # Scale
        img = img/255
        sample = np.array([img])

        # Make prediction
        prediction = ANN_model.predict(sample)
        prediction = np.argmax(prediction, axis=-1)[0]

        # Map prediction to its corresponding name
        class_names = ["airplane", "automobile", "bird", "cat",
"deer",
                      "dog", "frog", "horse", "ship", "truck"]
        prediction = class_names[prediction]

    except Exception as e:
        return ''

    return prediction

# Interface
interface = gr.Interface(
    fn=predict,
    inputs=gr.ImageEditor(label='Upload or Draw an Image',
type='numpy'),
    outputs=gr.Text(label='Prediction'),
    title='Image Classification',
    description='Upload an image to classify it as one of the
following: **airplane, automobile, bird, cat, deer, dog, frog, horse,
ship, or truck**.',
    live=True
```

```
)

# Launch app
interface.launch()

* Running on local URL:  http://127.0.0.1:7884

To create a public link, set `share=True` in `launch()`.

<IPython.core.display.HTML object>



Traceback (most recent call last):
  File "c:\Users\ethan\anaconda3\envs\ML_env\Lib\site-packages\gradio\
queueing.py", line 625, in process_events
    response = await route_utils.call_process_api(
               ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Users\ethan\anaconda3\envs\ML_env\Lib\site-packages\gradio\
route_utils.py", line 322, in call_process_api
    output = await app.get_blocks().process_api(
             ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Users\ethan\anaconda3\envs\ML_env\Lib\site-packages\gradio\
blocks.py", line 2132, in process_api
    inputs = await self.preprocess_data(
             ^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Users\ethan\anaconda3\envs\ML_env\Lib\site-packages\gradio\
blocks.py", line 1813, in preprocess_data
    processed_input.append(block.preprocess(inputs_cached))
                           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Users\ethan\anaconda3\envs\ML_env\Lib\site-packages\gradio\
components\image_editor.py", line 419, in preprocess
    self.blob_storage.pop(payload.id)
KeyError: 'r1gkvomr3q'

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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
```