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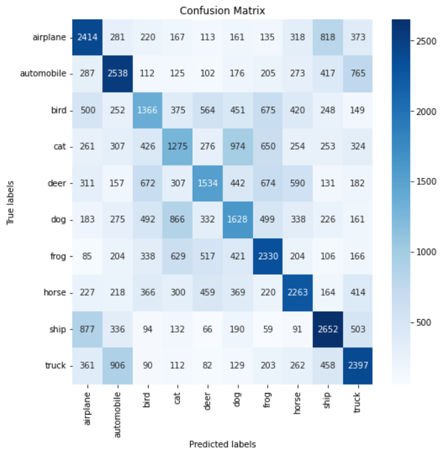
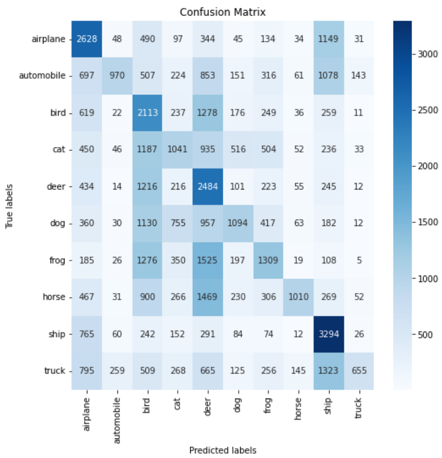
Programming Assignment #1

A public image dataset (Cifar10)

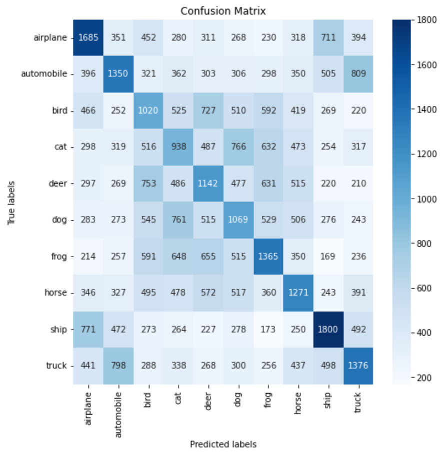
- First classifier: logistic regression (max_iter=100)



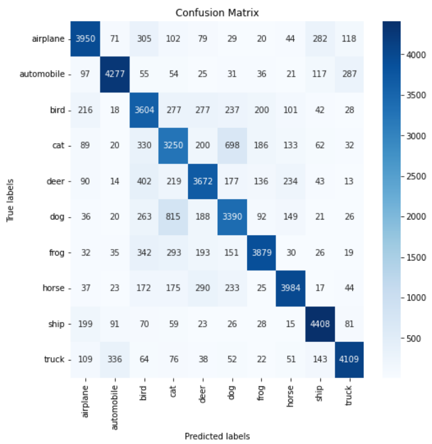
- Second classifier: KNN (n_neighbors=5)



- Third classifier: decision tree (max_depth=none)



- Fourth classifier: CNN



using different amounts of training data

Logistic regression (max_iter=100)

Number of training data	All (50000)	Half (25000)
accuracy	0.4079	0.3955
Precision	0.4026	0.3916
Recall	0.4079	0.3955
F1-score	0.4036	0.3913
ROC AUC score	0.8172	0.8119

KNN (n_neighbors=5)

Number of training data	All (50000)	Half (25000)
accuracy	0.3320	0.3131
Precision	0.4238	0.4039
Recall	0.3320	0.3130
F1-score	0.3180	0.2974
ROC AUC score	0.7264	0.7116

Decision tree (max_depth=none)

Number of training data	All (50000)	Half (25000)
accuracy	0.2603	0.2477
Precision	0.2613	0.2489
Recall	0.2604	0.2478
F1-score	0.2606	0.2481
ROC AUC score	0.5891	0.5821

CNN

Number of training data	All (50000)	Half (25000)
accuracy	0.7705	0.7298
Precision	0.7802	0.7314
Recall	0.7705	0.7298
F1-score	0.7717	0.7273
ROC AUC score	0.9731	0.9626

using different classifiers

model	Logistic regression	KNN	Decision tree	CNN
accuracy	0.4079	0.3320	0.2603	0.7705
Precision	0.4026	0.4238	0.2613	0.7802
Recall	0.4079	0.3320	0.2604	0.7705
F1-score	0.4036	0.3180	0.2606	0.7717
ROC AUC score	0.8172	0.7264	0.5891	0.9731

using different settings and/or hyper-parameters

Logistic regression

max_iter	100	200	400
accuracy	0.4079	0.4058	0.3945
Precision	0.4026	0.4024	0.3912
Recall	0.4079	0.4059	0.3946
F1-score	0.4036	0.4029	0.3922
ROC AUC score	0.8172	0.8173	0.8108

Decision tree

max_depth	none	10	20
accuracy	0.2603	0.2925	0.2632
Precision	0.2613	0.2920	0.2646
Recall	0.2604	0.2927	0.2633
F1-score	0.2606	0.2894	0.2636
ROC AUC score	0.5891	0.6071	0.5907

KNN

n_neighbors	3	5	10
accuracy	0.3232	0.3320	0.3289
Precision	0.4229	0.4238	0.4361
Recall	0.3233	0.3320	0.3290
F1-score	0.3103	0.3180	0.3121
ROC AUC score	0.6993	0.7264	0.7581

CNN

layers	simple	complex
accuracy	0.7705	0.9038
Precision	0.7802	0.9038
Recall	0.7705	0.9038
F1-score	0.7717	0.9034
ROC AUC score	0.9731	0.9932

For the first dataset, I use a popular image dataset – cifar10. It consists of 60000 32x32 color images in 10 classes, with 6000 images per class. In detail, it has 50000 for training and 10000 for testing.

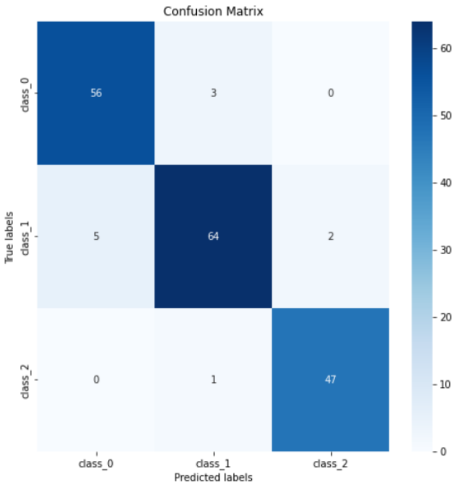
To begin with, I use four different model, logistic regression, KNN, decision tree and CNN, all using kfold(n=5), and all of their performance are affected by the amount of training data (50000 to 25000). As a result, we can tell that it is important to have a larger size of dataset.

Further more, as we can see, KNN and Decision tree perform badly on cifar10. I think it is because both of the models aren't suitable for complex problems, and 10 classes are too hard for them to predict correctly. As for logistic regression, since we can apply as many iterations as we want, making the model more "fit" on the dataset, its performance is slightly higher than previous models. Last, I use a CNN with simple architecture(detail in appendix), and it outperforms any other model. For one thing, CNN is good at image classification. For another, its architecture can be designed by coders, so we can choose those layers that are suitable for certain dataset. In other word, if we build a CNN with randomly chosen layers, its performance may drop significantly.

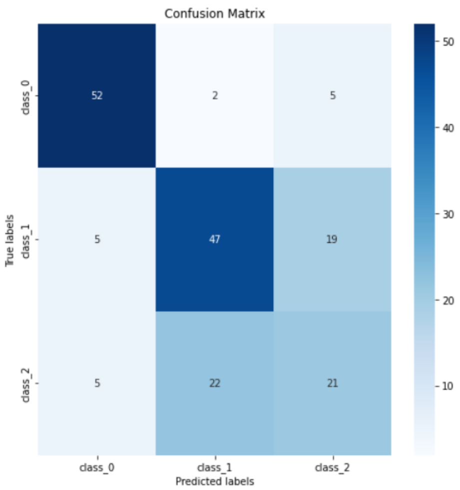
Next, I use different hyper-parameters on different models. For logistic regression, KNN and decision tree, different hyper-parameters seem not to affect the performance significantly. However, the architecture of CNN does affect the performance greatly (from 0.77 to 0.9). I think it is because the second architecture I used can fetch the feature more accurately, which lead to a higher accuracy.

A public non-image dataset (wine)

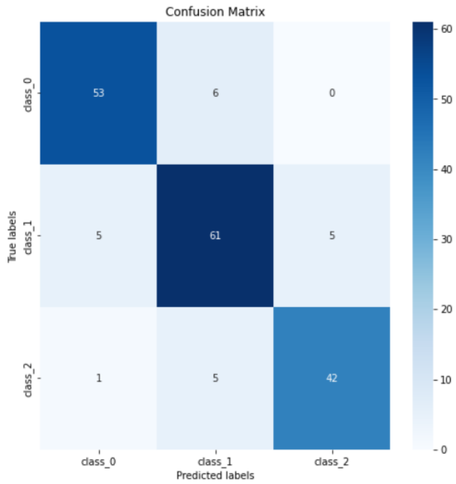
- First classifier: logistic regression (max_iter=100)



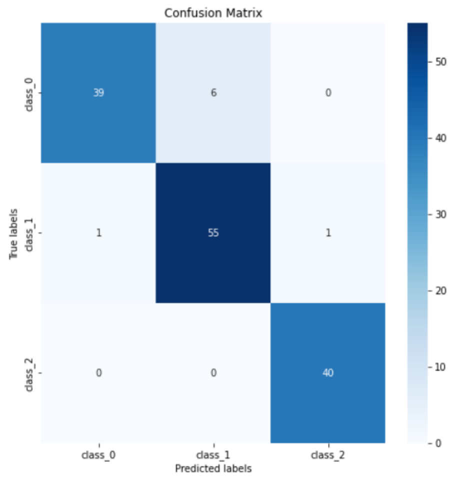
- Second classifier: KNN (n_neighbors=5)



- Third classifier: decision tree (max_depth=none)



- Fourth classifier: CNN



using different amounts of training data

Logistic regression (max_iter=100)

Number of training data	All (178)	Half (89)
accuracy	0.9383	0.7022
Precision	0.9431	0.4774
Recall	0.9420	0.6411
F1-score	0.9404	0.5454
ROC AUC score	0.9927	0.9401

Decision tree (max_depth=none)

Number of training data	All (178)	Half (89)
accuracy	0.8763	0.6962
Precision	0.8828	0.4656
Recall	0.8794	0.6390
F1-score	0.8786	0.5380
ROC AUC score	0.9096	nan

KNN (n_neighbors=5)

Number of training data	All (178)	Half (89)
accuracy	0.6746	0.6854
Precision	0.6628	0.4767
Recall	0.6599	0.6248
F1-score	0.6556	0.5366
ROC AUC score	0.8603	0.8996

CNN

Number of training data	All (178)	Half (89)
accuracy	0.9931	0.9771
Precision	0.9917	0.9750
Recall	0.9933	0.9773
F1-score	0.9920	0.9733
ROC AUC score	1.0	0.9959

using different classifiers

model	Logistic regression	KNN	Decision tree	CNN
accuracy	0.9383	0.6746	0.8763	0.9931
Precision	0.9431	0.6628	0.8828	0.9917
Recall	0.9420	0.6599	0.8794	0.9933
F1-score	0.9404	0.6556	0.8786	0.9920
ROC AUC score	0.9927	0.8603	0.9096	1.0

using different settings and/or hyper-parameters

Logistic regression

max_iter	100	50	20
accuracy	0.9383	0.9100	0.6802
Precision	0.9431	0.9196	0.7144
Recall	0.9420	0.9103	0.6477
F1-score	0.9404	0.9115	0.6313
ROC AUC score	0.9927	0.9807	0.8756

KNN

n_neighbors	3	5	10
accuracy	0.7083	0.6746	0.6802
Precision	0.7013	0.6628	0.6645
Recall	0.7022	0.6599	0.6603
F1-score	0.6965	0.6556	0.6576
ROC AUC score	0.8502	0.8603	0.8631

Decision tree

max_depth	none	3	2
accuracy	0.8763	0.8876	0.8600
Precision	0.8828	0.8970	0.8731
Recall	0.8794	0.8848	0.8651
F1-score	0.8786	0.8865	0.8582
ROC AUC score	0.9096	0.9270	0.9156

CNN

layers	simple	complex
accuracy	0.9931	0.9443
Precision	0.9917	0.9524
Recall	0.9933	0.9411
F1-score	0.9920	0.429
ROC AUC score	1.0	0.9822

For the Second dataset, I use a non-image dataset – wine. These data are the results of a chemical analysis of wines grown in the same region in Italy but derived from three different cultivars. The analysis determined the quantities of 13 constituents found in each of the three types of wines.

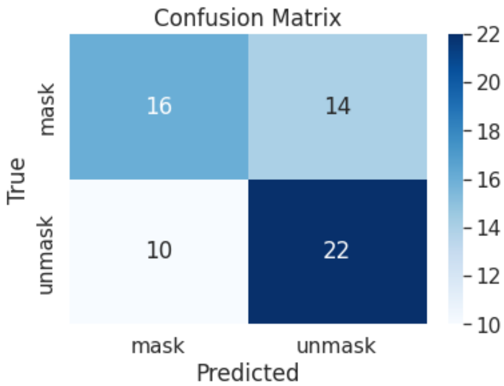
In this part, I use the same four models, but I changed the architecture of CNN to be more suitable in this dataset(detail in appendix). Similarly, most of the models' performances drop after I decrease the amount of training data. What's, more, since this dataset is much smaller than cifar10, so cutting the amount of training data into half has a larger impact on performances.

As I mentioned above, wine dataset is a small dataset. Consequently, except KNN, all models perform well on this dataset. For logistic regression, smaller amount makes it easier to find a linear pattern; for decision tree, only three classes are in the dataset, so it is more likely to distinguish from one class to another. As for KNN, I think it is the dataset's characteristic that makes KNN's performance poor, maybe the distribution of the data isn't dense enough for the model to predict. Also, CNN still performs best among all the models. I think the reasons are similar: I can decide what layer to use, which is a advantage of using CNN.

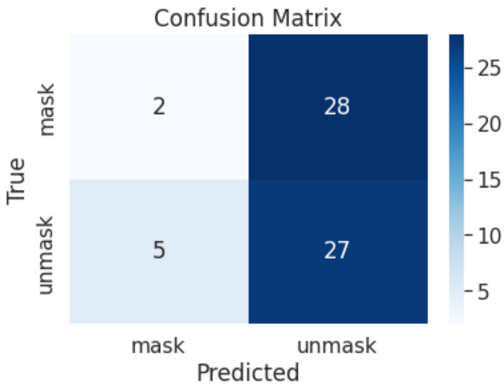
Last, the different hyper-parameters part. First, logistic regression, we can see that max_iter=20 is not enough for this situation, and the more iteration we apply, the better performance we get. Next, KNN, the performance of the model actually doesn't change a lot when using different n_neighbors, maybe it's because KNN already perform poor on wine dataset, using different hyper-parameters won't affect its performance, I guess. Third, decision tree, since the dataset is small enough, so max_depth=3 is already enough for a acceptable accuracy, which in fact has a higher accuracy than max_depth=5 one. Last but not least, CNN. In this dataset, a complex architecture performs poorer than a simple one. In my opinion, maybe I add a useless layer, or superfluous layer in the complex one. Nonetheless, both of the architectures still have high accuracy.

A self-made dataset

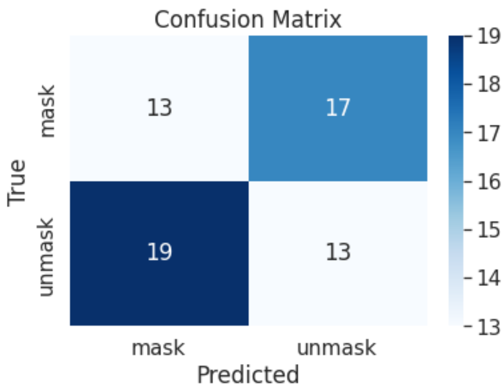
- First classifier: logistic regression (max_iter=100)



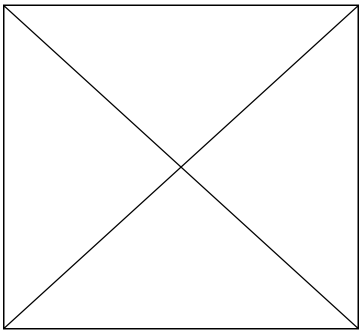
- Second classifier: KNN (n_neighbors=5)



- Third classifier: decision tree (max_depth=none)



- Fourth classifier: CNN



using different amounts of training data

Logistic regression (max_iter=100)

Number of training data	All (310)	Half (168)
accuracy	0.6129	0.5
Precision	0.6111	0.44
Recall	0.6875	0.7857
F1-score	0.6471	0.5641
ROC AUC score	0.6104	0.5429

KNN (n_neighbors=5)

Number of training data	All (310)	Half (168)
accuracy	0.4677	0.4118
Precision	0.4909	0.4062
Recall	0.8438	0.9286
F1-score	0.6207	0.5652
ROC AUC score	0.4552	0.4893

Decision tree (max_depth=none)

Number of training data	All (310)	Half (168)
accuracy	0.4194	0.4706
Precision	0.4333	0.4091
Recall	0.4062	0.6429
F1-score	0.4194	0.5
ROC AUC score	0.4198	0.4964

CNN

Number of training data	All (310)	Half (168)
accuracy	0.6774	0.4904

using different classifiers

model	Logistic regression	KNN	Decision tree	CNN
accuracy	0.6129	0.4677	0.4194	0.6774
Precision	0.6111	0.4909	0.4333	
Recall	0.6875	0.8438	0.4062	
F1-score	0.6471	0.6207	0.4194	
ROC AUC score	0.6104	0.4552	0.4198	

using different settings and/or hyper-parameters

Logistic regression

max_iter	100	20	10
accuracy	0.6129	0.629	0.5806
Precision	0.6111	0.6364	0.575
Recall	0.6875	0.6562	0.7188
F1-score	0.6471	0.6462	0.6389
ROC AUC score	0.6104	0.6281	0.576

KNN

n_neighbors	5	3	1
accuracy	0.4677	0.4032	0.4355
Precision	0.4909	0.451	0.4681
Recall	0.8438	0.7188	0.6875
F1-score	0.6207	0.5542	0.557
ROC AUC score	0.4552	0.3927	0.4271

Decision tree

max_depth	none	3	1
accuracy	0.4194	0.4677	0.5323
Precision	0.4333	0.4783	0.7143
Recall	0.4062	0.3438	0.1562
F1-score	0.4194	0.4	0.2564
ROC AUC score	0.4198	0.4719	0.5448

In this part, I choose to classify whether a person is wearing a face mask or not. As a result, my dataset has two kind of images: people with face masks and without face masks. The former has 161 images, and the latter has 148. All of the images are gathered from Internet.

In this part, we can also see the effect of decreasing the amount of training data, most of the models have lower accuracy with half amount of training data. In terms of using different classifiers, logistic regression and CNN perform better than the remaining two. However, they are only slightly higher than random guess (0.5, since my dataset is a binary classification). The reason of this, I think, is because of the quality and the size of the dataset. Since the images are from many websites, some of them may have complex background, making it more difficult to specify where the face is. Also, I only gathered 310 images in total, which is a very small amount. Another point I want to point out is, the performance of KNN, it still performs the worst among four models, no matter how I change its hyper-parameter.

Discussion

In this homework, I implement four different models of all the datasets, making it easier to compare their performance under different circumstances. In terms of their performances, CNN performs as good as I expected, which outperforms other three models on all the datasets. Nevertheless, KNN's performance is way lower than I expected, and it has low accuracy but high recall score, which is equivalent to the True Positive rate. After some research, I notice "the curse of dimensionality", which means that KNN performs best with a low number of features. When the number of features increases, then it requires more data. When there's more data, it creates an overfitting problem because no one knows which piece of noise will contribute to the model. To be more specific, we need less features in dataset to have a better KNN model.

Well, there are still many experiments that can be done. If time is available, I would do grid search on every model on every dataset to find the best combination of different settings/hyper-parameters. Also, I would try more different architectures of CNN, different loss function(MSE, cross-enropy…) or different optimizer, and a more complicated model such as SVM, which is somehow time-consuming and makes me didn't add the model into my implementation.

Last thing I want to note is, data preprocessing. Data preprocessing is an important part in machine learning, including feature concatenation, feature extraction, sampling, and etc. I wonder how different preprocessing steps would affect the final output. Maybe if I preprocess the data correctly, simple model like logistic regression can also catch on the performance of neural network? Who knows!

Appendix

CNN architecture

(part1)

Simple layers

```
model = keras.Sequential([
        keras.layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)),
        keras.layers.MaxPooling2D((2, 2)),
        keras.layers.Conv2D(64, (3, 3), activation='relu'),
        keras.layers.MaxPooling2D((2, 2)),
        keras.layers.Flatten(),
        keras.layers.Dense(64, activation='relu'),
        keras.layers.Dense(10, activation='softmax')
])
```

Complex layers

```
model = Sequential()

model.add(Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=x_train.shape[1:]))
model.add(BatchNormalization())
model.add(Conv2D(32, (3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(64, (3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(64, (3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(128, (3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(128, (3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(10, activation='softmax'))
```

(part2)

Simple layers

```
model = keras.Sequential([
        keras.layers.Dense(64, activation='relu', input_shape=(13,)),
        keras.layers.Dense(32, activation='relu'),
        keras.layers.Dense(num_classes, activation='softmax')
])
```

Complex layers

```
model = keras.Sequential([
        keras.layers.Reshape(target_shape=(13, 1), input_shape=(13,)),
        keras.layers.Conv1D(filters=16, kernel_size=3, activation='relu', input_shape=(13, 1)),
        keras.layers.MaxPooling1D(pool_size=2),
        keras.layers.Flatten(),
        keras.layers.Dense(32, activation='relu'),
        keras.layers.Dense(num_classes, activation='softmax')
])
```

(part3)

```
model = Sequential([
        Conv2D(32, (3, 3), activation='relu', input_shape=(img_width, img_height, 3)),
        MaxPooling2D((2, 2)),
        Conv2D(64, (3, 3), activation='relu'),
        MaxPooling2D((2, 2)),
        Conv2D(128, (3, 3), activation='relu'),
        MaxPooling2D((2, 2)),
        Flatten(),
        Dense(128, activation='relu'),
        Dense(1, activation='sigmoid')
])
```

Code

Logistic regression

```python
# Load the CIFAR-10 dataset
(X_train, y_train), (X_test, y_test) = cifar10.load_data()

# Flatten the images and scale pixel values to range [0, 1]
X_train = X_train.reshape(X_train.shape[0], -1) / 255.0
X_test = X_test.reshape(X_test.shape[0], -1) / 255.0

# Define the Logistic Regression model
model = LogisticRegression(max_iter=100)

# Define the k-fold cross-validation object
kf = KFold(n_splits=5, shuffle=True, random_state=42)

# Initialize lists to store the evaluation metrics
accuracy_scores = []
precision_scores = []
recall_scores = []
f1_scores = []
roc_auc_scores = []
conf_matrices = []

# Loop over the folds of the cross-validation
for train_index, val_index in kf.split(X_train):
    # Split the training set into a training subset and a validation subset
    X_train_sub, X_val = X_train[train_index], X_train[val_index]
    y_train_sub, y_val = y_train[train_index], y_train[val_index]

    # Train the model on the training subset
    model.fit(X_train_sub, y_train_sub.ravel())

    # Predict the labels on the validation subset
    y_pred = model.predict(X_val)

    # Evaluate the model using various metrics
    accuracy_scores.append(accuracy_score(y_val, y_pred))
    precision_scores.append(classification_report(y_val, y_pred, output_dict=True)['macro avg']['precision'])
    recall_scores.append(classification_report(y_val, y_pred, output_dict=True)['macro avg']['recall'])
    f1_scores.append(classification_report(y_val, y_pred, output_dict=True)['macro avg']['f1-score'])
    roc_auc_scores.append(roc_auc_score(y_val, model.predict_proba(X_val), multi_class='ovr'))
    conf_matrices.append(confusion_matrix(y_val, y_pred))
```

KNN

```python
# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Reshape input data
X = x_train.reshape((x_train.shape[0], -1))
y = y_train.reshape((-1,))

# Create a KNN classifier object
knn = KNeighborsClassifier(n_neighbors=5)

# Create KFold cross-validation object
kf = KFold(n_splits=5, shuffle=True, random_state=42)

# Perform cross-validation
scores = cross_val_score(knn, X, y, cv=kf, scoring='accuracy')

# Compute precision, recall, f1-score, and roc_auc_score for each fold
precision_scores = []
recall_scores = []
f1_scores = []
roc_auc_scores = []
confusion_matrices = []
for train_idx, test_idx in kf.split(X):
    X_train, X_test = X[train_idx], X[test_idx]
    y_train, y_test = y[train_idx], y[test_idx]
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    precision_scores.append(precision_score(y_test, y_pred, average='macro'))
    recall_scores.append(recall_score(y_test, y_pred, average='macro'))
    f1_scores.append(f1_score(y_test, y_pred, average='macro'))
    roc_auc_scores.append(roc_auc_score(y_test, knn.predict_proba(X_test), multi_class='ovr'))
    confusion_matrices.append(confusion_matrix(y_test, y_pred))

# Print the mean accuracy and mean scores for each metric
print("Accuracy:", np.mean(scores))
print('Precision:', round(np.mean(precision_scores), 4))
print('Recall:', round(np.mean(recall_scores), 4))
print('F1-score:', round(np.mean(f1_scores), 4))
print('ROC AUC score:', round(np.mean(roc_auc_scores), 4))
```

Decision tree

```
# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Reshape input data
X = x_train.reshape((x_train.shape[0], -1))
y = y_train.reshape((-1,))

# Initialize decision tree classifier
tree = DecisionTreeClassifier(random_state=42)

# Define k-fold cross-validation with 5 folds
kf = KFold(n_splits=5, shuffle=True, random_state=42)

# Initialize lists to store evaluation metrics for each fold
accuracy_list = []
precision_list = []
recall_list = []
f1_list = []
roc_auc_list = []
conf_matrix_list = []

# Perform k-fold cross-validation
for train_index, test_index in kf.split(X):
    # Split data into training and testing sets
    X_train, X_test = X[train_index], X[test_index]
    y_train, y_test = y[train_index], y[test_index]

    # Fit model on training set
    tree.fit(X_train, y_train)

    # Make predictions on testing set
    y_pred = tree.predict(X_test)

    # Convert y_test and y_pred to one-hot encoding
    y_test = to_categorical(y_test)
    y_pred = to_categorical(y_pred)

    # Compute accuracy, precision, recall, f1-score, ROC AUC score, and confusion matrix for this fold
    accuracy = accuracy_score(y_test.argmax(axis=1), y_pred.argmax(axis=1))
    precision = precision_score(y_test, y_pred, average="macro")
    recall = recall_score(y_test, y_pred, average="macro")
    f1 = f1_score(y_test, y_pred, average="macro")
```

```
roc_auc = roc_auc_score(y_test, y_pred, average="macro", multi_class="ovo")
conf_matrix = confusion_matrix(y_test.argmax(axis=1), y_pred.argmax(axis=1))

# Append evaluation metrics to lists
accuracy_list.append(accuracy)
precision_list.append(precision)
recall_list.append(recall)
f1_list.append(f1)
roc_auc_list.append(roc_auc)
conf_matrix_list.append(conf_matrix)
```

CNN

```python
# Load the CIFAR10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Normalize pixel values between 0 and 1
x_train = x_train.astype('float32') / 255
x_test = x_test.astype('float32') / 255

# Convert labels to one-hot encoding
y_train = keras.utils.to_categorical(y_train, 10)
y_test = keras.utils.to_categorical(y_test, 10)

# Define the CNN model architecture
model = keras.Sequential([
    keras.layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)),
    keras.layers.MaxPooling2D((2, 2)),
    keras.layers.Conv2D(64, (3, 3), activation='relu'),
    keras.layers.MaxPooling2D((2, 2)),
    keras.layers.Flatten(),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dense(10, activation='softmax')
])

# Compile the model with categorical crossentropy loss and Adam optimizer
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Define KFold cross-validation
kf = KFold(n_splits=5, shuffle=True, random_state=42)

# Initialize arrays to store results
accuracy_scores = []
precision_scores = []
recall_scores = []
f1_scores = []
roc_auc_scores = []
conf_matrices = []

# Train and evaluate the model for each fold
for train_idx, test_idx in kf.split(x_train):
    x_train_fold, y_train_fold = x_train[train_idx], y_train[train_idx]
    x_test_fold, y_test_fold = x_train[test_idx], y_train[test_idx]
    model.fit(x_train_fold, y_train_fold, epochs=10, batch_size=64)
    y_pred_fold = model.predict(x_test_fold)
```

```
    y_pred_fold_classes = np.argmax(y_pred_fold, axis=1)
    y_test_fold_classes = np.argmax(y_test_fold, axis=1)
    accuracy_scores.append(accuracy_score(y_test_fold_classes, y_pred_fold_classes))
    precision_scores.append(classification_report(y_test_fold_classes, y_pred_fold_classes, output_dict=True)['weighted avg']['precision'])
    recall_scores.append(classification_report(y_test_fold_classes, y_pred_fold_classes, output_dict=True)['weighted avg']['recall'])
    f1_scores.append(classification_report(y_test_fold_classes, y_pred_fold_classes, output_dict=True)['weighted avg']['f1-score'])
    roc_auc_scores.append(roc_auc_score(y_test_fold, y_pred_fold, multi_class='ovr'))
    conf_matrices.append(confusion_matrix(y_test_fold_classes, y_pred_fold_classes))

# Compute the mean of the evaluation scores over all folds
mean_accuracy = np.mean(accuracy_scores)
mean_precision = np.mean(precision_scores)
mean_recall = np.mean(recall_scores)
mean_f1 = np.mean(f1_scores)
mean_roc_auc = np.mean(roc_auc_scores)
mean_conf_matrix = np.mean(conf_matrices, axis=0)
```