In [25]:
```
from keras.datasets import mnist;
from keras.utils import to_categorical
#wczytanie obrazów z biblioteki mnist
(train_images, train_labels), (test_images, test_labels) = mnist.load_dat


x_train = train_images.reshape((60000,28,28,1))
x_test = test_images.reshape((10000,28,28,1))

x_train = x_train.astype('float32')/255
x_test = x_test.astype('float32')/255

y_train = to_categorical(train_labels)
y_test = to_categorical(test_labels)
```

In [26]:
```
from keras import models
from keras import layers
model = models.Sequential()
model.add( layers.Input(shape=(28,28,1)))
model.add( layers.Conv2D(32, (3,3), activation='relu') )
model.add( layers.MaxPooling2D((2,2)) )
#model.add( layers.Conv2D(64, (3,3), activation='relu') )
#model.add( layers.MaxPooling2D((2,2)) )
model.add( layers.Flatten() )
model.add( layers.Dense(64,activation='relu') )
model.add( layers.Dense(10,activation='softmax') )
model.compile( optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])


print( model.summary() )
```

Model: "sequential_3"

Layer (type)	Output Shape
conv2d_5 (Conv2D)	(None, 26, 26, 32)
max_pooling2d_5 (MaxPooling2D)	(None, 13, 13, 32)
flatten_3 (Flatten)	(None, 5408)
dense_6 (Dense)	(None, 64)
dense_7 (Dense)	(None, 10)

Total params: 347,146 (1.32 MB)
Trainable params: 347,146 (1.32 MB)
Non-trainable params: 0 (0.00 B)
None

Zadanie nr 1

Podzadanie nr 1

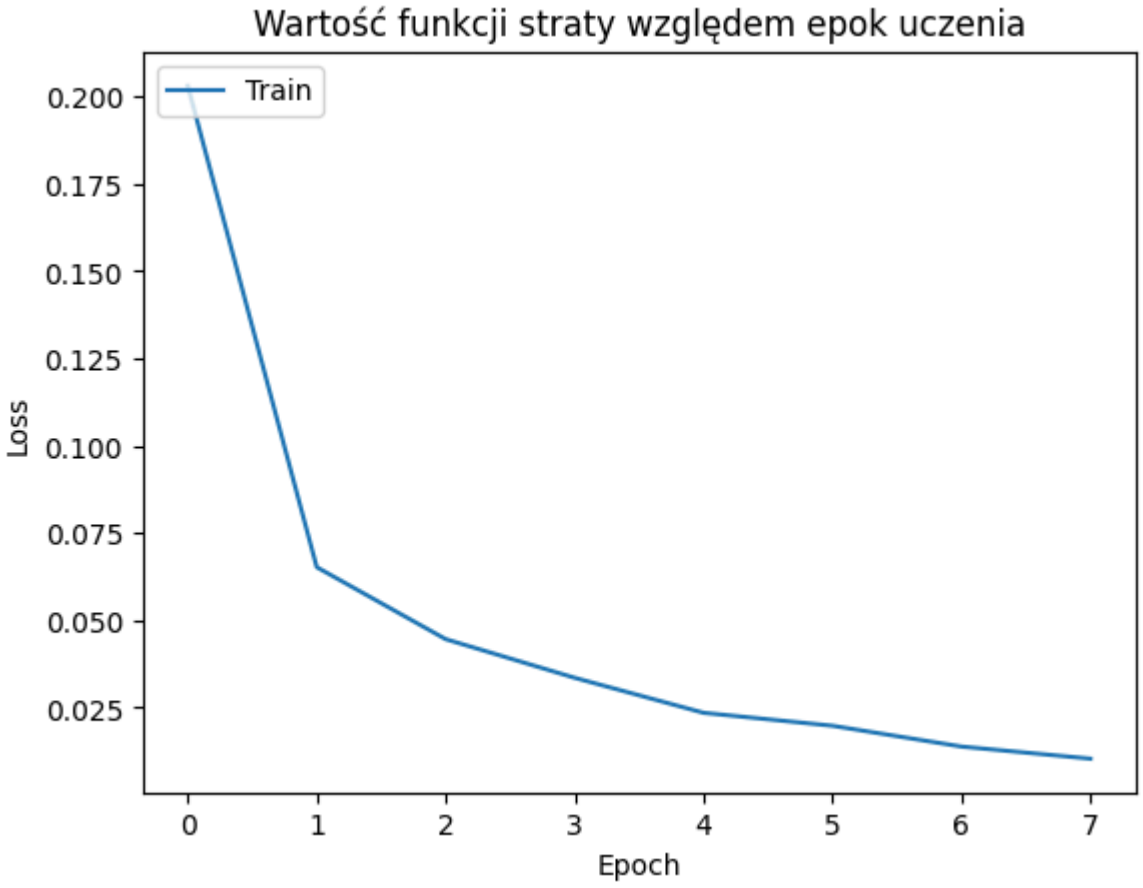
In [27]:
```
#nauka sieci
history = model.fit(x_train, y_train, epochs=8, batch_size=64,
validation_data=(x_test, y_test))
```

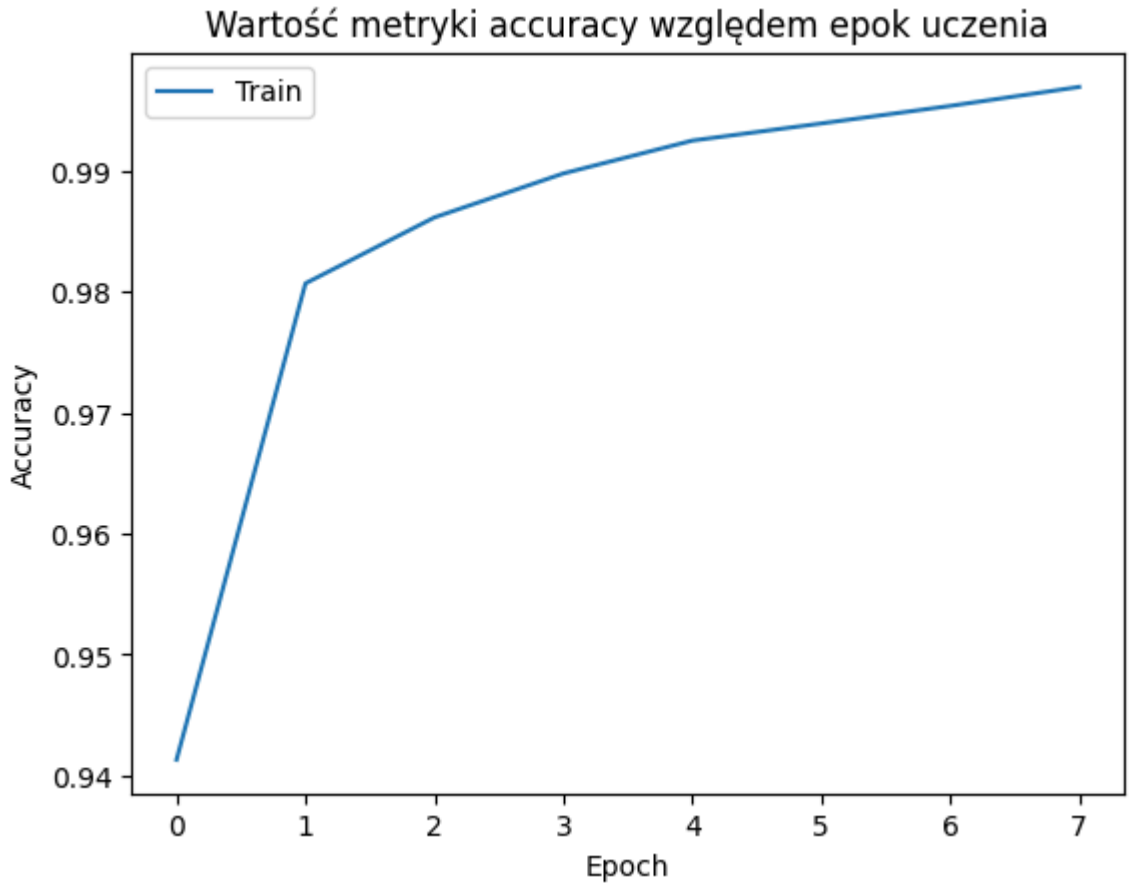
```
Epoch 1/8
938/938 ━━━━━━━━━━━━━━━━━━━━ 34s 32ms/step - accuracy: 0.8858 - loss: 0.39
87 - val_accuracy: 0.9742 - val_loss: 0.0878
Epoch 2/8
938/938 ━━━━━━━━━━━━━━━━━━━━ 29s 31ms/step - accuracy: 0.9799 - loss: 0.06
96 - val_accuracy: 0.9805 - val_loss: 0.0613
Epoch 3/8
938/938 ━━━━━━━━━━━━━━━━━━━━ 38s 28ms/step - accuracy: 0.9865 - loss: 0.04
43 - val_accuracy: 0.9836 - val_loss: 0.0517
Epoch 4/8
938/938 ━━━━━━━━━━━━━━━━━━━━ 26s 28ms/step - accuracy: 0.9902 - loss: 0.03
25 - val_accuracy: 0.9853 - val_loss: 0.0464
Epoch 5/8
938/938 ━━━━━━━━━━━━━━━━━━━━ 41s 28ms/step - accuracy: 0.9921 - loss: 0.02
44 - val_accuracy: 0.9866 - val_loss: 0.0438
Epoch 6/8
938/938 ━━━━━━━━━━━━━━━━━━━━ 26s 28ms/step - accuracy: 0.9944 - loss: 0.01
86 - val_accuracy: 0.9841 - val_loss: 0.0496
Epoch 7/8
938/938 ━━━━━━━━━━━━━━━━━━━━ 40s 27ms/step - accuracy: 0.9961 - loss: 0.01
21 - val_accuracy: 0.9849 - val_loss: 0.0518
Epoch 8/8
938/938 ━━━━━━━━━━━━━━━━━━━━ 26s 28ms/step - accuracy: 0.9973 - loss: 0.00
96 - val_accuracy: 0.9853 - val_loss: 0.0489
```

Podzadanie nr 2

In [28]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, precision_score, recall_score
import numpy as np
from keras.losses import categorical_crossentropy
plt.plot(history.history['loss'])
plt.title('Wartość funkcji straty względem epok uczenia')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train'], loc='upper left')
plt.show()

plt.plot(history.history['accuracy'])
plt.title('Wartość metryki accuracy względem epok uczenia')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train'], loc='upper left')
plt.show()

predicted_y = model.predict(x_test)
predicted_y_rounded = np.argmax(predicted_y, axis=1)
val_loss = categorical_crossentropy(y_test, predicted_y)
val_accuracy = accuracy_score(predicted_y_rounded, test_labels)
print("Dla testowego zbioru:")
print("val_loss:", val_loss)
print("val_accuracy:", val_accuracy)

#-------przygotowanie macierzy pomyłek i obliczenie metryk
```

```
# TESTOWE:
# Uzyskanie macierzy pomyłek
conf_matrix_test = confusion_matrix(test_labels, predicted_y_rounded)

# Obliczenie metryk
accuracy_test = accuracy_score(test_labels, predicted_y_rounded)
precision_test = precision_score(test_labels, predicted_y_rounded, averag
recall_test = recall_score(test_labels, predicted_y_rounded, average="mac

print("conf_matrix_test",conf_matrix_test)
print("accuracy_test",accuracy_test)
print("precision_test",precision_test)
print("recall_test",recall_test)
# TRENINGOWE:
predicted_y_train = model.predict(x_train)
predicted_y_train_rounded = np.argmax(predicted_y_train, axis=1)

# Uzyskanie macierzy pomyłek
conf_matrix_train = confusion_matrix(train_labels, predicted_y_train_roun

# Obliczenie metryk
accuracy_train = accuracy_score(train_labels, predicted_y_train_rounded)
precision_train = precision_score(train_labels, predicted_y_train_rounded
recall_train = recall_score(train_labels, predicted_y_train_rounded, aver
print("conf_matrix_train",conf_matrix_train)
print("accuracy_train",accuracy_train)
print("precision_train",precision_train)
print("recall_train",recall_train)
```






```
313/313 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step
Dla testowego zbioru:
val_loss: tf.Tensor(
[3.3378658e-06 1.1920930e-07 9.5367886e-06 ... 1.1920930e-07 2.7180087e-05
 1.1920930e-07], shape=(10000,), dtype=float32)
val_accuracy: 0.9853
conf_matrix_test [[ 972    0    2    1    0    1    2    0    1    1]
 [   0 1129    2    0    0    0    2    0    2    0]
 [   0    3 1022    0    0    0    0    5    2    0]
 [   0    0    4  996    0    7    0    1    2    0]
 [   0    0    2    0  973    0    1    0    1    5]
 [   1    0    1    6    0  882    2    0    0    0]
 [   5    2    1    1    1    3  943    0    2    0]
 [   0    2   13    0    0    0    0 1010    1    2]
 [   3    0    8    6    2    4    0    2  942    7]
 [   1    2    1    3    9    5    0    3    1  984]]
accuracy_test 0.9853
precision_test 0.9852837789421318
recall_test 0.9851824786629008
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step
conf_matrix_train [[5915    0    2    0    0    0    2    0    2    2]
 [   0 6741    0    0    0    0    0    0    1    0]
 [   0    0 5957    0    1    0    0    0    0    0]
 [   0    0   10 6113    0    5    0    0    2    1]
 [   0    1    0    0 5832    1    2    0    0    6]
 [   0    0    0    0    0 5418    0    0    2    1]
 [   0    0    0    0    0    2 5911    0    5    0]
 [   0    5    7    1    1    0    0 6247    1    3]
 [   0    1    5    4    2    8    1    0 5828    2]
 [   0    0    3    0    3    1    0    1    1 5940]]
accuracy_train 0.9983666666666666
precision_train 0.9983386104539406
recall_train 0.9983632374234116
```

Podzadanie nr 3

Wyniki z laboratorium nr 7:

```
Metryki i macierz pomyłek dla zbioru treningowego:
Accuracy: 0.9544666666666667
Precision: 0.9542385739932907
Recall: 0.9542385739932907
Confusion Matrix:
 [[5812    1   12    4    1   13   31    5   41    3]
 [   1 6643   22    8    3    7    3   10   37    8]
 [  28   30 5632   64   28    8   50   31   79    8]
 [  20   23   87 5683    2  116   16   27  127   30]
 [  10   17   33    8 5553    6   67    8   39  101]
 [  31   31   15  102   13 5046   85    3   81   14]
 [  15    9    6    3   15   43 5805    3   18    1]
 [  21   19   20   23   30    5    5 6022   35   85]
 [  20   67   21   69   17   53   33    8 5549   14]
 [  22   11    6   55  108   35    7   96   86 5523]]

Metryki i macierz pomyłek dla zbioru testowego:
Accuracy: 0.9288
Precision: 0.9282213884893157
Recall: 0.9282213884893157
Confusion Matrix:
 [ 960    0    2    2    0    2    8    2    4    0]
 [   0 1110    4    2    2    2    5    0    9    1]
 [   9    9  930   15   12    7   16    8   26    0]
 [   2    4   16  920    2   26    3   10   24    3]
```

```
[   1    2    9    7  898    4   17    7    3   34]

[   5    3    2   24    5  810   17    1   18    7]

[   9    4    7    1    3   10  918    2    4    0]

[   2    9   14   14    5    2    0  947    8   27]

[   5   13    7   14    9   14   10    9  888    5]

[   8    6    0   11   26    8    0   25   18  907]
```

Porównanie:

Jak możemy zobaczyć nowy model osiąga o wiele lepsze wyniki w o wiele krótszym czasie niż porzedni. Wystarczyła bowiem tylko jedna epoka aby model nauczył się wystarczający by wartość funkcji straty spadła poniżej 0,1. Nowy model posiada accuracy rzędu 0.9872 w porównaniu z poprzednim wynikiem 0.9542 / 0.9288. Jest to zaprawdę dobry wynik.

Podzadanie nr 4

In [29]:
```
from keras import models
from keras import layers
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, precision_score, recall_score
import numpy as np
from keras.losses import categorical_crossentropy
model2 = models.Sequential()
model2.add( layers.Input(shape=(28,28,1)))
model2.add( layers.Conv2D(32, (3,3), activation='relu') )
model2.add( layers.MaxPooling2D((2,2)) )
model2.add( layers.Conv2D(64, (3,3), activation='relu') )
model2.add( layers.MaxPooling2D((2,2)) )
model2.add( layers.Flatten() )
model2.add( layers.Dense(64,activation='relu') )
model2.add( layers.Dense(10,activation='softmax') )
model2.compile( optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])

print( model2.summary() )

#nauka sieci
history2 = model2.fit(x_train, y_train, epochs=5, batch_size=64,
validation_data=(x_test, y_test))


plt.plot(history2.history['loss'])
plt.title('Wartość funkcji straty względem epok uczenia')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train'], loc='upper left')
plt.show()

plt.plot(history2.history['accuracy'])
```

```
plt.title('Wartość metryki accuracy względem epok uczenia')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train'], loc='upper left')
plt.show()

predicted_y2 = model.predict(x_test)
predicted_y_rounded2 = np.argmax(predicted_y2, axis=1)
val_loss2 = categorical_crossentropy(y_test, predicted_y2)
val_accuracy2 = accuracy_score(predicted_y_rounded2, test_labels)
print("Dla testowego zbioru:")
print("val_loss:", val_loss2)
print("val_accuracy:", val_accuracy2)

#-------przygotowanie macierzy pomyłek i obliczenie metryk
# TESTOWE:
# Uzyskanie macierzy pomyłek
conf_matrix_test2 = confusion_matrix(test_labels, predicted_y_rounded2)

# Obliczenie metryk
accuracy_test2 = accuracy_score(test_labels, predicted_y_rounded2)
precision_test2 = precision_score(test_labels, predicted_y_rounded2, aver
recall_test2 = recall_score(test_labels, predicted_y_rounded2, average="m

print("conf_matrix_test",conf_matrix_test2)
print("accuracy_test",accuracy_test2)
print("precision_test",precision_test2)
print("recall_test",recall_test2)

# TRENINGOWE:
predicted_y_train2 = model.predict(x_train)
predicted_y_train_rounded2 = np.argmax(predicted_y_train2, axis=1)

# Uzyskanie macierzy pomyłek
conf_matrix_train2 = confusion_matrix(train_labels, predicted_y_train_rou

# Obliczenie metryk
accuracy_train2 = accuracy_score(train_labels, predicted_y_train_rounded2
precision_train2 = precision_score(train_labels, predicted_y_train_rounde
recall_train2 = recall_score(train_labels, predicted_y_train_rounded2, av

print("conf_matrix_train",conf_matrix_train2)
print("accuracy_train",accuracy_train2)
print("precision_train",precision_train2)
print("recall_train",recall_train2)
```

Model: "sequential_4"

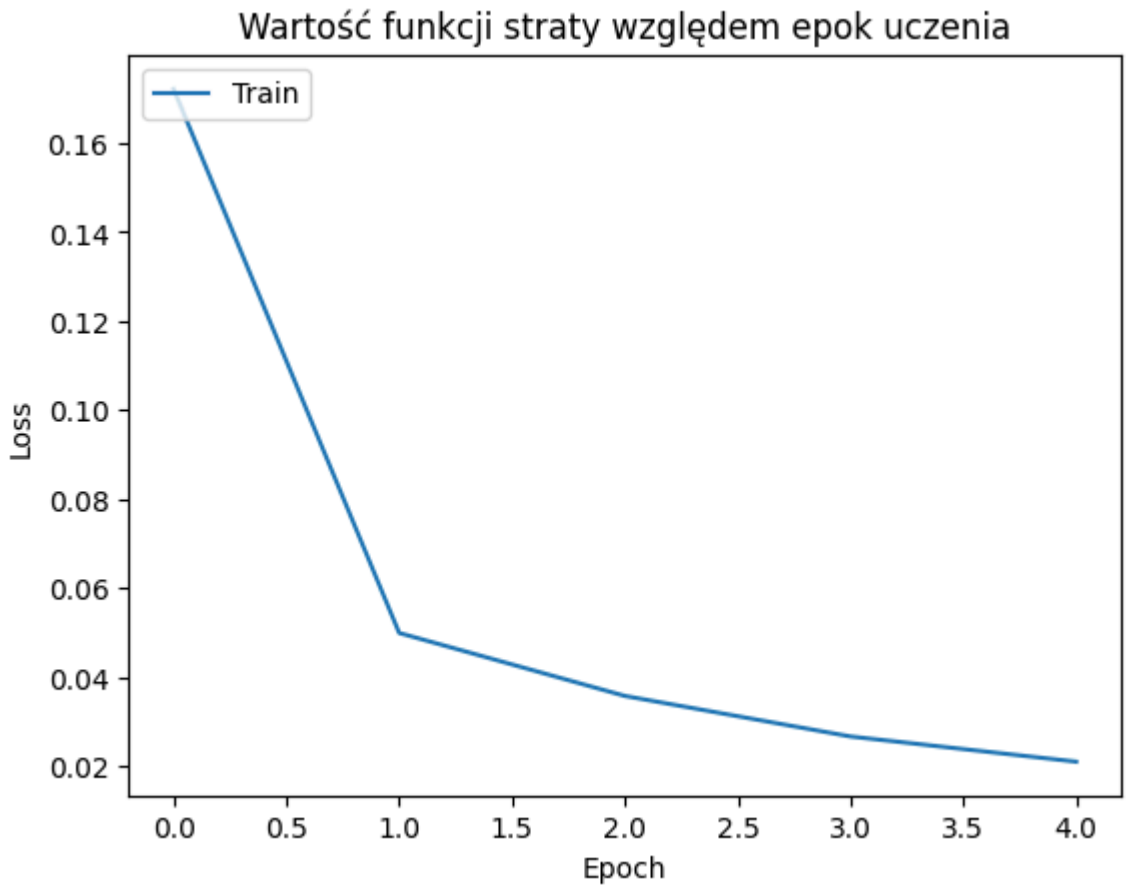
Layer (type)	Output Shape
conv2d_6 (Conv2D)	(None, 26, 26, 32)
max_pooling2d_6 (MaxPooling2D)	(None, 13, 13, 32)
conv2d_7 (Conv2D)	(None, 11, 11, 64)
max_pooling2d_7 (MaxPooling2D)	(None, 5, 5, 64)
flatten_4 (Flatten)	(None, 1600)
dense_8 (Dense)	(None, 64)
dense_9 (Dense)	(None, 10)

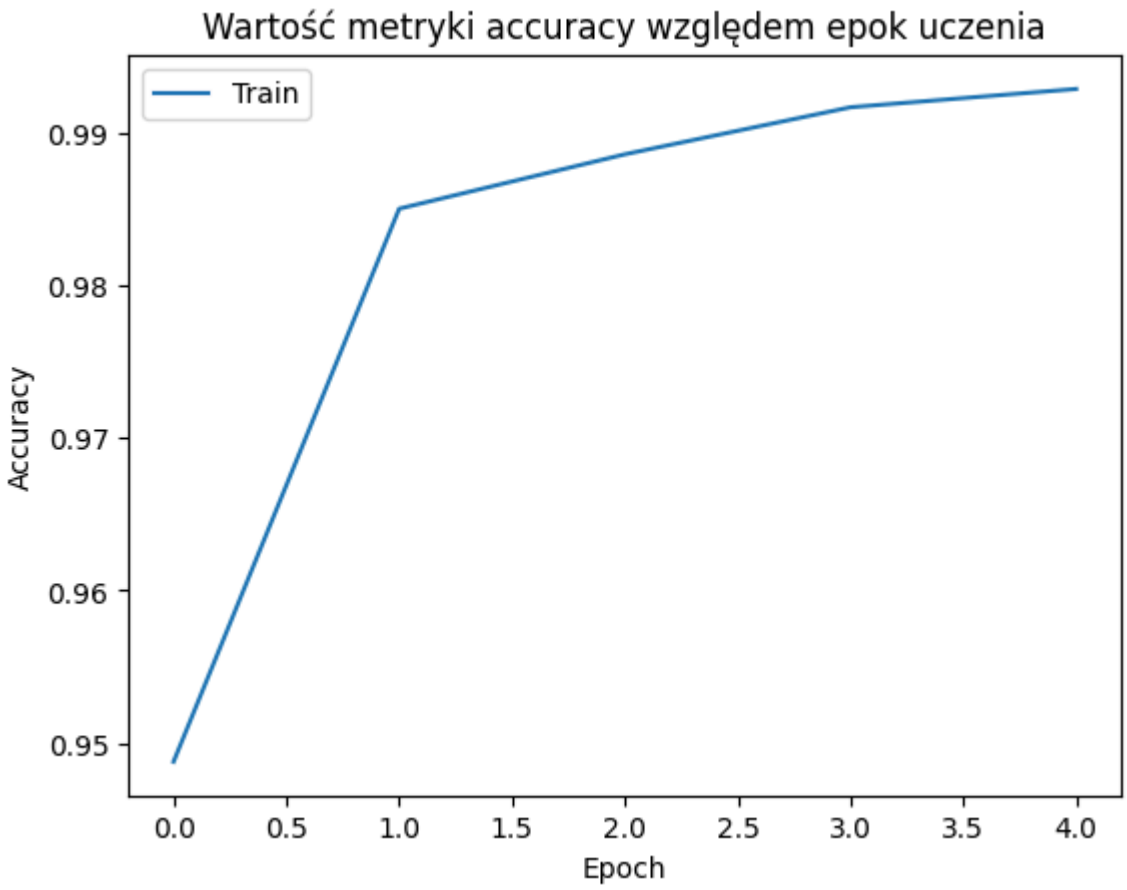
Total params: 121,930 (476.29 KB)

Trainable params: 121,930 (476.29 KB)

Non-trainable params: 0 (0.00 B)

```
None
Epoch 1/5
938/938 ━━━━━━━━━━━━━━━━━━━━ 51s 52ms/step - accuracy: 0.8808 - loss: 0.40
18 - val_accuracy: 0.9824 - val_loss: 0.0532
Epoch 2/5
938/938 ━━━━━━━━━━━━━━━━━━━━ 47s 50ms/step - accuracy: 0.9845 - loss: 0.05
12 - val_accuracy: 0.9886 - val_loss: 0.0348
Epoch 3/5
938/938 ━━━━━━━━━━━━━━━━━━━━ 84s 53ms/step - accuracy: 0.9888 - loss: 0.03
55 - val_accuracy: 0.9897 - val_loss: 0.0320
Epoch 4/5
938/938 ━━━━━━━━━━━━━━━━━━━━ 78s 48ms/step - accuracy: 0.9920 - loss: 0.02
58 - val_accuracy: 0.9902 - val_loss: 0.0313
Epoch 5/5
938/938 ━━━━━━━━━━━━━━━━━━━━ 46s 49ms/step - accuracy: 0.9929 - loss: 0.02
00 - val_accuracy: 0.9897 - val_loss: 0.0314
```


Wartość funkcji straty względem epok uczenia
Train
Loss
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Epoch


Wartość metryki accuracy względem epok uczenia
Train
Accuracy
0.99
0.98
0.97
0.96
0.95
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Epoch

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step
Dla testowego zbioru:
val_loss: tf.Tensor(
[3.3378658e-06 1.1920930e-07 9.5367886e-06 ... 1.1920930e-07 2.7180087e-05
 1.1920930e-07], shape=(10000,), dtype=float32)
val_accuracy: 0.9853
conf_matrix_test [[ 972    0    2    1    0    1    2    0    1    1]
 [   0 1129    2    0    0    0    2    0    2    0]
 [   0    3 1022    0    0    0    0    5    2    0]
 [   0    0    4  996    0    7    0    1    2    0]
 [   0    0    2    0  973    0    1    0    1    5]
 [   1    0    1    6    0  882    2    0    0    0]
 [   5    2    1    1    1    3  943    0    2    0]
 [   0    2   13    0    0    0    0 1010    1    2]
 [   3    0    8    6    2    4    0    2  942    7]
 [   1    2    1    3    9    5    0    3    1  984]]
accuracy_test 0.9853
precision_test 0.9852837789421318
recall_test 0.9851824786629008
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step
conf_matrix_train [[5915    0    2    0    0    0    2    0    2    2]
 [   0 6741    0    0    0    0    0    0    1    0]
 [   0    0 5957    0    1    0    0    0    0    0]
 [   0    0   10 6113    0    5    0    0    2    1]
 [   0    1    0    0 5832    1    2    0    0    6]
 [   0    0    0    0    0 5418    0    0    2    1]
 [   0    0    0    0    0    2 5911    0    5    0]
 [   0    5    7    1    1    0    0 6247    1    3]
 [   0    1    5    4    2    8    1    0 5828    2]
 [   0    0    3    0    3    1    0    1    1 5940]]
accuracy_train 0.9983666666666666
precision_train 0.9983386104539406
recall_train 0.9983632374234116
```

Możemy zauważyć niewielką poprawę w dokładności klasyfikacji obrazów aczkolwiek jest ona moim zdaniem tak mała, że można by ją pominąć i stosować mniej skomplikowaną architekturę cechującą się mniejszą złożonością obliczeniową modelu, co bezpośrednio przekłada się na czas propagacji danych z wejściaa do wyjścia układu (modelu).

Zadanie nr 2

Podzadanie nr 1

In [30]:
```
from keras.datasets import cifar10
(train_images, train_labels), (test_images, test_labels) = cifar10.load_d
```

Podzadanie nr 2

In [31]:
```
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',
'dog', 'frog', 'horse', 'ship', 'truck']
```

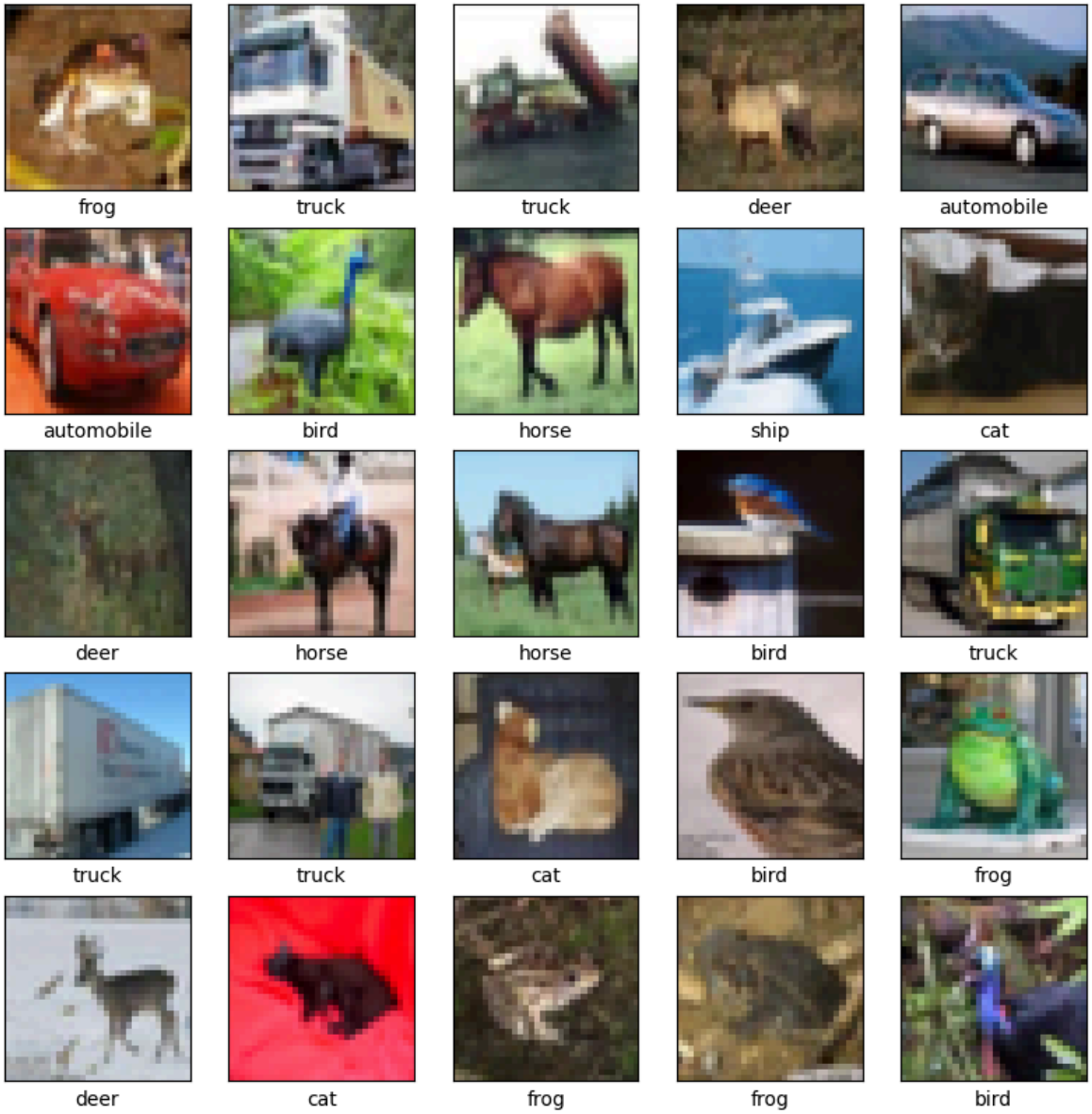
Podzadanie nr 3

In [32]:
```
print('train images size',train_images.shape)
print('test images size',test_images.shape)

train_images_norm = train_images / 256
test_images_norm = test_images / 256


train_labels = train_labels.reshape(-1,)
test_labels = test_labels.reshape(-1,)
num_classes = 10
y_train_labels = to_categorical(train_labels, num_classes)
y_test_labels = to_categorical(test_labels, num_classes)
```

```
train images size (50000, 32, 32, 3)
test images size (10000, 32, 32, 3)
```

Podzadanie nr 4

In [33]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=[10,10])
for i in range (25): # pierwsze 25 obrazków
  plt.subplot(5, 5, i+1)
  plt.xticks([])
  plt.yticks([])
  plt.grid(False)
  plt.imshow(train_images[i], cmap=plt.cm.binary)
  plt.xlabel(class_names[train_labels[i]])
```



Podzadanie nr 5

In [65]:
```
from keras import models
from keras import layers
import matplotlib.pyplot as plt

#utworzenie modelu

model3 = models.Sequential()
model3.add( layers.Input(shape=(32,32,3)))
model3.add( layers.Conv2D(32, (3,3), activation='relu') )
model3.add( layers.MaxPooling2D((2,2)) )
model3.add( layers.Conv2D(64, (3,3), activation='relu') )
model3.add( layers.MaxPooling2D((2,2)) )
model3.add( layers.Conv2D(128, (3,3), activation='relu') )
model3.add( layers.MaxPooling2D((2,2)) )
model3.add( layers.Flatten() )
model3.add( layers.Dense(64,activation='relu') )
model3.add( layers.Dense(64,activation='relu') )
model3.add( layers.Dense(64,activation='relu') )
model3.add( layers.Dense(10,activation='softmax') )
model3.compile( optimizer='adam', loss='categorical_crossentropy',
```

```
metrics=['accuracy'])

print( model2.summary() )
```

Model: "sequential_4"

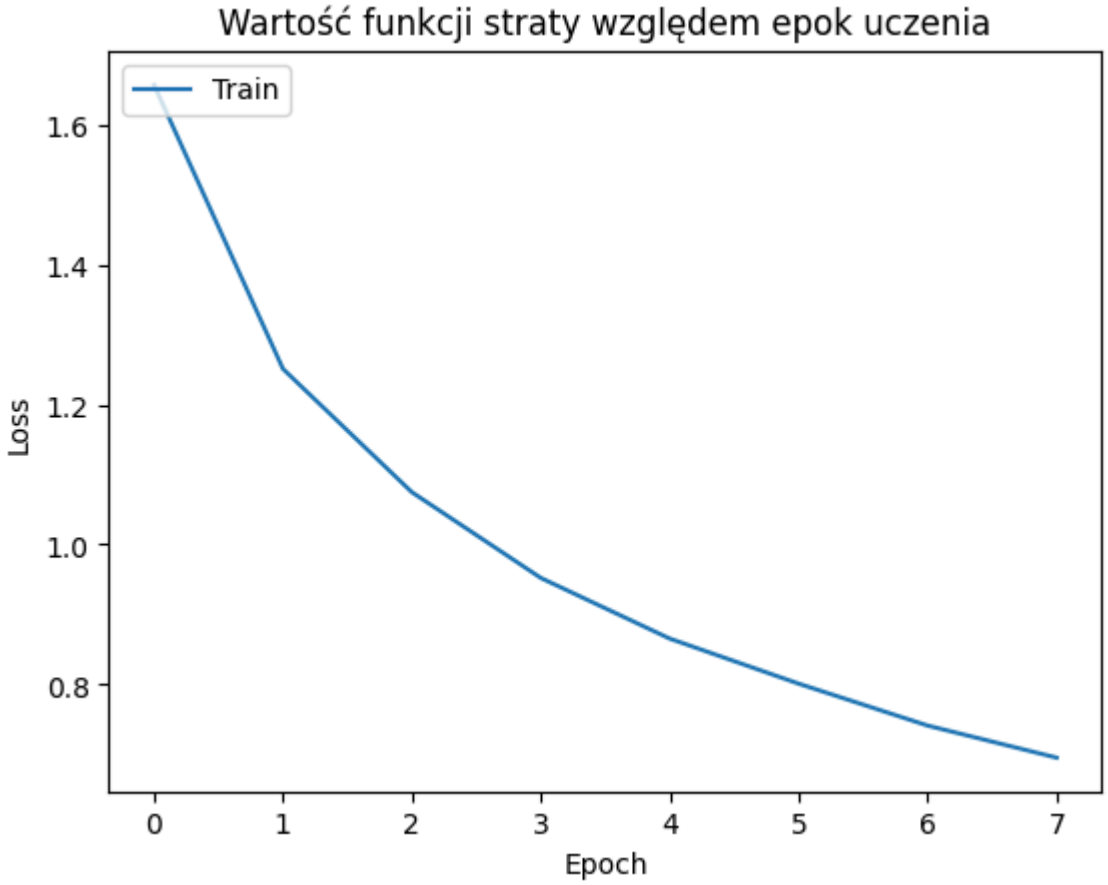
Layer (type)	Output Shape
conv2d_6 (Conv2D)	(None, 26, 26, 32)
max_pooling2d_6 (MaxPooling2D)	(None, 13, 13, 32)
conv2d_7 (Conv2D)	(None, 11, 11, 64)
max_pooling2d_7 (MaxPooling2D)	(None, 5, 5, 64)
flatten_4 (Flatten)	(None, 1600)
dense_8 (Dense)	(None, 64)
dense_9 (Dense)	(None, 10)

Total params: 365,792 (1.40 MB)
Trainable params: 121,930 (476.29 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 243,862 (952.59 KB)
None

Podzadanie nr 6

In [66]:
```
history3 = model3.fit(train_images_norm, y_train_labels, epochs=8, batch_
validation_data=(test_images_norm, y_test_labels))

plt.plot(history3.history['loss'])
plt.title('Wartość funkcji straty względem epok uczenia')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train'], loc='upper left')
plt.show()
print("Accuracy:", history3.history['accuracy'][-1])
```

```
Epoch 1/8
782/782 ━━━━━━━━━━━━━━━━━━━━ 72s 88ms/step - accuracy: 0.2873 - loss: 1.89
05 - val_accuracy: 0.5150 - val_loss: 1.3287
Epoch 2/8
782/782 ━━━━━━━━━━━━━━━━━━━━ 80s 86ms/step - accuracy: 0.5330 - loss: 1.29
38 - val_accuracy: 0.5881 - val_loss: 1.1447
Epoch 3/8
782/782 ━━━━━━━━━━━━━━━━━━━━ 80s 83ms/step - accuracy: 0.6083 - loss: 1.10
47 - val_accuracy: 0.6373 - val_loss: 1.0351
Epoch 4/8
782/782 ━━━━━━━━━━━━━━━━━━━━ 68s 87ms/step - accuracy: 0.6589 - loss: 0.96
34 - val_accuracy: 0.6677 - val_loss: 0.9606
Epoch 5/8
782/782 ━━━━━━━━━━━━━━━━━━━━ 81s 86ms/step - accuracy: 0.6937 - loss: 0.87
10 - val_accuracy: 0.6830 - val_loss: 0.9225
Epoch 6/8
782/782 ━━━━━━━━━━━━━━━━━━━━ 67s 86ms/step - accuracy: 0.7211 - loss: 0.79
88 - val_accuracy: 0.6883 - val_loss: 0.8998
Epoch 7/8
782/782 ━━━━━━━━━━━━━━━━━━━━ 81s 86ms/step - accuracy: 0.7450 - loss: 0.73
24 - val_accuracy: 0.6871 - val_loss: 0.9116
Epoch 8/8
782/782 ━━━━━━━━━━━━━━━━━━━━ 82s 86ms/step - accuracy: 0.7621 - loss: 0.68
01 - val_accuracy: 0.6890 - val_loss: 0.9039
```




```
Accuracy: 0.7571399807929993
```

Podzadanie nr 7

In [69]:
```
from keras.losses import categorical_crossentropy
from sklearn.metrics import accuracy_score, precision_score, recall_score
import numpy as np
def metrics(y_pred, _y,label):
```

```
  # Zaokrąglenie wyników przewidywań
  y_pred_rounded = np.argmax(y_pred, axis=1)
  # obliczanie wartości funkcji straty

  # Obliczenie metryk
  accuracy = accuracy_score(_y, y_pred_rounded)
  precision = precision_score(_y, y_pred_rounded, average="macro")
  recall = recall_score(_y, y_pred_rounded, average="macro")
  # Uzyskanie macierzy pomyłek
  conf_matrix = confusion_matrix(_y, y_pred_rounded)
  # Wyświetlanie wyników
  print(label)
  print("Accuracy:", accuracy)
  print("Precision:", precision)
  print("Recall:", precision)
  print("Confusion Matrix:\n", conf_matrix)
def countMistakes(y_pred, _y):
  mistakes = 0
  for i in range(len(_y)):
    if(y_pred[i] != _y[i]):
      mistakes += 1
  return mistakes
# zbiór treningowy:
train_y_pred = model3.predict(train_images_norm)
loss = categorical_crossentropy(y_train_labels,train_y_pred)
loss = sum(loss) / len(loss)
print("loss:",loss)
metrics(train_y_pred,train_labels, "Wartości średniej funkcji straty oraz
print("Liczba błędów: ", countMistakes(np.argmax(train_y_pred,axis=1), tr
# zbiór testowy:
test_y_pred = model3.predict(test_images_norm)
loss = categorical_crossentropy(y_test_labels,test_y_pred)
loss = sum(loss) / len(loss)
print("loss:",loss)
metrics(test_y_pred,test_labels, "Wartości średniej funkcji straty oraz m
print("Liczba błędów: ", countMistakes(np.argmax(test_y_pred, axis=1), te
```

```
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 20s 13ms/step
loss: tf.Tensor(0.6669084, shape=(), dtype=float32)
Wartości funkcji straty oraz metryk dla zbioru treningowego
Accuracy: 0.76672
Precision: 0.7799227254803096
Recall: 0.7799227254803096
Confusion Matrix:
 [[4106  134  338   95   66   37   54   29  114   27]
 [  33 4686   43   24    4   25   76   16   35   58]
 [ 199   22 3676  176  251  233  386   23   27    7]
 [  71   10  391 2659  164 1085  549   46   24    1]
 [  56    4  483  210 3635  164  360   74   10    4]
 [  15    9  247  512  186 3770  175   72   11    3]
 [   9   13  165  109   65   91 4531    5    9    3]
 [  19   14  243  188  549  418   41 3518    7    3]
 [ 316  235  113  100   24   42   52    6 4069   43]
 [ 153  573   75  139   21   89  145   55   64 3686]]
Liczba błędów:  11664 z 50000  wszystkich próbek.
313/313 ━━━━━━━━━━━━━━━━━━━━ 5s 15ms/step
loss: tf.Tensor(0.9038903, shape=(), dtype=float32)
Wartości funkcji straty oraz metryk dla zbioru testowego
Accuracy: 0.689
Precision: 0.7051358959714612
Recall: 0.7051358959714612
Confusion Matrix:
 [[760  33  90  13  20   4  16   8  39  17]
 [ 12 887  14  13   3   9  18   1  14  29]
 [ 50   6 647  53  55  84  86   8   5   6]
 [ 20  16  89 431  52 244 126  10   6   6]
 [ 22   4 132  54 622  35  99  27   5   0]
 [ 12   4  70 126  41 672  54  17   3   1]
 [  4   2  44  27  27  27 863   3   3   0]
 [ 11   5  62  56 125 115  14 605   1   6]
 [105  67  29  25   7  13   8   2 737   7]
 [ 30 143  19  37  10  19  25  26  25 666]]
Liczba błędów:  3110 z 10000  wszystkich próbek.
```

Podzadanie nr 8

In [70]:

```python
import numpy as np
badIndexes = []
test_y_pred_rounded = np.argmax(test_y_pred, axis=1)
# wyznaczenie indeksów źle sklasyfikowanych obrazów
for i in range(len(test_labels)):
  if(test_y_pred_rounded[i] != test_labels[i]):
    badIndexes.append(i)

len_badIndexes = len(badIndexes)
# wyswietlenie 4 obrazków źle sklasyfikowanych
for i in range(4):
  if i < len_badIndexes:
    ind = badIndexes[i]
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(test_images[ind], cmap=plt.cm.binary)
    plt.show()
```

```
    print("Sklasyfikowano jako:",class_names[test_y_pred_rounded[ind]])
    print("Poprawna klasyfikacja:",class_names[test_labels[ind]])
```

```
Sklasyfikowano jako: automobile
Poprawna klasyfikacja: ship
```

```
Sklasyfikowano jako: deer
Poprawna klasyfikacja: dog
```

```
Sklasyfikowano jako: cat
Poprawna klasyfikacja: horse
```

```
Sklasyfikowano jako: airplane
Poprawna klasyfikacja: deer
```