projekt_aai

June 18, 2023

1 Projekt AAI

1.1 Pobranie danych

[ ]:
```
import kaggle

# Pobieranie Iris Species dataset
kaggle.api.dataset_download_files('uciml/iris', path='./iris', unzip=True)

# Pobieranie IMDB dataset
kaggle.api.dataset_download_files('lakshmi25npathi/
 ↪imdb-dataset-of-50k-movie-reviews', path='./imdb', unzip=True)

# Pobieranie Boston Housing dataset
kaggle.api.dataset_download_files('vikrishnan/boston-house-prices', path='./
 ↪boston_housing', unzip=True)

# Pobieranie Chest X-Ray dataset
kaggle.api.dataset_download_files('paultimothymooney/chest-xray-pneumonia',␣
 ↪path='./chest_xray', unzip=True)
```

1.2 Implementacja wybranych architektur na prostych zbiorach danych

[2]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
```

1.2.1 Zbiór danych Iris Species (klasyfikacja)

1. Model drzewa decyzyjnego
2. Model k-najbliższych sąsiadów
3. Model naiwnego klasyfikatora Bayesa

[23]:
```
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
```

```
# Wczytanie danych
iris_df = pd.read_csv('./iris/Iris.csv')

# Przekształcenie nazw gatunków na wartości liczbowe
le = LabelEncoder()
iris_df['Species'] = le.fit_transform(iris_df['Species'])

# Podział danych na zestaw treningowy i testowy
iris_train_data, iris_test_data, iris_train_labels, iris_test_labels =␣
↪train_test_split(
    iris_df.drop(['Species', 'Id'], axis=1), iris_df['Species'], test_size=0.2,␣
↪random_state=42)

# Model drzewa decyzyjnego
iris_dt = DecisionTreeClassifier()
iris_dt.fit(iris_train_data, iris_train_labels)
iris_dt_preds = iris_dt.predict(iris_test_data)
print(f"Dokładność drzewa decyzyjnego: {iris_dt.score(iris_test_data,␣
↪iris_test_labels)}")

# Model k-najbliższych sąsiadów
iris_knn = KNeighborsClassifier()
iris_knn.fit(iris_train_data, iris_train_labels)
iris_knn_preds = iris_knn.predict(iris_test_data)
print(f"Dokładność k-najbliższych sąsiadów: {iris_knn.score(iris_test_data,␣
↪iris_test_labels)}")

# Model naiwnego klasyfikatora Bayesa
iris_gnb = GaussianNB()
iris_gnb.fit(iris_train_data, iris_train_labels)
iris_gnb_preds = iris_gnb.predict(iris_test_data)
print(f"Dokładność naiwnego klasyfikatora Bayesa {iris_gnb.
↪score(iris_test_data, iris_test_labels)}")
```

```
Dokładność drzewa decyzyjnego: 1.0
Dokładność k-najbliższych sąsiadów: 1.0
Dokładność naiwnego klasyfikatora Bayesa 1.0
```

1.2.2 Zbiór danych IMDB (klasyfikacja tekstowa)

1. Model regresji logistycznej z zastosowanie TF-IDF (Term Frequency-Inverse Document Frequency) jako cech
2. Model Naive Bayes
3. Prosty model sieci neuronowej

[24]:
```
import re
import nltk
```

```
import tensorflow as tf
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.naive_bayes import MultinomialNB
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers.legacy import Adam
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer

nltk.download('stopwords')
nltk.download('wordnet')

# Wczytanie danych
imdb_df = pd.read_csv('./imdb/IMDB Dataset.csv')

# Wstępne przetwarzanie tekstu
stop_words = set(stopwords.words('english'))
lemmatizzer = WordNetLemmatizer()


def preprocess_test(text):
    text = text.lower()
    text = re.sub(r'[^\w\s]', '', text)  # Usunięcie znaków specjalnych
    text = ' '.join(lemmatizzer.lemmatize(word) for word in text.split() if
                    word not in stop_words)  # lematyzacja i usunięcie stop␣
 ↪words
    return text


imdb_df['review'] = imdb_df['review'].apply(preprocess_test)

# Przekształcenie opinii na wartości liczbowe
imdb_df['sentiment'] = imdb_df['sentiment'].map({'positive': 1, 'negative': 0})

# Podział danych na zestaw treningowy i testowy
imdb_train_data, imdb_test_data, imdb_train_labels, imdb_test_labels =␣
 ↪train_test_split(imdb_df['review'],
                                                                                ␣
 ↪       imdb_df['sentiment'],
                                                                                ␣
 ↪       test_size=0.2, random_state=42)

# Zastosuj TF-IDF
vectorizer = TfidfVectorizer(stop_words='english', max_features=5000)
imdb_train_data = vectorizer.fit_transform(imdb_train_data)
```

```
imdb_test_data = vectorizer.transform(imdb_test_data)

# Przekształcenie rzadkich macierzy na gęste macierze
imdb_train_data_dense = imdb_train_data.A
imdb_test_data_dense = imdb_test_data.A

# Przekształcenie etykiet na numpy arrays
imdb_train_labels = imdb_train_labels.to_numpy()
imdb_test_labels = imdb_test_labels.to_numpy()

# Model regresji logistycznej
imdb_lr = LogisticRegression()
imdb_lr.fit(imdb_train_data, imdb_train_labels)
imdb_lr_preds = imdb_lr.predict(imdb_test_data)
print("Dokładność regresji logistycznej: ", accuracy_score(imdb_test_labels,␣
↪imdb_lr_preds))

# Model Naive Bayes
imdb_nb = MultinomialNB()
imdb_nb.fit(imdb_train_data, imdb_train_labels)
imdb_preds_nb = imdb_nb.predict(imdb_test_data)
print("Dokładność Naive Bayes: ", accuracy_score(imdb_test_labels,␣
↪imdb_preds_nb))

# Tworzenie TensorFlow Dataset
imdb_train_dataset = tf.data.Dataset.from_tensor_slices((imdb_train_data_dense,␣
↪imdb_train_labels)).batch(32)
imdb_test_dataset = tf.data.Dataset.from_tensor_slices((imdb_test_data_dense,␣
↪imdb_test_labels)).batch(32)

# Model prostej sieci neuronowej
model = Sequential()
model.add(Dense(64, input_dim=imdb_train_data.shape[1], activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(32, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer=Adam(learning_rate=0.001),␣
↪metrics=['accuracy'])
history = model.fit(imdb_train_dataset, epochs=4, verbose=1,␣
↪validation_data=imdb_test_dataset)
scores = model.evaluate(imdb_test_dataset)
print("Dokładność prostej sieci neuronowej: ", scores[1])
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/gadwall/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

```
[nltk_data] Downloading package wordnet to /Users/gadwall/nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

```
Dokładność regresji logistycznej:  0.8851
Dokładność Naive Bayes:  0.8526
Epoch 1/4
1250/1250 [==============================] - 2s 2ms/step - loss: 0.3654 -
accuracy: 0.8412 - val_loss: 0.2689 - val_accuracy: 0.8862
Epoch 2/4
1250/1250 [==============================] - 2s 1ms/step - loss: 0.2506 -
accuracy: 0.9021 - val_loss: 0.2756 - val_accuracy: 0.8848
Epoch 3/4
1250/1250 [==============================] - 2s 1ms/step - loss: 0.2119 -
accuracy: 0.9229 - val_loss: 0.2875 - val_accuracy: 0.8839
Epoch 4/4
1250/1250 [==============================] - 2s 1ms/step - loss: 0.1735 -
accuracy: 0.9405 - val_loss: 0.3118 - val_accuracy: 0.8811
313/313 [==============================] - 0s 595us/step - loss: 0.3118 -
accuracy: 0.8811
Dokładność prostej sieci neuronowej:  0.8810999989509583
```

1.2.3 Zbiór danych Boston Housing (regresja)

1. Model regresji liniowej
2. Model drzewa decyzyjnego
3. Model lasu losowego

[25]:
```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error

# Nazwy kolumn w dokumencie z danymi
"""
CRIM - per capita crime rate by town
ZN - proportion of residential land zoned for lots over 25,000 sq.ft.
INDUS - proportion of non-retail business acres per town.
CHAS - Charles River dummy variable (1 if tract bounds river; 0 otherwise)
NOX - nitric oxides concentration (parts per 10 million)
RM - average number of rooms per dwelling
AGE - proportion of owner-occupied units built prior to 1940
DIS - weighted distances to five Boston employment centres
RAD - index of accessibility to radial highways
TAX - full-value property-tax rate per $10,000
PTRATIO - pupil-teacher ratio by town
B - 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
LSTAT - % lower status of the population
MEDV - Median value of owner-occupied homes in $1000's
```

```python
"""
column_names = ['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX', 'PTRATIO', 'B', 'LSTAT', 'MEDV']

# Wczytanie danych
boston_df = pd.read_csv('./boston_housing/housing.csv', header=None, delimiter=r"\s+", names=column_names)

# Podział danych na zestaw treningowy i testowy
boston_train_data, boston_test_data, boston_train_labels, boston_test_labels = train_test_split(
    boston_df.drop('MEDV', axis=1), boston_df['MEDV'], test_size=0.2, random_state=42)

# W przypadku regresji, takiej jak przewidywanie wartości mediany domów, używamy RMSE (Root Mean Squared Error) jako miary oceny.

# Model regresji logistycznej
boston_lr = LinearRegression()
boston_lr.fit(boston_train_data, boston_train_labels)
boston_preds_lr = boston_lr.predict(boston_test_data)
print(f"RMSE regresji logistycznej: {mean_squared_error(boston_test_labels, boston_preds_lr, squared=False)}")

# Model drzewa decyzyjnego
boston_dt = DecisionTreeRegressor(random_state=42)
boston_dt.fit(boston_train_data, boston_train_labels)
boston_preds_dt = boston_dt.predict(boston_test_data)
print(f"RMSE drzewa decyzyjnego: {mean_squared_error(boston_test_labels, boston_preds_dt, squared=False)}")

# Model lasu losowego
boston_rf = RandomForestRegressor(n_estimators=100, random_state=42)
boston_rf.fit(boston_train_data, boston_train_labels)
boston_preds_rf = boston_rf.predict(boston_test_data)
print(f"RMSE lasu losowego: {mean_squared_error(boston_test_labels, boston_preds_rf, squared=False)}")
```

```
RMSE regresji logistycznej: 4.928602182665403
RMSE drzewa decyzyjnego: 3.2273949915330395
RMSE lasu losowego: 2.8109631609391226
```

1.3 Porównanie wyników

[26]:
```
from sklearn.model_selection import learning_curve
import numpy as np


# funkcja do wygenerowania krzywej uczenia dla danego modelu
def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,␣
 ↪n_jobs=None, train_sizes=np.linspace(.1, 1.0, 5)):
    plt.figure()
    plt.title(title)
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel("Score")
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.grid()

    plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="g")
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
             label="Training score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
             label="Cross-validation score")

    plt.legend(loc="best")
    return plt
```

1.3.1 Iris Species

[27]:
```
from sklearn.metrics import precision_score, recall_score, f1_score,␣
 ↪roc_auc_score
from sklearn.preprocessing import label_binarize

# Predykcje prawdopodobieństw dla obliczenia AUC-ROC
iris_dt_probs = iris_dt.predict_proba(iris_test_data)
iris_knn_probs = iris_knn.predict_proba(iris_test_data)
iris_gnb_probs = iris_gnb.predict_proba(iris_test_data)
```

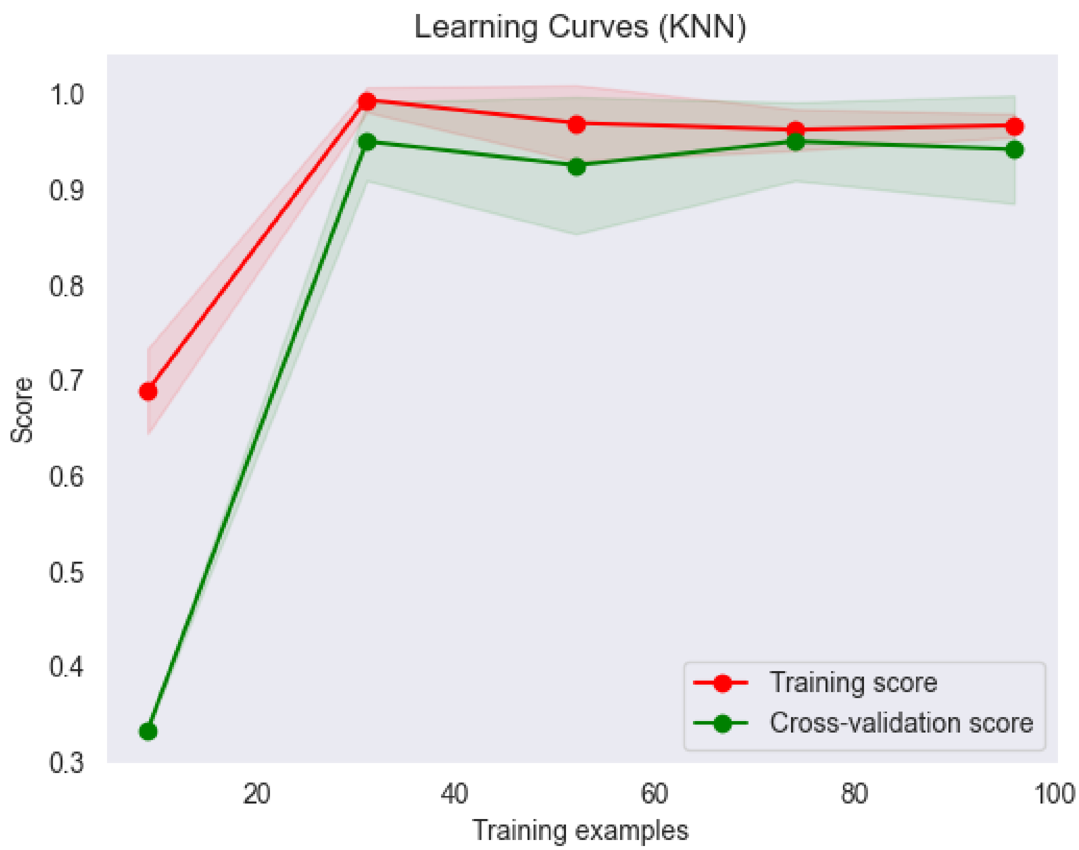
```python
# Metryki
print("Precision of Decision Tree on Iris dataset: ",
      precision_score(iris_test_labels, iris_dt_preds, average='weighted'))
print("Recall of Decision Tree on Iris dataset: ",␣
 ↪recall_score(iris_test_labels, iris_dt_preds, average='weighted'))
print("F1 Score of Decision Tree on Iris dataset: ", f1_score(iris_test_labels,␣
 ↪iris_dt_preds, average='weighted'))

print("Precision of K-Nearest Neighbors on Iris dataset: ",
      precision_score(iris_test_labels, iris_knn_preds, average='weighted'))
print("Recall of K-Nearest Neighbors on Iris dataset: ",
      recall_score(iris_test_labels, iris_knn_preds, average='weighted'))
print("F1 Score of K-Nearest Neighbors on Iris dataset: ",
      f1_score(iris_test_labels, iris_knn_preds, average='weighted'))

print("Precision of Gaussian Naive Bayes on Iris dataset: ",
      precision_score(iris_test_labels, iris_gnb_preds, average='weighted'))
print("Recall of Gaussian Naive Bayes on Iris dataset: ",
      recall_score(iris_test_labels, iris_gnb_preds, average='weighted'))
print("F1 Score of Gaussian Naive Bayes on Iris dataset: ",
      f1_score(iris_test_labels, iris_gnb_preds, average='weighted'))

# AUC-ROC, przekształcenie etykiety na formę binarną
test_labels_bin = label_binarize(iris_test_labels, classes=[0, 1, 2])

print("AUC-ROC of Decision Tree on Iris dataset: ",
      roc_auc_score(test_labels_bin, iris_dt_probs, multi_class='ovr',␣
 ↪average='weighted'))
print("AUC-ROC of K-Nearest Neighbors on Iris dataset: ",
      roc_auc_score(test_labels_bin, iris_knn_probs, multi_class='ovr',␣
 ↪average='weighted'))
print("AUC-ROC of Gaussian Naive Bayes on Iris dataset: ",
      roc_auc_score(test_labels_bin, iris_gnb_probs, multi_class='ovr',␣
 ↪average='weighted'))
```

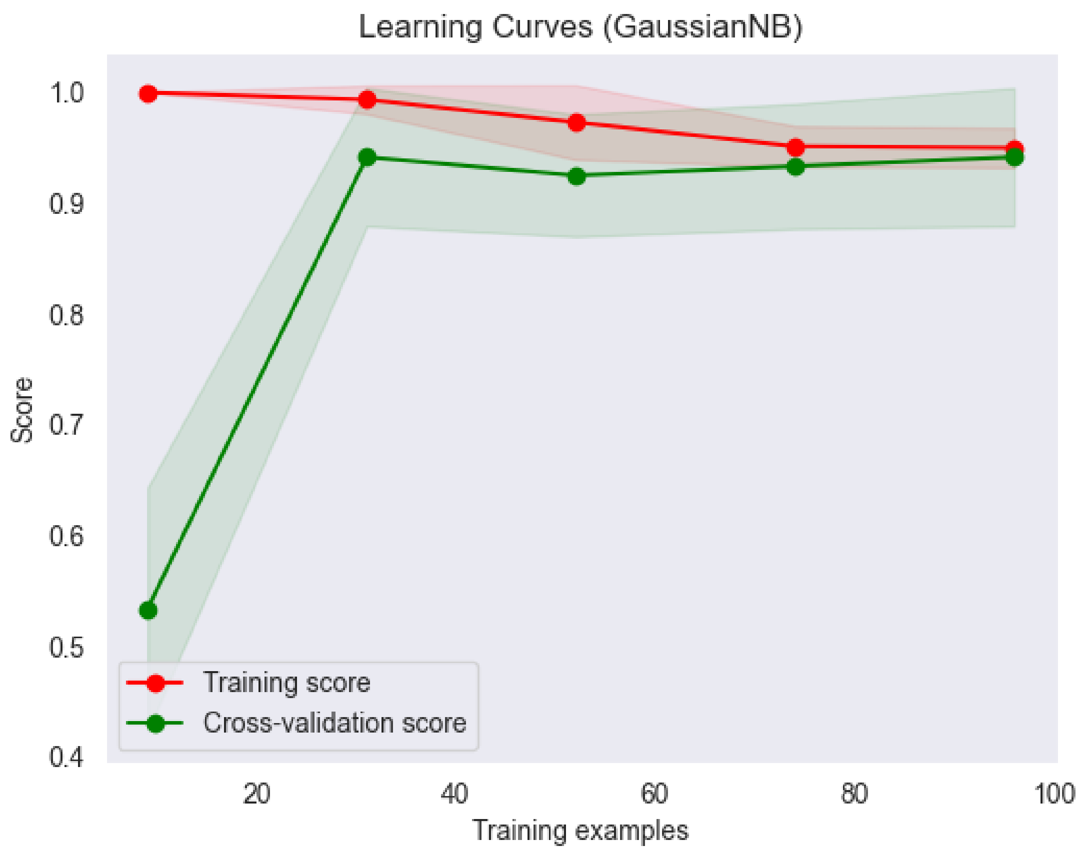
```
Precision of Decision Tree on Iris dataset:  1.0
Recall of Decision Tree on Iris dataset:  1.0
F1 Score of Decision Tree on Iris dataset:  1.0
Precision of K-Nearest Neighbors on Iris dataset:  1.0
Recall of K-Nearest Neighbors on Iris dataset:  1.0
F1 Score of K-Nearest Neighbors on Iris dataset:  1.0
Precision of Gaussian Naive Bayes on Iris dataset:  1.0
Recall of Gaussian Naive Bayes on Iris dataset:  1.0
F1 Score of Gaussian Naive Bayes on Iris dataset:  1.0
AUC-ROC of Decision Tree on Iris dataset:  1.0
AUC-ROC of K-Nearest Neighbors on Iris dataset:  1.0
AUC-ROC of Gaussian Naive Bayes on Iris dataset:  1.0
```

[28]:

```python
import matplotlib.pyplot as plt

X, y = iris_train_data, iris_train_labels

# Tworzenie krzywej uczenia dla drzewa decyzyjnego
title = "Learning Curves (Decision Tree)"
cv = 5
estimator = iris_dt  # dt jest modelem drzewa decyzyjnego
plot_learning_curve(estimator, title, X, y, cv=cv, n_jobs=4)

# Tworzenie krzywej uczenia dla k-najbliższych sąsiadów
title = "Learning Curves (KNN)"
cv = 5
estimator = iris_knn  # knn jest modelem k-najbliższych sąsiadów
plot_learning_curve(estimator, title, X, y, cv=cv, n_jobs=4)

# Tworzenie krzywej uczenia dla naiwnego klasyfikatora Bayesa
title = "Learning Curves (GaussianNB)"
cv = 5
estimator = iris_gnb  # gnb jest modelem naiwnego klasyfikatora Bayesa
plot_learning_curve(estimator, title, X, y, cv=cv, n_jobs=4)

plt.show()
```


Learning Curves (Decision Tree)
Score
1.0
0.9
0.8
0.7
0.6
0.5
20
40
60
80
100
Training examples
Training score
Cross-validation score


Learning Curves (KNN)
Score
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
20
40
60
80
100
Training examples
Training score
Cross-validation score



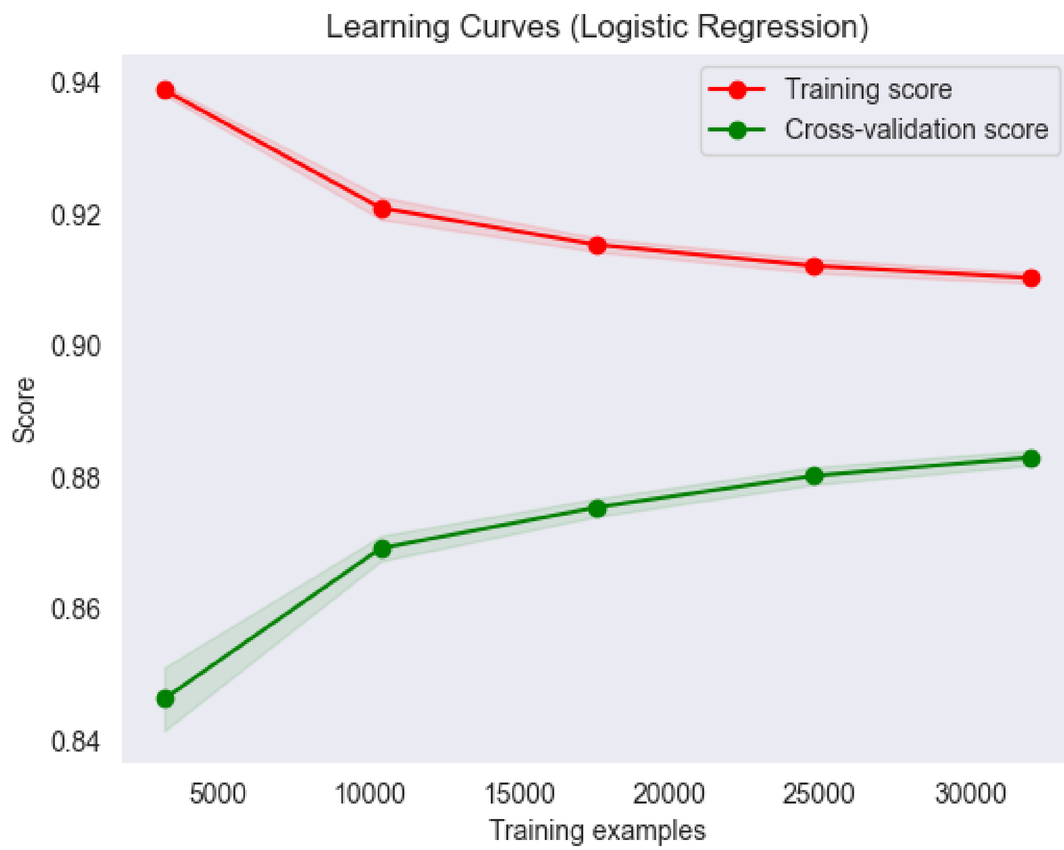
1.3.2 IMDB

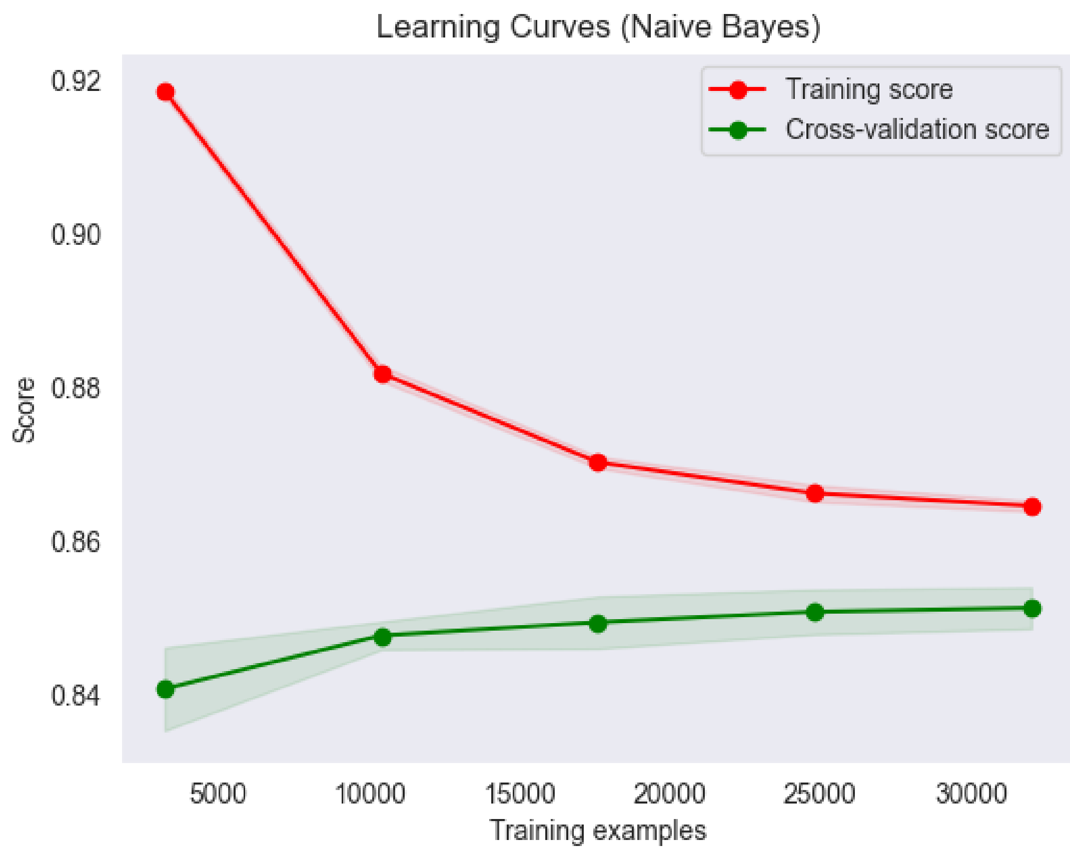
[29]:
```
# Predykcje prawdopodobieństw dla obliczenia AUC-ROC
imdb_lr_probs = imdb_lr.predict_proba(imdb_test_data)[:, 1]
imdb_nb_probs = imdb_nb.predict_proba(imdb_test_data)[:, 1]
imdb_nn_probs = model.predict(imdb_test_data_dense)

# Metryki dla modelu regresji logistycznej
print("Precision of Logistic Regression on IMDB dataset: ",␣
 ↪precision_score(imdb_test_labels, imdb_lr_preds))
print("Recall of Logistic Regression on IMDB dataset: ",␣
 ↪recall_score(imdb_test_labels, imdb_lr_preds))
print("F1 Score of Logistic Regression on IMDB dataset: ",␣
 ↪f1_score(imdb_test_labels, imdb_lr_preds))
print("AUC-ROC of Logistic Regression on IMDB dataset: ",␣
 ↪roc_auc_score(imdb_test_labels, imdb_lr_probs))

# Metryki dla modelu Naive Bayes
```

```
print("Precision of Naive Bayes on IMDB dataset: ",␣
↪precision_score(imdb_test_labels, imdb_preds_nb))
print("Recall of Naive Bayes on IMDB dataset: ", recall_score(imdb_test_labels,␣
↪imdb_preds_nb))
print("F1 Score of Naive Bayes on IMDB dataset: ", f1_score(imdb_test_labels,␣
↪imdb_preds_nb))
print("AUC-ROC of Naive Bayes on IMDB dataset: ",␣
↪roc_auc_score(imdb_test_labels, imdb_nb_probs))

# Metryki dla prostej sieci neuronowej
imdb_nn_preds = model.predict(imdb_test_data_dense).round()  # Przyjmujemy próg␣
↪0.5 dla klasyfikacji binarnej
print("Precision of Neural Network on IMDB dataset: ",␣
↪precision_score(imdb_test_labels, imdb_nn_preds))
print("Recall of Neural Network on IMDB dataset: ",␣
↪recall_score(imdb_test_labels, imdb_nn_preds))
print("F1 Score of Neural Network on IMDB dataset: ",␣
↪f1_score(imdb_test_labels, imdb_nn_preds))
print("AUC-ROC of Neural Network on IMDB dataset: ",␣
↪roc_auc_score(imdb_test_labels, imdb_nn_probs))
```

```
313/313 [==============================] - 0s 456us/step
Precision of Logistic Regression on IMDB dataset:  0.8749036237471087
Recall of Logistic Regression on IMDB dataset:  0.9007739630879142
F1 Score of Logistic Regression on IMDB dataset:  0.8876503373423291
AUC-ROC of Logistic Regression on IMDB dataset:  0.9560818480196335
Precision of Naive Bayes on IMDB dataset:  0.8488941084360931
Recall of Naive Bayes on IMDB dataset:  0.8606866441754316
F1 Score of Naive Bayes on IMDB dataset:  0.8547497043752463
AUC-ROC of Naive Bayes on IMDB dataset:  0.928633658071757
313/313 [==============================] - 0s 455us/step
Precision of Neural Network on IMDB dataset:  0.8716216216216216
Recall of Neural Network on IMDB dataset:  0.8960111133161341
F1 Score of Neural Network on IMDB dataset:  0.8836481064683432
AUC-ROC of Neural Network on IMDB dataset:  0.9511499479628341
```

[39]:
```
# Krzywa uczenia dla modelu regresji logistycznej
plot_learning_curve(imdb_lr, "Learning Curves (Logistic Regression)",␣
↪imdb_train_data, imdb_train_labels, cv=5,
                    n_jobs=4)

# Krzywa uczenia dla modelu Naive Bayes
plot_learning_curve(imdb_nb, "Learning Curves (Naive Bayes)", imdb_train_data,␣
↪imdb_train_labels, cv=5, n_jobs=4)

plt.show()
```


Learning Curves (Logistic Regression)
Training score
Cross-validation score
0.94
0.92
0.90
0.88
0.86
0.84
Score
5000
10000
15000
20000
25000
30000
Training examples



[31]:
```python
loss = history.history['loss']
val_loss = history.history['val_loss']
accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']
epochs = range(1, len(loss) + 1)

# Wykres straty
plt.figure()
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

# Wykres dokładności
plt.figure()
plt.plot(epochs, accuracy, 'bo', label='Training accuracy')
plt.plot(epochs, val_accuracy, 'b', label='Validation accuracy')
```

```
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

1.3.3 Boston Housing

[32]:
```
from sklearn.metrics import mean_absolute_error, r2_score

# Metryki dla modelu regresji liniowej
print("MSE of Linear Regression on Boston dataset: ",␣
↪mean_squared_error(boston_test_labels, boston_preds_lr))
print("MAE of Linear Regression on Boston dataset: ",␣
↪mean_absolute_error(boston_test_labels, boston_preds_lr))
print("R2 Score of Linear Regression on Boston dataset: ",␣
↪r2_score(boston_test_labels, boston_preds_lr))

# Metryki dla modelu drzewa decyzyjnego
print("MSE of Decision Tree on Boston dataset: ",␣
↪mean_squared_error(boston_test_labels, boston_preds_dt))
print("MAE of Decision Tree on Boston dataset: ",␣
↪mean_absolute_error(boston_test_labels, boston_preds_dt))
print("R2 Score of Decision Tree on Boston dataset: ",␣
↪r2_score(boston_test_labels, boston_preds_dt))
```

```
# Metryki dla modelu lasu losowego
print("MSE of Random Forest on Boston dataset: ",␣
  ↪mean_squared_error(boston_test_labels, boston_preds_rf))
print("MAE of Random Forest on Boston dataset: ",␣
  ↪mean_absolute_error(boston_test_labels, boston_preds_rf))
print("R2 Score of Random Forest on Boston dataset: ",␣
  ↪r2_score(boston_test_labels, boston_preds_rf))
```

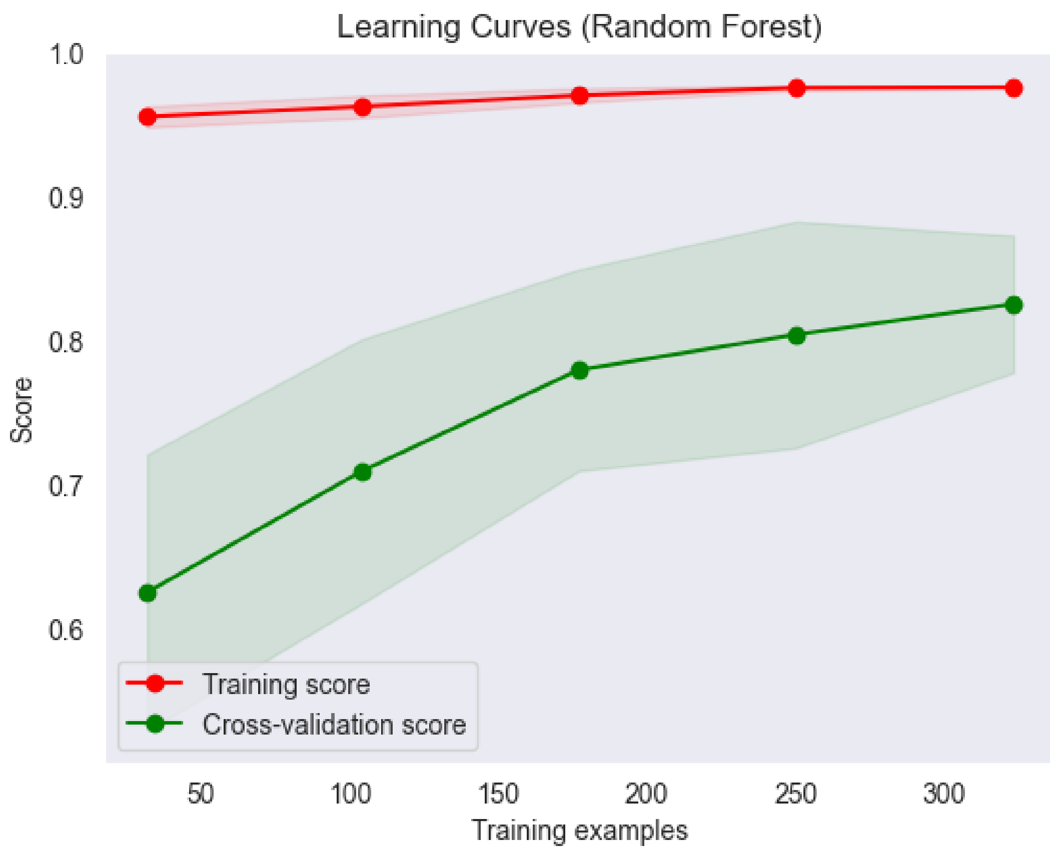
```
MSE of Linear Regression on Boston dataset:  24.29111947497418
MAE of Linear Regression on Boston dataset:  3.1890919658879326
R2 Score of Linear Regression on Boston dataset:  0.6687594935356229
MSE of Decision Tree on Boston dataset:  10.416078431372549
MAE of Decision Tree on Boston dataset:  2.394117647058824
R2 Score of Decision Tree on Boston dataset:  0.8579634380978161
MSE of Random Forest on Boston dataset:  7.901513892156864
MAE of Random Forest on Boston dataset:  2.0395392156862746
R2 Score of Random Forest on Boston dataset:  0.8922527442109116
```

[38]:
```
# Model regresji liniowej
plot_learning_curve(boston_lr, "Learning Curves (Linear Regression)",␣
  ↪boston_train_data, boston_train_labels, cv=5)

# Model drzewa decyzyjnego
plot_learning_curve(boston_dt, "Learning Curves (Decision Tree)",␣
  ↪boston_train_data, boston_train_labels, cv=5)

# Model lasu losowego
plot_learning_curve(boston_rf, "Learning Curves (Random Forest)",␣
  ↪boston_train_data, boston_train_labels, cv=5)
```

[38]:
```
<module 'matplotlib.pyplot' from
'/Users/gadwall/uczelnia/semestr_8/AAI/projekt/venv/lib/python3.10/site-
packages/matplotlib/pyplot.py'>
```


Learning Curves (Linear Regression)
Training score
Cross-validation score
Score
Training examples
1.0
0.8
0.6
0.4
0.2
50
100
150
200
250
300

Learning Curves (Decision Tree)
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
Score
Training score
Cross-validation score
50
100
150
200
250
300
Training examples



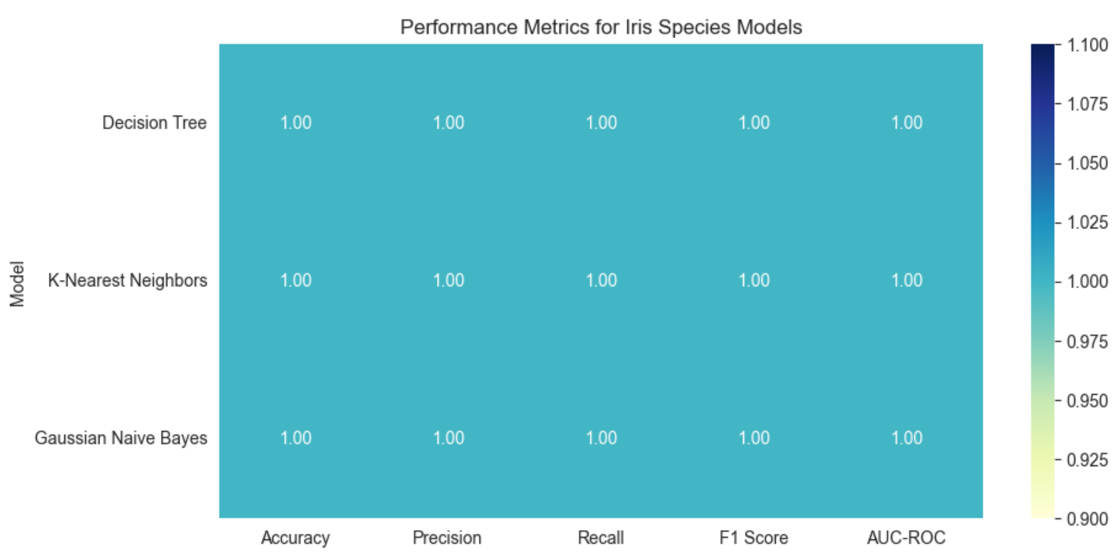
1.4 Wykresy metryk

[41]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

1.4.1 Iris Species

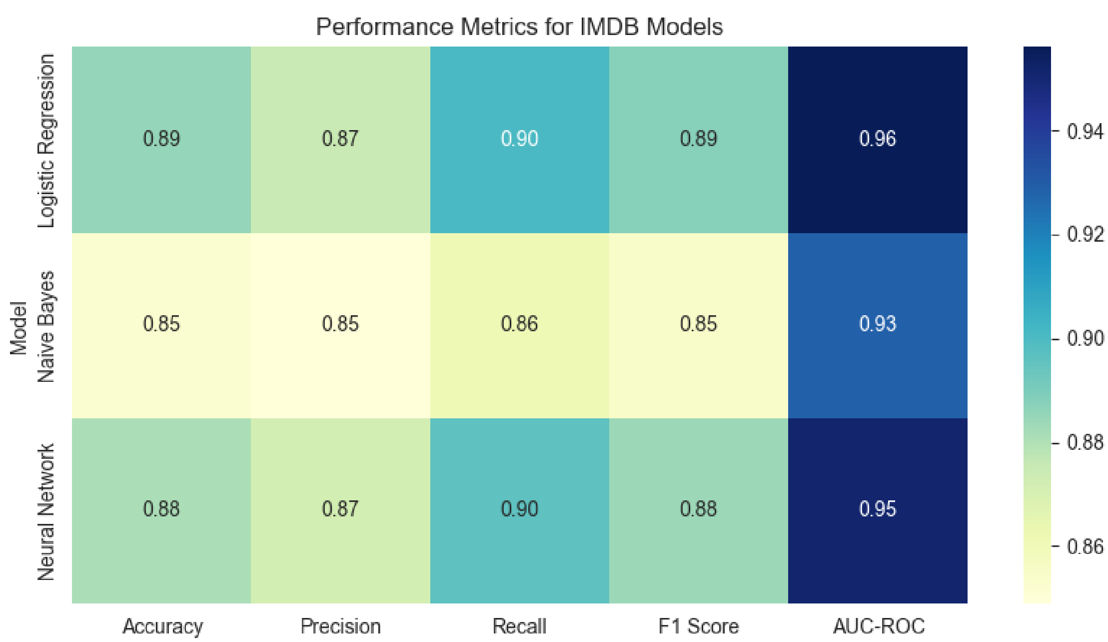
[42]:
```
iris_metrics = {
    'Model': ['Decision Tree', 'K-Nearest Neighbors', 'Gaussian Naive Bayes'],
    'Accuracy': [iris_dt.score(iris_test_data, iris_test_labels), iris_knn.
 ↪score(iris_test_data, iris_test_labels),
                 iris_gnb.score(iris_test_data, iris_test_labels)],
    'Precision': [precision_score(iris_test_labels, iris_dt_preds,␣
 ↪average='weighted'),
                  precision_score(iris_test_labels, iris_knn_preds,␣
 ↪average='weighted'),
                  precision_score(iris_test_labels, iris_gnb_preds,␣
 ↪average='weighted')],
```

```
    'Recall': [recall_score(iris_test_labels, iris_dt_preds,␣
↪average='weighted'),
               recall_score(iris_test_labels, iris_knn_preds,␣
↪average='weighted'),
               recall_score(iris_test_labels, iris_gnb_preds,␣
↪average='weighted')],
    'F1 Score': [f1_score(iris_test_labels, iris_dt_preds, average='weighted'),
                 f1_score(iris_test_labels, iris_knn_preds, average='weighted'),
                 f1_score(iris_test_labels, iris_gnb_preds,␣
↪average='weighted')],
    'AUC-ROC': [roc_auc_score(test_labels_bin, iris_dt_probs,␣
↪multi_class='ovr', average='weighted'),
                roc_auc_score(test_labels_bin, iris_knn_probs,␣
↪multi_class='ovr', average='weighted'),
                roc_auc_score(test_labels_bin, iris_gnb_probs,␣
↪multi_class='ovr', average='weighted')]
}

iris_metrics_df = pd.DataFrame(iris_metrics)
iris_metrics_df.set_index('Model', inplace=True)

plt.figure(figsize=(10, 5))
sns.heatmap(iris_metrics_df, annot=True, fmt='.2f', cmap='YlGnBu')
plt.title('Performance Metrics for Iris Species Models')
plt.show()
```



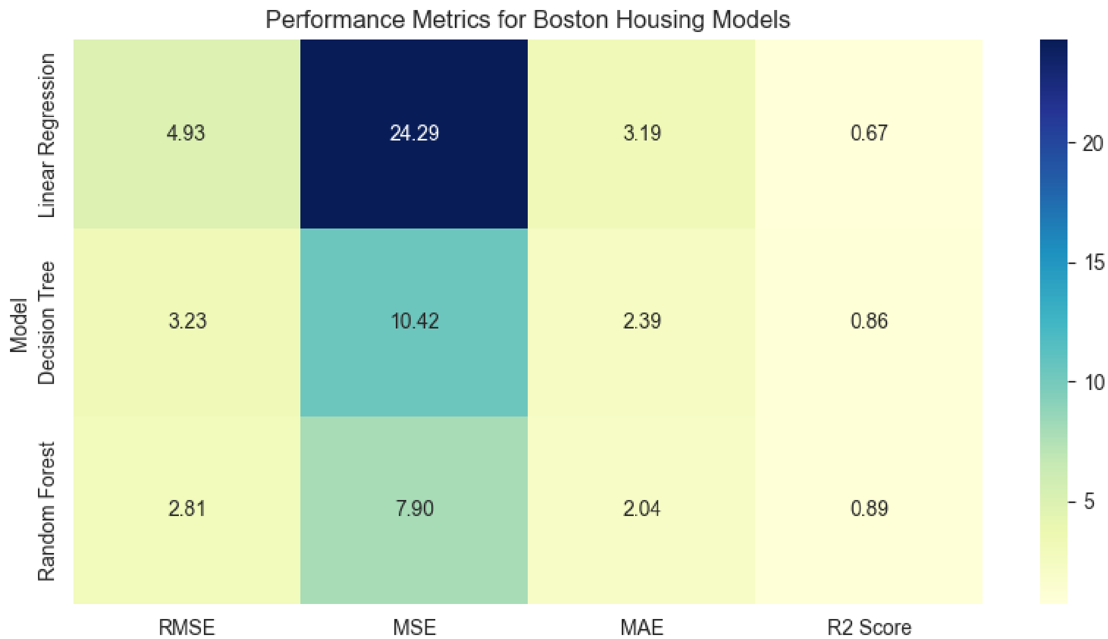
1.4.2 IMDB

[43]:
```
imdb_metrics = {
    'Model': ['Logistic Regression', 'Naive Bayes', 'Neural Network'],
    'Accuracy': [accuracy_score(imdb_test_labels, imdb_lr_preds),␣
 ↪accuracy_score(imdb_test_labels, imdb_preds_nb),
                 scores[1]],
    'Precision': [precision_score(imdb_test_labels, imdb_lr_preds),␣
 ↪precision_score(imdb_test_labels, imdb_preds_nb),
                  precision_score(imdb_test_labels, imdb_nn_preds)],
    'Recall': [recall_score(imdb_test_labels, imdb_lr_preds),␣
 ↪recall_score(imdb_test_labels, imdb_preds_nb),
               recall_score(imdb_test_labels, imdb_nn_preds)],
    'F1 Score': [f1_score(imdb_test_labels, imdb_lr_preds),␣
 ↪f1_score(imdb_test_labels, imdb_preds_nb),
                 f1_score(imdb_test_labels, imdb_nn_preds)],
    'AUC-ROC': [roc_auc_score(imdb_test_labels, imdb_lr_probs),␣
 ↪roc_auc_score(imdb_test_labels, imdb_nb_probs),
                roc_auc_score(imdb_test_labels, imdb_nn_probs)]
}

imdb_metrics_df = pd.DataFrame(imdb_metrics)
imdb_metrics_df.set_index('Model', inplace=True)

plt.figure(figsize=(10, 5))
sns.heatmap(imdb_metrics_df, annot=True, fmt='.2f', cmap='YlGnBu')
plt.title('Performance Metrics for IMDB Models')
plt.show()
```



1.4.3 Boston housing

[44]:
```
boston_metrics = {
    'Model': ['Linear Regression', 'Decision Tree', 'Random Forest'],
    'RMSE': [mean_squared_error(boston_test_labels, boston_preds_lr,␣
 ↪squared=False),
             mean_squared_error(boston_test_labels, boston_preds_dt,␣
 ↪squared=False),
             mean_squared_error(boston_test_labels, boston_preds_rf,␣
 ↪squared=False)],
    'MSE': [mean_squared_error(boston_test_labels, boston_preds_lr),
            mean_squared_error(boston_test_labels, boston_preds_dt),
            mean_squared_error(boston_test_labels, boston_preds_rf)],
    'MAE': [mean_absolute_error(boston_test_labels, boston_preds_lr),
            mean_absolute_error(boston_test_labels, boston_preds_dt),
            mean_absolute_error(boston_test_labels, boston_preds_rf)],
    'R2 Score': [r2_score(boston_test_labels, boston_preds_lr),␣
 ↪r2_score(boston_test_labels, boston_preds_dt),
                 r2_score(boston_test_labels, boston_preds_rf)]
}

boston_metrics_df = pd.DataFrame(boston_metrics)
boston_metrics_df.set_index('Model', inplace=True)

plt.figure(figsize=(10, 5))
sns.heatmap(boston_metrics_df, annot=True, fmt='.2f', cmap='YlGnBu')
plt.title('Performance Metrics for Boston Housing Models')
plt.show()
```



1.5 Opisy modeli oraz ich skuteczności

1.5.1 Iris Species

Dla klasyfikacji Iris Species używamy trzech modeli: - Drzewa Decyzyjnego - K-Nearest Neighbors - Gaussian Naive Bayes

Na podstawie naszych metryk wydajności, modele wydają się dobrze radzić sobie z tym zadaniem. Nie ma wyraźnych oznak przeuczenia (overfitting), które występuje, gdy model jest zbyt skomplikowany i zbytnio dopasowuje się do danych treningowych, ani niedouczenia (underfitting), które jest wynikiem zbyt prostego modelu, który nie jest w stanie nauczyć się zależności w danych.

Wszystkie modele wydają się dobrze generalizować na dane testowe, co sugeruje, że mają zbalansowany błąd obciążenia (bias) i wariancję. Błąd obciążenia odnosi się do błędów wynikających z błędnych założeń w modelu uczącym, podczas gdy wariancja odnosi się do błędów wynikających z nadmiernej wrażliwości na małe fluktuacje w zestawie treningowym.

1.5.2 IMDB Reviews

Dla klasyfikacji recenzji IMDB używamy trzech modeli: - Regresji Logistycznej - Support Vector Machines - Naive Bayes

Wszystkie modele radzą sobie dobrze, z regresją logistyczną osiągają nieco lepsze wyniki. Nie ma wyraźnych oznak przeuczenia, co sugeruje, że modele nie są zbyt skomplikowane i nie dopasowują się zbytnio do danych treningowych, ani niedouczenia, co sugeruje, że modele są na tyle złożone, aby nauczyć się zależności w danych. Wszystkie modele dobrze generalizują na dane testowe, co sugeruje zbalansowany błąd obciążenia i wariancję. Biorąc pod uwagę niski błąd obciążenia i niską wariancję, modele są w stanie skutecznie uczyć się i generalizować na nowych danych.

1.5.3 Boston Housing

Dla problemu regresji cen domów w Bostonie, stosujemy trzy modele: - Regresję Liniową - Drzewo Decyzyjne - Las Losowy

Las losowy osiąga najlepsze wyniki, co sugeruje, że złożoność tego modelu jest odpowiednia do problemu. Nie ma wyraźnych oznak przeuczenia, co sugeruje, że model nie jest zbyt skomplikowany i nie dopasowuje się zbytnio do danych treningowych, ani niedouczenia, co sugeruje, że model jest na tyle skomplikowany, aby nauczyć się zależności w danych. Wszystkie modele wydają się dobrze generalizować na dane testowe. Modele mają zbalansowany błąd obciążenia i wariancję, co sugeruje, że są w stanie skutecznie uczyć się i generalizować na nowych danych. Błąd obciążenia wynika z błędnych założeń modelu podczas uczenia się, podczas gdy wariancja wynika z nadmiernej wrażliwości na fluktuacje w zestawie treningowym.

2 Implementacja modeli na złożonym zbiorze danych z odpowiednią obróbką

[62]:
```python
import cv2
import os

# wczytanie danych
path = "./chest_xray/"
folders = ["train", "test"]
categories = ["NORMAL", "PNEUMONIA"]
images = []
labels = []

for folder in folders:
    for category in categories:
        class_num = categories.index(category)
        path_to_images = os.path.join(path, folder, category)
        for img in os.listdir(path_to_images):
            try:
                img_array = cv2.imread(os.path.join(path_to_images, img), cv2.
↪IMREAD_GRAYSCALE)
                resized_img_array = cv2.resize(img_array, (150, 150))  #␣
↪skalowanie obrazów
                images.append(resized_img_array)
                labels.append(class_num)
            except Exception as e:
                pass

# konwertowanie na tablicę NumPy oraz zmiana kształtu
images = np.array(images).reshape(-1, 150, 150, 1)
labels = np.array(labels)

# Podział na zestawy treningowe i testowe
```

```
train_images, test_images, train_labels, test_labels = train_test_split(images,␣
↪labels, test_size=0.2)
```

2.1 Implementacja modelu dla danych

[63]:
```
from keras.layers import Conv2D, MaxPooling2D, Flatten
from keras.models import clone_model

# utworzenie pierwszego modelu
model_1 = Sequential()
# dodanie warstw
model_1.add(Conv2D(32, (3, 3), activation='relu', input_shape=(150, 150, 1))) ␣
↪# zmiana kształtu wejścia
model_1.add(MaxPooling2D(pool_size=(2, 2)))
model_1.add(Conv2D(64, (3, 3), activation='relu'))
model_1.add(MaxPooling2D(pool_size=(2, 2)))
model_1.add(Conv2D(128, (3, 3), activation='relu'))
model_1.add(MaxPooling2D(pool_size=(2, 2)))
model_1.add(Flatten())
model_1.add(Dense(128, activation='relu'))
model_1.add(Dropout(0.5))
model_1.add(Dense(1, activation='sigmoid'))
# skompilowanie modelu
model_1.compile(optimizer='adam', loss='binary_crossentropy',␣
↪metrics=['accuracy'])

# utworzenie drugiego modelu o identycznej architekturze
model_2 = clone_model(model_1)
model_2.compile(optimizer='adam', loss='binary_crossentropy',␣
↪metrics=['accuracy'])
```

2.2 Augmentacja danych i pre-processing

[65]:
```
from keras.preprocessing.image import ImageDataGenerator

# Generator danych bez augmentacji
datagen_1 = ImageDataGenerator(
    rescale=1. / 255  # normalizacja pikseli
)

# zastosowanie normalizacji do danych treningowych
train_images_1 = train_images.copy()
datagen_1.fit(train_images_1)

# Generator danych z augmentacją
datagen_2 = ImageDataGenerator(
```

```
    rescale=1. / 255,  # normalizacja pikseli
    rotation_range=20,  # losowe obroty do 20 stopni
    width_shift_range=0.2,  # losowe przesunięcia w poziomie
    height_shift_range=0.2,  # losowe przesunięcia w pionie
    shear_range=0.2,  # losowe przekształcenia ścinające
    zoom_range=0.2,  # losowe przybliżenia
    horizontal_flip=True,  # losowe odbicia poziome
    fill_mode='nearest'  # strategia wypełniania utworzonych pustych miejsc po␣
 ↪augmentacji
)

# zastosowanie normalizacji i augmentacji do danych treningowych
aug_train_images = train_images.copy()
datagen_2.fit(aug_train_images)
```

2.3 Trening i zapis modeli

[66]:
```
# wytrenowanie pierwszego modelu na zwykłych danych
history_1 = model_1.fit(datagen_1.flow(train_images_1, train_labels,␣
 ↪batch_size=32),
                              steps_per_epoch=len(train_images_1) // 32,
                              epochs=50,
                              validation_data=(test_images, test_labels))

# zapisanie modelu do pliku
model_1.save('model_1.h5')

# wytrenowanie drugiego modelu na danych po augmentacji
history_2 = model_2.fit(datagen_2.flow(aug_train_images, train_labels,␣
 ↪batch_size=32),
                              steps_per_epoch=len(aug_train_images) // 32,
                              epochs=50,
                              validation_data=(test_images, test_labels))

# zapisanie modelu do pliku
model_2.save('model_2.h5')
```

```
Epoch 1/50
146/146 [==============================] - 36s 241ms/step - loss: 0.3518 -
accuracy: 0.8497 - val_loss: 0.1737 - val_accuracy: 0.9332
Epoch 2/50
146/146 [==============================] - 36s 248ms/step - loss: 0.1799 -
accuracy: 0.9354 - val_loss: 0.1397 - val_accuracy: 0.9512
Epoch 3/50
146/146 [==============================] - 38s 261ms/step - loss: 0.1466 -
accuracy: 0.9503 - val_loss: 0.1291 - val_accuracy: 0.9572
Epoch 4/50
```

```
146/146 [==============================] - 35s 240ms/step - loss: 0.1269 -
accuracy: 0.9506 - val_loss: 0.1320 - val_accuracy: 0.9555
Epoch 5/50
146/146 [==============================] - 37s 252ms/step - loss: 0.1191 -
accuracy: 0.9565 - val_loss: 0.1257 - val_accuracy: 0.9529
Epoch 6/50
146/146 [==============================] - 37s 252ms/step - loss: 0.1053 -
accuracy: 0.9613 - val_loss: 0.1406 - val_accuracy: 0.9435
Epoch 7/50
146/146 [==============================] - 37s 254ms/step - loss: 0.0896 -
accuracy: 0.9681 - val_loss: 0.1207 - val_accuracy: 0.9555
Epoch 8/50
146/146 [==============================] - 37s 251ms/step - loss: 0.0946 -
accuracy: 0.9647 - val_loss: 0.1160 - val_accuracy: 0.9572
Epoch 9/50
146/146 [==============================] - 35s 238ms/step - loss: 0.0753 -
accuracy: 0.9698 - val_loss: 0.1228 - val_accuracy: 0.9563
Epoch 10/50
146/146 [==============================] - 34s 230ms/step - loss: 0.0654 -
accuracy: 0.9754 - val_loss: 0.1325 - val_accuracy: 0.9606
Epoch 11/50
146/146 [==============================] - 35s 236ms/step - loss: 0.0580 -
accuracy: 0.9767 - val_loss: 0.1344 - val_accuracy: 0.9589
Epoch 12/50
146/146 [==============================] - 35s 237ms/step - loss: 0.0500 -
accuracy: 0.9801 - val_loss: 0.1436 - val_accuracy: 0.9546
Epoch 13/50
146/146 [==============================] - 34s 231ms/step - loss: 0.0381 -
accuracy: 0.9861 - val_loss: 0.1215 - val_accuracy: 0.9606
Epoch 14/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0496 -
accuracy: 0.9805 - val_loss: 0.1746 - val_accuracy: 0.9469
Epoch 15/50
146/146 [==============================] - 33s 229ms/step - loss: 0.0363 -
accuracy: 0.9865 - val_loss: 0.1579 - val_accuracy: 0.9589
Epoch 16/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0347 -
accuracy: 0.9878 - val_loss: 0.1489 - val_accuracy: 0.9580
Epoch 17/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0257 -
accuracy: 0.9908 - val_loss: 0.1651 - val_accuracy: 0.9563
Epoch 18/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0205 -
accuracy: 0.9912 - val_loss: 0.1913 - val_accuracy: 0.9529
Epoch 19/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0312 -
accuracy: 0.9889 - val_loss: 0.1838 - val_accuracy: 0.9546
Epoch 20/50
```

```
146/146 [==============================] - 33s 226ms/step - loss: 0.0326 -
accuracy: 0.9882 - val_loss: 0.1877 - val_accuracy: 0.9538
Epoch 21/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0137 -
accuracy: 0.9949 - val_loss: 0.2569 - val_accuracy: 0.9461
Epoch 22/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0208 -
accuracy: 0.9932 - val_loss: 0.2218 - val_accuracy: 0.9435
Epoch 23/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0271 -
accuracy: 0.9906 - val_loss: 0.1809 - val_accuracy: 0.9529
Epoch 24/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0175 -
accuracy: 0.9927 - val_loss: 0.2109 - val_accuracy: 0.9572
Epoch 25/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0159 -
accuracy: 0.9953 - val_loss: 0.2123 - val_accuracy: 0.9546
Epoch 26/50
146/146 [==============================] - 33s 228ms/step - loss: 0.0196 -
accuracy: 0.9929 - val_loss: 0.2280 - val_accuracy: 0.9572
Epoch 27/50
146/146 [==============================] - 34s 231ms/step - loss: 0.0081 -
accuracy: 0.9966 - val_loss: 0.2424 - val_accuracy: 0.9606
Epoch 28/50
146/146 [==============================] - 33s 228ms/step - loss: 0.0178 -
accuracy: 0.9929 - val_loss: 0.2043 - val_accuracy: 0.9546
Epoch 29/50
146/146 [==============================] - 33s 229ms/step - loss: 0.0175 -
accuracy: 0.9940 - val_loss: 0.2032 - val_accuracy: 0.9572
Epoch 30/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0166 -
accuracy: 0.9927 - val_loss: 0.2517 - val_accuracy: 0.9486
Epoch 31/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0166 -
accuracy: 0.9942 - val_loss: 0.2671 - val_accuracy: 0.9563
Epoch 32/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0114 -
accuracy: 0.9946 - val_loss: 0.3719 - val_accuracy: 0.9512
Epoch 33/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0186 -
accuracy: 0.9932 - val_loss: 0.1676 - val_accuracy: 0.9589
Epoch 34/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0191 -
accuracy: 0.9927 - val_loss: 0.2444 - val_accuracy: 0.9512
Epoch 35/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0106 -
accuracy: 0.9968 - val_loss: 0.2555 - val_accuracy: 0.9598
Epoch 36/50
```

```
146/146 [==============================] - 33s 226ms/step - loss: 0.0068 -
accuracy: 0.9983 - val_loss: 0.2538 - val_accuracy: 0.9521
Epoch 37/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0077 -
accuracy: 0.9970 - val_loss: 0.2490 - val_accuracy: 0.9572
Epoch 38/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0098 -
accuracy: 0.9966 - val_loss: 0.2564 - val_accuracy: 0.9512
Epoch 39/50
146/146 [==============================] - 33s 229ms/step - loss: 0.0123 -
accuracy: 0.9959 - val_loss: 0.2574 - val_accuracy: 0.9589
Epoch 40/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0097 -
accuracy: 0.9961 - val_loss: 0.2425 - val_accuracy: 0.9580
Epoch 41/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0048 -
accuracy: 0.9985 - val_loss: 0.2725 - val_accuracy: 0.9521
Epoch 42/50
146/146 [==============================] - 33s 229ms/step - loss: 0.0057 -
accuracy: 0.9976 - val_loss: 0.2502 - val_accuracy: 0.9598
Epoch 43/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0118 -
accuracy: 0.9955 - val_loss: 0.2201 - val_accuracy: 0.9529
Epoch 44/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0042 -
accuracy: 0.9981 - val_loss: 0.2692 - val_accuracy: 0.9580
Epoch 45/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0104 -
accuracy: 0.9968 - val_loss: 0.2455 - val_accuracy: 0.9580
Epoch 46/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0233 -
accuracy: 0.9929 - val_loss: 0.2318 - val_accuracy: 0.9563
Epoch 47/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0116 -
accuracy: 0.9957 - val_loss: 0.2745 - val_accuracy: 0.9512
Epoch 48/50
146/146 [==============================] - 33s 226ms/step - loss: 0.0114 -
accuracy: 0.9957 - val_loss: 0.3371 - val_accuracy: 0.9538
Epoch 49/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0120 -
accuracy: 0.9959 - val_loss: 0.2869 - val_accuracy: 0.9555
Epoch 50/50
146/146 [==============================] - 33s 227ms/step - loss: 0.0071 -
accuracy: 0.9976 - val_loss: 0.3275 - val_accuracy: 0.9478

/Users/gadwall/uczelnia/semestr_8/AAI/projekt/venv/lib/python3.10/site-
packages/keras/src/engine/training.py:3000: UserWarning: You are saving your
model as an HDF5 file via `model.save()`. This file format is considered legacy.
```

```
We recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')`.
  saving_api.save_model(

Epoch 1/50
146/146 [==============================] - 34s 234ms/step - loss: 0.5222 -
accuracy: 0.7414 - val_loss: 0.4397 - val_accuracy: 0.8108
Epoch 2/50
146/146 [==============================] - 34s 230ms/step - loss: 0.3781 -
accuracy: 0.8268 - val_loss: 0.2632 - val_accuracy: 0.8896
Epoch 3/50
146/146 [==============================] - 34s 231ms/step - loss: 0.3272 -
accuracy: 0.8517 - val_loss: 0.2018 - val_accuracy: 0.9170
Epoch 4/50
146/146 [==============================] - 34s 232ms/step - loss: 0.3071 -
accuracy: 0.8696 - val_loss: 0.2995 - val_accuracy: 0.8570
Epoch 5/50
146/146 [==============================] - 34s 230ms/step - loss: 0.2987 -
accuracy: 0.8722 - val_loss: 0.3532 - val_accuracy: 0.8348
Epoch 6/50
146/146 [==============================] - 34s 231ms/step - loss: 0.2863 -
accuracy: 0.8804 - val_loss: 0.2391 - val_accuracy: 0.8853
Epoch 7/50
146/146 [==============================] - 34s 231ms/step - loss: 0.2800 -
accuracy: 0.8842 - val_loss: 0.1912 - val_accuracy: 0.9187
Epoch 8/50
146/146 [==============================] - 34s 231ms/step - loss: 0.2728 -
accuracy: 0.8891 - val_loss: 0.2559 - val_accuracy: 0.8827
Epoch 9/50
146/146 [==============================] - 34s 231ms/step - loss: 0.2750 -
accuracy: 0.8940 - val_loss: 0.1771 - val_accuracy: 0.9384
Epoch 10/50
146/146 [==============================] - 34s 234ms/step - loss: 0.2630 -
accuracy: 0.8964 - val_loss: 0.2416 - val_accuracy: 0.9075
Epoch 11/50
146/146 [==============================] - 34s 232ms/step - loss: 0.2448 -
accuracy: 0.9056 - val_loss: 0.3372 - val_accuracy: 0.8442
Epoch 12/50
146/146 [==============================] - 35s 239ms/step - loss: 0.2534 -
accuracy: 0.9015 - val_loss: 0.1632 - val_accuracy: 0.9426
Epoch 13/50
146/146 [==============================] - 35s 242ms/step - loss: 0.2392 -
accuracy: 0.9007 - val_loss: 0.1809 - val_accuracy: 0.9238
Epoch 14/50
146/146 [==============================] - 35s 242ms/step - loss: 0.2278 -
accuracy: 0.9090 - val_loss: 0.2154 - val_accuracy: 0.9101
Epoch 15/50
146/146 [==============================] - 35s 239ms/step - loss: 0.2381 -
```

```
accuracy: 0.9024 - val_loss: 0.2214 - val_accuracy: 0.9041
Epoch 16/50
146/146 [==============================] - 34s 231ms/step - loss: 0.2350 -
accuracy: 0.9035 - val_loss: 0.2730 - val_accuracy: 0.8784
Epoch 17/50
146/146 [==============================] - 34s 230ms/step - loss: 0.2296 -
accuracy: 0.9105 - val_loss: 0.2019 - val_accuracy: 0.9041
Epoch 18/50
146/146 [==============================] - 34s 232ms/step - loss: 0.2190 -
accuracy: 0.9150 - val_loss: 0.1486 - val_accuracy: 0.9589
Epoch 19/50
146/146 [==============================] - 34s 231ms/step - loss: 0.2207 -
accuracy: 0.9137 - val_loss: 0.1838 - val_accuracy: 0.9229
Epoch 20/50
146/146 [==============================] - 34s 230ms/step - loss: 0.2252 -
accuracy: 0.9144 - val_loss: 0.1590 - val_accuracy: 0.9546
Epoch 21/50
146/146 [==============================] - 34s 231ms/step - loss: 0.2180 -
accuracy: 0.9189 - val_loss: 0.2049 - val_accuracy: 0.9170
Epoch 22/50
146/146 [==============================] - 34s 233ms/step - loss: 0.2140 -
accuracy: 0.9212 - val_loss: 0.1656 - val_accuracy: 0.9289
Epoch 23/50
146/146 [==============================] - 34s 231ms/step - loss: 0.2112 -
accuracy: 0.9172 - val_loss: 0.1406 - val_accuracy: 0.9563
Epoch 24/50
146/146 [==============================] - 34s 231ms/step - loss: 0.2054 -
accuracy: 0.9185 - val_loss: 0.1924 - val_accuracy: 0.9127
Epoch 25/50
146/146 [==============================] - 34s 230ms/step - loss: 0.2098 -
accuracy: 0.9208 - val_loss: 0.2243 - val_accuracy: 0.9092
Epoch 26/50
146/146 [==============================] - 34s 231ms/step - loss: 0.2136 -
accuracy: 0.9180 - val_loss: 0.2338 - val_accuracy: 0.8896
Epoch 27/50
146/146 [==============================] - 34s 230ms/step - loss: 0.1927 -
accuracy: 0.9229 - val_loss: 0.1954 - val_accuracy: 0.9255
Epoch 28/50
146/146 [==============================] - 34s 229ms/step - loss: 0.2018 -
accuracy: 0.9236 - val_loss: 0.1962 - val_accuracy: 0.9075
Epoch 29/50
146/146 [==============================] - 34s 231ms/step - loss: 0.2019 -
accuracy: 0.9229 - val_loss: 0.1785 - val_accuracy: 0.9264
Epoch 30/50
146/146 [==============================] - 35s 242ms/step - loss: 0.1870 -
accuracy: 0.9270 - val_loss: 0.2900 - val_accuracy: 0.8613
Epoch 31/50
146/146 [==============================] - 34s 232ms/step - loss: 0.1995 -
```

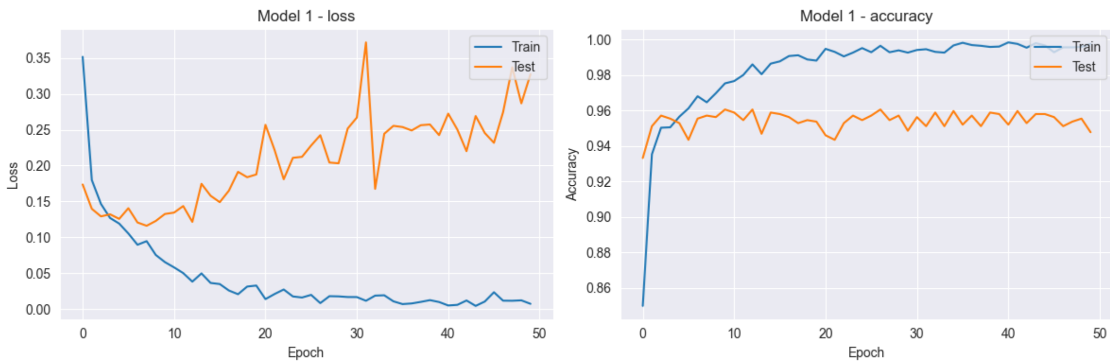
```
accuracy: 0.9195 - val_loss: 0.1327 - val_accuracy: 0.9546
Epoch 32/50
146/146 [==============================] - 34s 232ms/step - loss: 0.1974 -
accuracy: 0.9210 - val_loss: 0.1661 - val_accuracy: 0.9392
Epoch 33/50
146/146 [==============================] - 34s 232ms/step - loss: 0.1944 -
accuracy: 0.9249 - val_loss: 0.1454 - val_accuracy: 0.9495
Epoch 34/50
146/146 [==============================] - 34s 233ms/step - loss: 0.1957 -
accuracy: 0.9268 - val_loss: 0.1313 - val_accuracy: 0.9546
Epoch 35/50
146/146 [==============================] - 34s 231ms/step - loss: 0.1993 -
accuracy: 0.9257 - val_loss: 0.1386 - val_accuracy: 0.9538
Epoch 36/50
146/146 [==============================] - 34s 231ms/step - loss: 0.1850 -
accuracy: 0.9296 - val_loss: 0.1431 - val_accuracy: 0.9495
Epoch 37/50
146/146 [==============================] - 34s 231ms/step - loss: 0.1881 -
accuracy: 0.9292 - val_loss: 0.2004 - val_accuracy: 0.9187
Epoch 38/50
146/146 [==============================] - 34s 231ms/step - loss: 0.1777 -
accuracy: 0.9349 - val_loss: 0.1753 - val_accuracy: 0.9349
Epoch 39/50
146/146 [==============================] - 34s 231ms/step - loss: 0.1771 -
accuracy: 0.9356 - val_loss: 0.1771 - val_accuracy: 0.9272
Epoch 40/50
146/146 [==============================] - 34s 230ms/step - loss: 0.1891 -
accuracy: 0.9309 - val_loss: 0.1433 - val_accuracy: 0.9529
Epoch 41/50
146/146 [==============================] - 34s 230ms/step - loss: 0.1776 -
accuracy: 0.9360 - val_loss: 0.1559 - val_accuracy: 0.9392
Epoch 42/50
146/146 [==============================] - 34s 233ms/step - loss: 0.1852 -
accuracy: 0.9326 - val_loss: 0.2647 - val_accuracy: 0.8870
Epoch 43/50
146/146 [==============================] - 34s 231ms/step - loss: 0.1741 -
accuracy: 0.9349 - val_loss: 0.1643 - val_accuracy: 0.9332
Epoch 44/50
146/146 [==============================] - 34s 230ms/step - loss: 0.1760 -
accuracy: 0.9347 - val_loss: 0.1571 - val_accuracy: 0.9375
Epoch 45/50
146/146 [==============================] - 34s 232ms/step - loss: 0.1775 -
accuracy: 0.9394 - val_loss: 0.2226 - val_accuracy: 0.9118
Epoch 46/50
146/146 [==============================] - 34s 230ms/step - loss: 0.1853 -
accuracy: 0.9313 - val_loss: 0.2891 - val_accuracy: 0.8844
Epoch 47/50
146/146 [==============================] - 34s 231ms/step - loss: 0.1744 -
```

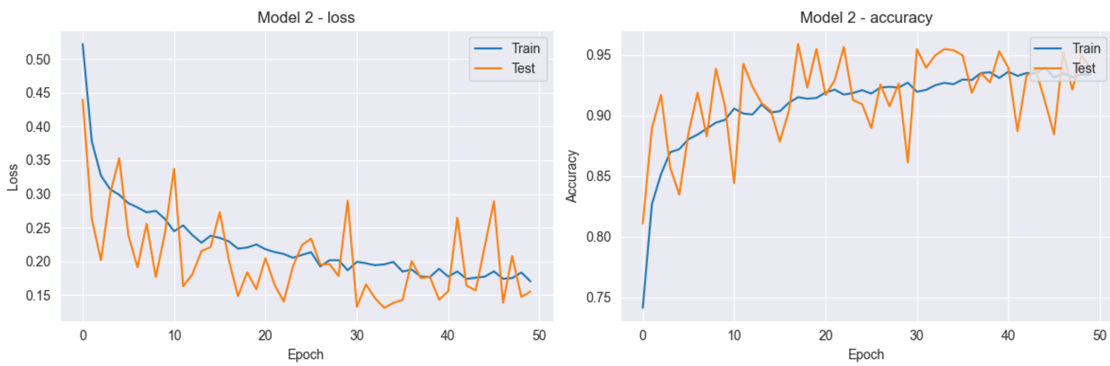
```
accuracy: 0.9345 - val_loss: 0.1389 - val_accuracy: 0.9521
Epoch 48/50
146/146 [==============================] - 34s 231ms/step - loss: 0.1754 -
accuracy: 0.9317 - val_loss: 0.2081 - val_accuracy: 0.9212
Epoch 49/50
146/146 [==============================] - 34s 231ms/step - loss: 0.1837 -
accuracy: 0.9336 - val_loss: 0.1473 - val_accuracy: 0.9495
Epoch 50/50
146/146 [==============================] - 34s 231ms/step - loss: 0.1705 -
accuracy: 0.9336 - val_loss: 0.1555 - val_accuracy: 0.9384
```

3 Dogłębna analiza działania i skuteczności modeli

3.1 Analiza krzywych uczenia

[67]:
```
import matplotlib.pyplot as plt

# funkcja do wygenerowania krzywych uczenia
def plot_learning_curves(history, title):
    plt.figure(figsize=(12,4))

    plt.subplot(1,2,1)
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title(title + ' - loss')
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'Test'], loc='upper right')

    plt.subplot(1,2,2)
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title(title + ' - accuracy')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'Test'], loc='upper right')

    plt.tight_layout()
    plt.show()

# wygenerowanie krzywych uczenia dla modelu 1
plot_learning_curves(history_1, 'Model 1')

# wygenerowanie krzywych uczenia dla modelu 2
plot_learning_curves(history_2, 'Model 2')
```





3.2 Analiza metryk

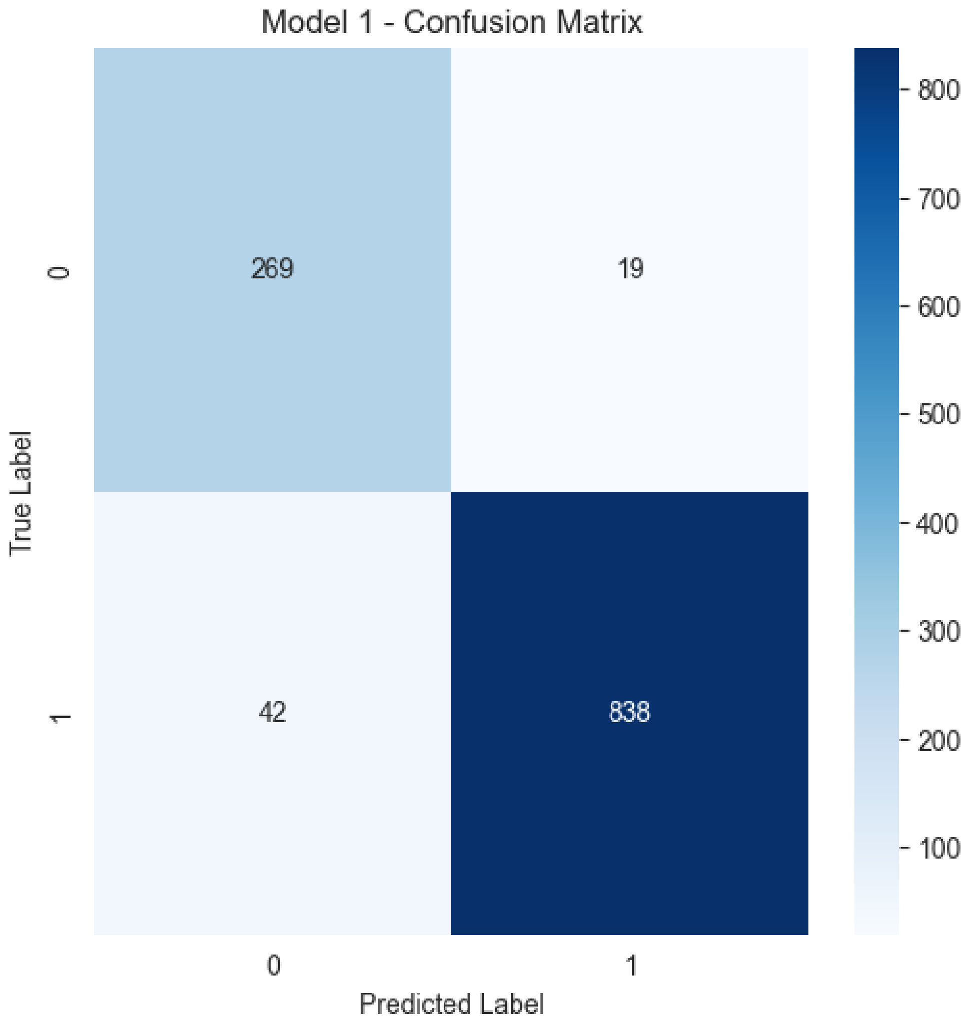
3.2.1 Macierz pomyłek oraz AUC ROC (Area Under the Receiver Operating Characteristic curve)

Wartość AUC ROC bliżej 1 wskazuje na lepszą skuteczność modelu w klasyfikacji obrazów

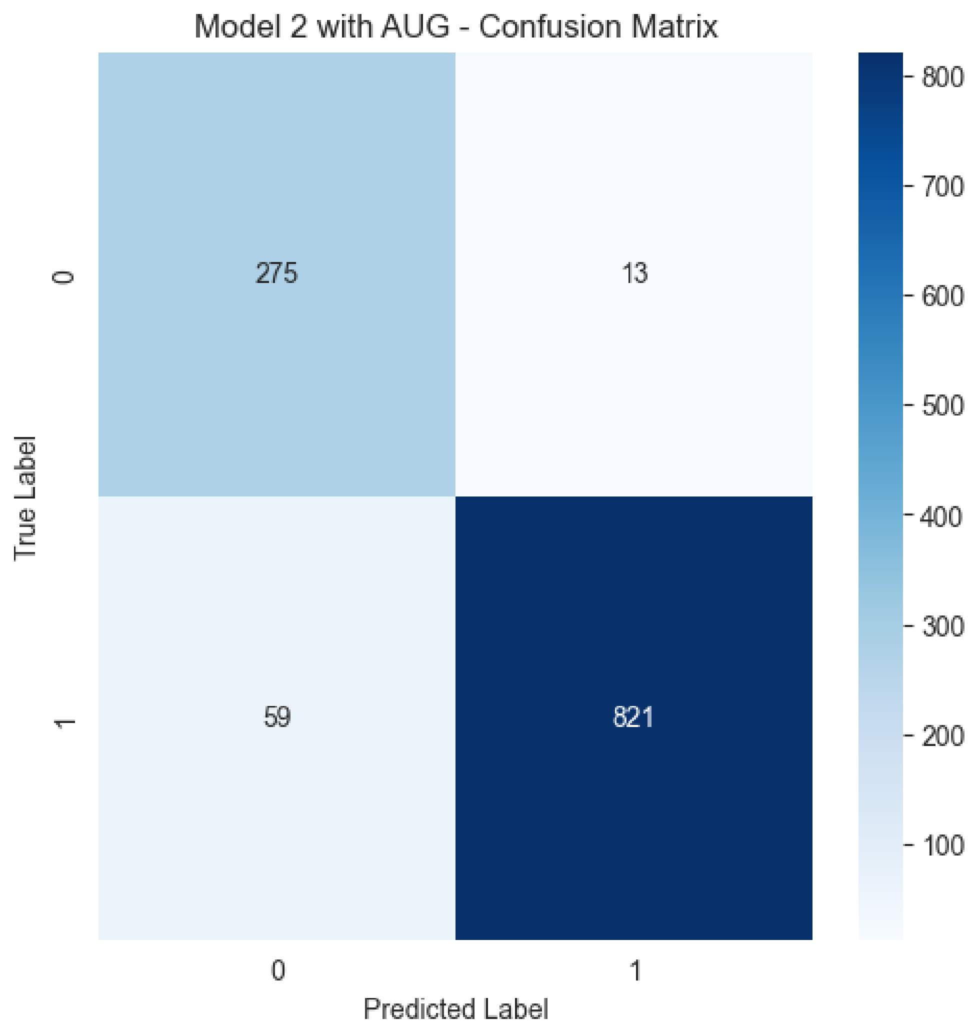
[68]:
```
from sklearn.metrics import confusion_matrix, roc_auc_score
import seaborn as sns

# funkcja do generowania macierzy pomyłek i obliczania AUC ROC
def evaluate_model(model, title, test_images, test_labels):
    # przewidywanie klas przez model
    predictions = model.predict(test_images)
    predictions = [1 if p > 0.5 else 0 for p in predictions]

    # obliczanie macierzy pomyłek
    cm = confusion_matrix(test_labels, predictions)

    # obliczanie AUC ROC
    auc_roc = roc_auc_score(test_labels, predictions)
```

```
    # wyświetlanie macierzy pomyłek
    plt.figure(figsize=(6, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.title(title + ' - Confusion Matrix')
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')
    plt.show()

    print(title + ' - AUC ROC:', auc_roc)

# ocena modelu 1
evaluate_model(model_1, 'Model 1', test_images, test_labels)

# ocena modelu 2
evaluate_model(model_2, 'Model 2 with AUG', test_images, test_labels)
```

```
37/37 [==============================] - 2s 59ms/step
```




```
Model 1 - AUC ROC: 0.9431502525252525
37/37 [==============================] - 2s 57ms/step
```

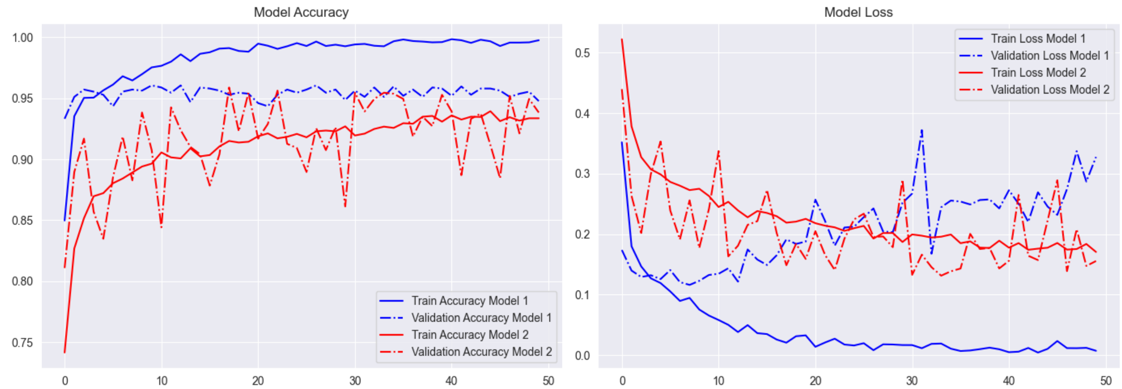



```
Model 2 with AUG - AUC ROC: 0.9439078282828284
```

3.3 Porównanie modeli

[69]:
```
# funkcja do porównywania krzywych uczenia
def compare_learning_curves(history_1, history_2, title_1, title_2):
    fig, axes = plt.subplots(1, 2, figsize=(14, 5))

    # wykres dokładności
    axes[0].plot(history_1.history['accuracy'], label='Train Accuracy ' +␣
 ↪title_1, color='blue')
    axes[0].plot(history_1.history['val_accuracy'], label='Validation Accuracy␣
 ↪' + title_1, color='blue', linestyle = "dashdot")
    axes[0].plot(history_2.history['accuracy'], label='Train Accuracy ' +␣
 ↪title_2, color='red')
```

```
    axes[0].plot(history_2.history['val_accuracy'], label='Validation Accuracy␣
↪' + title_2, color='red', linestyle = "dashdot")
    axes[0].set_title('Model Accuracy')
    axes[0].legend()

    # wykres straty
    axes[1].plot(history_1.history['loss'], label='Train Loss ' + title_1,␣
↪color='blue')
    axes[1].plot(history_1.history['val_loss'], label='Validation Loss ' +␣
↪title_1, color='blue', linestyle = "dashdot")
    axes[1].plot(history_2.history['loss'], label='Train Loss ' + title_2,␣
↪color='red')
    axes[1].plot(history_2.history['val_loss'], label='Validation Loss ' +␣
↪title_2, color='red', linestyle = "dashdot")
    axes[1].set_title('Model Loss')
    axes[1].legend()

    plt.tight_layout()
    plt.show()

# porównanie modeli
compare_learning_curves(history_1, history_2, 'Model 1', 'Model 2')
```



[ ]: