

Для вашего проекта решите указанные задачи.

1) Используя табличные данные части №1, решите задачу регрессии с помощью нейронных сетей.

- Рассмотрите минимум 3 архитектуры нейронной сети с минимум 3 разными параметрами модели и обучения.
- Визуализируйте архитектуры моделей.
- Постройте графики зависимости значений метрик и функции потерь от номера эпохи.
- Выберите лучшую модель.
- Настройте гиперпараметры модели и определите метрики работы модели при этих значениях.
- Оцените качество работы модели на тестовых данных и оцените недообучение и переобучение.

2) Используя табличные данные части №1, повторите действия п.1, решив задачу классификации.

3) Возьмите датасет или изображений, или видео, или текстов, или звуковых/речевых данных, которые связаны с вашим проектом и нужны для решения задач проекта или создания нового умного функционала продукта/сервиса проекта.

- Проведите обработку взятых данных с помощью нейронных сетей (аналогично предыдущим пунктам).
- Выполните п.3, используя AutoKeras.

\*Если ваш проект связан с рекомендательными системами или обучением с подкреплением, то можно адаптировать/изменить п.3 для решения такой задачи.

Описание проекта:

Будем работать с датасетом физической активности, которую собирает приложение о туристических маршрутах.

В этом датасете собраны данные 30 человек, выполняющих различные действия со смартфоном на поясе. Данные записывались с помощью датчиков (акселерометра и гироскопа) в этом смартфоне. Были зафиксированы: "3-осевое линейное ускорение" (tAcc-XYZ) и "3-осевая угловая скорость" (tGyro-XYZ).

```
1 import pandas as pd
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import seaborn as sns
```

```
1 train = pd.read_csv('train.csv')
2 test = pd.read_csv('test.csv')
```

```
1 # Проверка на пропуски
2 print("Пропуски в тренировочном наборе данных:")
3 print(train.isnull().sum().sum())
4 print("\nПропуски в тестовом наборе данных:")
5 print(test.isnull().sum().sum())
```

```
➦ Пропуски в тренировочном наборе данных:
0
```

```
Пропуски в тестовом наборе данных:
0
```

```
1 # Проверка типов данных
2 print("\nТипы данных в тренировочном наборе:")
3 print(train.dtypes)
4 print("\nТипы данных в тестовом наборе:")
5 print(test.dtypes)
```

```
➦ Типы данных в тренировочном наборе:
tBodyAcc-mean()-X      float64
tBodyAcc-mean()-Y      float64
tBodyAcc-mean()-Z      float64
tBodyAcc-std()-X       float64
tBodyAcc-std()-Y       float64
...
angle(X,gravityMean)    float64
angle(Y,gravityMean)    float64
angle(Z,gravityMean)    float64
subject                int64
Activity               object
Length: 563, dtype: object
```

```
Типы данных в тестовом наборе:
tBodyAcc-mean()-X      float64
tBodyAcc-mean()-Y      float64
tBodyAcc-mean()-Z      float64
tBodyAcc-std()-X       float64
```

```
tBodyAcc-std()-Y      float64
...
angle(X,gravityMean)  float64
angle(Y,gravityMean)  float64
angle(Z,gravityMean)  float64
subject              int64
Activity              object
Length: 563, dtype: object
```

```
1 # Проверка на дубликаты
2 print("\nДубликаты в тренировочном наборе:")
3 print(train.duplicated().sum())
4 print("\nДубликаты в тестовом наборе:")
5 print(test.duplicated().sum())
```



Дубликаты в тренировочном наборе:  
0

Дубликаты в тестовом наборе:  
0

```
1 # Проверка статистических данных
2 print("\nОписательная статистика тренировочного набора:")
3 print(train.describe())
4 print("\nОписательная статистика тестового набора:")
5 print(test.describe())
```



Описательная статистика тренировочного набора:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	\
count	7352.000000	7352.000000	7352.000000	
mean	0.274488	-0.017695	-0.109141	
std	0.070261	0.040811	0.056635	
min	-1.000000	-1.000000	-1.000000	
25%	0.262975	-0.024863	-0.120993	
50%	0.277193	-0.017219	-0.108676	
75%	0.288461	-0.010783	-0.097794	
max	1.000000	1.000000	1.000000	

	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	\
count	7352.000000	7352.000000	7352.000000	7352.000000	
mean	-0.605438	-0.510938	-0.604754	-0.630512	
std	0.448734	0.502645	0.418687	0.424073	
min	-1.000000	-0.999873	-1.000000	-1.000000	
25%	-0.992754	-0.978129	-0.980233	-0.993591	
50%	-0.946196	-0.851897	-0.859365	-0.950709	
75%	-0.242813	-0.034231	-0.262415	-0.292680	
max	1.000000	0.916238	1.000000	1.000000	

	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X	...	\
count	7352.000000	7352.000000	7352.000000	...	
mean	-0.526907	-0.606150	-0.468604	...	
std	0.485942	0.414122	0.544547	...	
min	-1.000000	-1.000000	-1.000000	...	
25%	-0.978162	-0.980251	-0.936219	...	
50%	-0.857328	-0.857143	-0.881637	...	
75%	-0.066701	-0.265671	-0.017129	...	
max	0.967664	1.000000	1.000000	...	

	fBodyBodyGyroJerkMag-skewness()	fBodyBodyGyroJerkMag-kurtosis()	\
count	7352.000000	7352.000000	
mean	-0.307009	-0.625294	
std	0.321011	0.307584	
min	-0.995357	-0.999765	
25%	-0.542602	-0.845573	
50%	-0.343685	-0.711692	
75%	-0.126979	-0.503878	
max	0.989538	0.956845	

	angle(tBodyAccMean,gravity)	angle(tBodyAccJerkMean,gravityMean)	\
count	7352.000000	7352.000000	
mean	0.008684	0.002186	
std	0.336787	0.448306	
min	-0.976580	-1.000000	
25%	-0.121527	-0.289549	
50%	0.009509	0.008943	
75%	0.150865	0.292861	
max	1.000000	1.000000	

	angle(tBodyGyroMean,gravityMean)	angle(tBodyGyroJerkMean,gravityMean)	\
count	7352.000000	7352.000000	
mean	0.008726	-0.005981	
std	0.608303	0.477975	
min	-1.000000	-1.000000	
25%	-0.482273	-0.376341	

```
1 train.head()
```

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X	...	fBodyBodyGyroJerk
0	0.288585	-0.020294	-0.132905	-0.995279	-0.983111	-0.913526	-0.995112	-0.983185	-0.923527	-0.934724	...	-0.
1	0.278419	-0.016411	-0.123520	-0.998245	-0.975300	-0.960322	-0.998807	-0.974914	-0.957686	-0.943068	...	-0.
2	0.279653	-0.019467	-0.113462	-0.995380	-0.967187	-0.978944	-0.996520	-0.963668	-0.977469	-0.938692	...	-0.
3	0.279174	-0.026201	-0.123283	-0.996091	-0.983403	-0.990675	-0.997099	-0.982750	-0.989302	-0.938692	...	-0.
4	0.276629	-0.016570	-0.115362	-0.998139	-0.980817	-0.990482	-0.998321	-0.979672	-0.990441	-0.942469	...	-0.

5 rows × 563 columns

```
1 test.head()
```

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X	...	fBodyBodyGyroJerk
0	0.257178	-0.023285	-0.014654	-0.938404	-0.920091	-0.667683	-0.952501	-0.925249	-0.674302	-0.894088	...	-0.
1	0.286027	-0.013163	-0.119083	-0.975415	-0.967458	-0.944958	-0.986799	-0.968401	-0.945823	-0.894088	...	-0.
2	0.275485	-0.026050	-0.118152	-0.993819	-0.969926	-0.962748	-0.994403	-0.970735	-0.963483	-0.939260	...	-0.
3	0.270298	-0.032614	-0.117520	-0.994743	-0.973268	-0.967091	-0.995274	-0.974471	-0.968897	-0.938610	...	-0.
4	0.274833	-0.027848	-0.129527	-0.993852	-0.967445	-0.978295	-0.994111	-0.965953	-0.977346	-0.938610	...	-0.

5 rows × 563 columns

```
1 # Вывод всех признаков тренировочного набора данных
2 print("Признаки тренировочного набора данных:")
3 int(train.columns.tolist())
4
5 # Вывод всех признаков тестового набора данных
6 print("\nПризнаки тестового набора данных:")
7 print(test.columns.tolist())
```

```
Признаки тренировочного набора данных:
['tBodyAcc-mean()-X', 'tBodyAcc-mean()-Y', 'tBodyAcc-mean()-Z', 'tBodyAcc-std()-X', 'tBodyAcc-std()-Y', 'tBodyAcc-std()-Z', 'tBodyAcc-mad()-X', 'tBodyAcc-mad()-Y', 'tBodyAcc-mad()-Z', 'tBodyAcc-max()-X', 'fBodyBodyGyroJerk']

Признаки тестового набора данных:
['tBodyAcc-mean()-X', 'tBodyAcc-mean()-Y', 'tBodyAcc-mean()-Z', 'tBodyAcc-std()-X', 'tBodyAcc-std()-Y', 'tBodyAcc-std()-Z', 'tBodyAcc-mad()-X', 'tBodyAcc-mad()-Y', 'tBodyAcc-mad()-Z', 'tBodyAcc-max()-X', 'fBodyBodyGyroJerk']
```

## ✓ 1) Задача регрессии с помощью нейронных сетей

Архитектура 1: Простая полносвязная сеть

За целевую переменную возьмем например tBodyAcc-max()-X

```
1 from keras.models import Sequential
2 from keras.layers import Dense

1 y_train = train["tBodyAcc-max()-X"]
2 y_test = test["tBodyAcc-max()-X"]

1 X_train = train[["tBodyAccMag-mean()", "tBodyGyroJerk-mad()-X", "tGravityAcc-min()-X", "fBodyAcc-bandsEnergy()-1,8.2", "angle(X,gravityMean)", "angle(X,gravityMean)"])
2 X_test = test[["tBodyAccMag-mean()", "tBodyGyroJerk-mad()-X", "tGravityAcc-min()-X", "fBodyAcc-bandsEnergy()-1,8.2", "angle(X,gravityMean)", "angle(X,gravityMean)"]]

1 # Архитектура модели
2 model_1 = Sequential()
3 model_1.add(Dense(64, input_dim=X_train.shape[1], activation='relu'))
4 model_1.add(Dense(1, activation='linear'))
5
6 # Компиляция модели
7 model_1.compile(optimizer='adam', loss='mean_squared_error', metrics=['mae'])
8
9 # Обучение модели
10 history_1 = model_1.fit(X_train, y_train, epochs=100, batch_size=32, validation_split=0.2, verbose=0)
```

```

1 # Оценка модели
2 eval_result = model_1.evaluate(X_test, y_test)
3 print("[test loss, test mae]:", eval_result)

93/93 [=====] - 0s 2ms/step - loss: 0.0189 - mae: 0.0803
[test loss, test mae]: [0.018851246684789658, 0.08025195449590683]

```

## Архитектура 2: Глубокая полносвязная сеть

```

1 # Архитектура модели
2 model_2 = Sequential()
3 model_2.add(Dense(128, input_dim=X_train.shape[1], activation='relu'))
4 model_2.add(Dense(64, activation='relu'))
5 model_2.add(Dense(64, activation='relu'))
6 model_2.add(Dense(64, activation='relu'))
7 model_2.add(Dense(64, activation='relu'))
8 model_2.add(Dense(32, activation='relu'))
9 model_2.add(Dense(1, activation='linear'))
10
11 # Компиляция модели
12 model_2.compile(optimizer='sgd', loss='mean_squared_error', metrics=['mae'])
13
14 # Обучение модели
15 history_2 = model_2.fit(X_train, y_train, epochs=100, batch_size=64, validation_split=0.2, verbose=0)
16

1 # Оценка модели
2 eval_result = model_2.evaluate(X_test, y_test)
3 print("[test loss, test mae]:", eval_result)

93/93 [=====] - 0s 3ms/step - loss: 0.0147 - mae: 0.0739
[test loss, test mae]: [0.01474537793546915, 0.07393579185009003]

```

## Архитектура 3: Сеть с регуляризацией

```

1 from keras.layers import Dropout
2 from keras.regularizers import l2
3
4 # Архитектура модели
5 model_3 = Sequential()
6 model_3.add(Dense(64, input_dim=X_train.shape[1], activation='relu', kernel_regularizer=l2(0.01)))
7 model_3.add(Dropout(0.5))
8 model_3.add(Dense(32, activation='relu', kernel_regularizer=l2(0.01)))
9 model_3.add(Dropout(0.5))
10 model_3.add(Dense(1, activation='linear'))
11
12 # Компиляция модели
13 model_3.compile(optimizer='rmsprop', loss='mean_squared_error', metrics=['mae'])
14
15 # Обучение модели
16 history_3 = model_3.fit(X_train, y_train, epochs=100, batch_size=32, validation_split=0.2, verbose=0)
17

1 # Оценка модели
2 eval_result = model_3.evaluate(X_test, y_test)
3 print("[test loss, test mae]:", eval_result)

93/93 [=====] - 0s 2ms/step - loss: 0.0293 - mae: 0.1102
[test loss, test mae]: [0.029261024668812752, 0.1101958230137825]

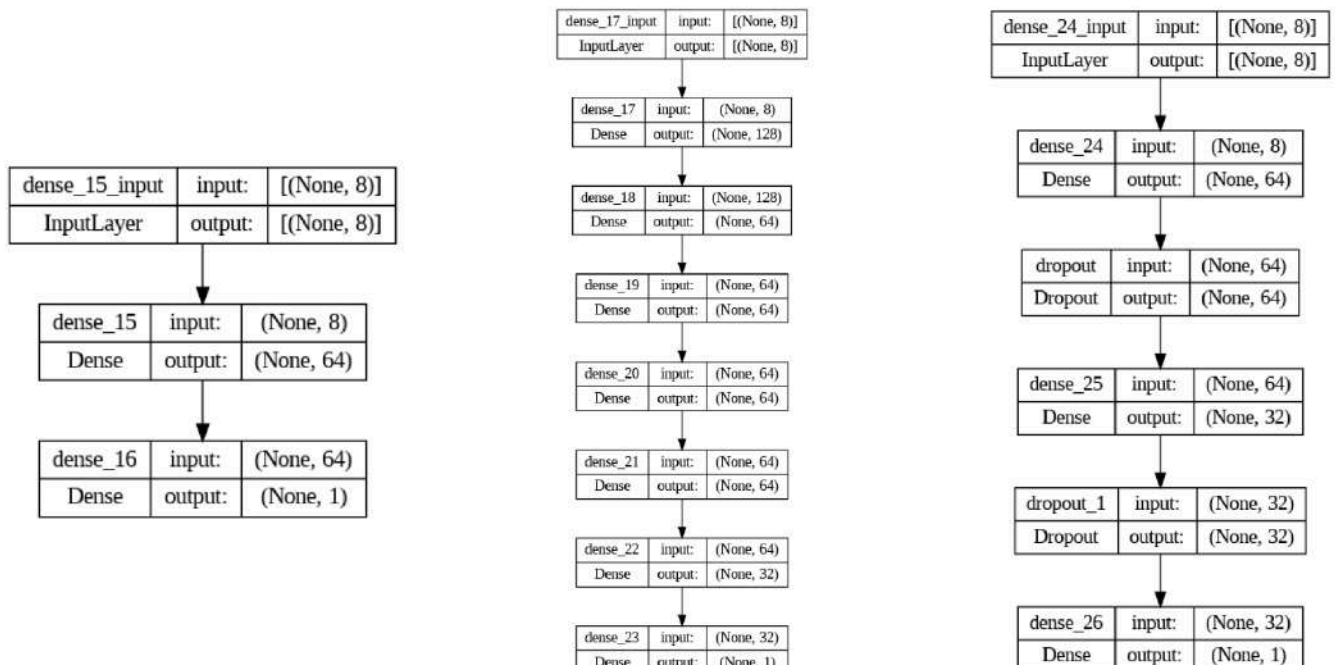
```

## Визуализация архитектур моделей

```

1 from tensorflow.keras.utils import plot_model
2 from IPython.display import Image
3 import matplotlib.image as mpimg
4
5 # Сохранение визуализаций архитектур моделей в файлы
6 plot_model(model_1, to_file='model_1.png', show_shapes=True, show_layer_names=True)
7 plot_model(model_2, to_file='model_2.png', show_shapes=True, show_layer_names=True)
8 plot_model(model_3, to_file='model_3.png', show_shapes=True, show_layer_names=True)
9
10 # Отображение изображений архитектур моделей на одном plot
11 fig, axs = plt.subplots(1, 3, figsize=(20, 10))
12
13 # Отображение модели 1
14 img_1 = mpimg.imread('model_1.png')
15 axs[0].imshow(img_1)
16 axs[0].axis('off') # Скрыть оси
17
18 # Отображение модели 2
19 img_2 = mpimg.imread('model_2.png')
20 axs[1].imshow(img_2)
21 axs[1].axis('off')
22
23 # Отображение модели 3
24 img_3 = mpimg.imread('model_3.png')
25 axs[2].imshow(img_3)
26 axs[2].axis('off')
27
28 plt.show()
29
30

```



Визуализация метрик и функции потерь

Для построения графиков зависимости метрик и функции потерь от номера эпохи

```

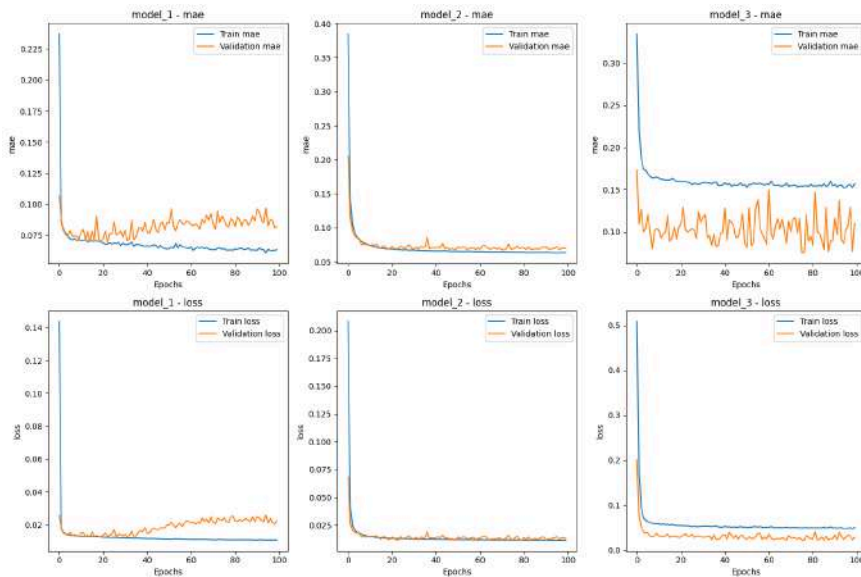
1 def plot_all_metrics(histories, metric_names):
2     fig, axes = plt.subplots(nrows=len(metric_names), ncols=len(histories), figsize=(15, 10))
3
4     for col, (model_name, history) in enumerate(histories.items()):
5         for row, metric_name in enumerate(metric_names):
6             axes[row, col].plot(history.history[metric_name], label=f'Train {metric_name}')
7             axes[row, col].plot(history.history[f'val_{metric_name}'], label=f'Validation {metric_name}')
8             axes[row, col].set_title(f'{model_name} - {metric_name}')
9             axes[row, col].set_xlabel('Epochs')
10            axes[row, col].set_ylabel(metric_name)
11            axes[row, col].legend()
12
13 plt.tight_layout()
14 plt.show()

```

```

1 histories = {
2     'model_1': history_1,
3     'model_2': history_2,
4     'model_3': history_3
5 }
6
7 # Метрики, которые вы хотите визуализировать
8 metric_names = ['mae', 'loss']
9
10 # Вызов функции для визуализации
11 plot_all_metrics(histories, metric_names)

```



```
1 !pip install keras-tuner --upgrade
```



```

Collecting keras-tuner
  Downloading keras_tuner-1.4.7-py3-none-any.whl (129 kB)
    129.1/129.1 kB 2.7 MB/s eta 0:00:00
Requirement already satisfied: keras in /usr/local/lib/python3.10/dist-packages (from keras-tuner) (2.15.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from keras-tuner) (24.0)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from keras-tuner) (2.31.0)
Collecting kt-legacy (from keras-tuner)
  Downloading kt_legacy-1.0.5-py3-none-any.whl (9.6 kB)
Requirement already satisfied: charset-normalizer<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (2024.6.2)
Installing collected packages: kt-legacy, keras-tuner
Successfully installed keras-tuner-1.4.7 kt-legacy-1.0.5

```



```

1 import kerastuner as kt
2 from keras.models import Sequential
3 from keras.layers import Dense
4 from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
5
6 def build_model(hp):
7     model = Sequential()
8     model.add(Dense(units=hp.Int('units', min_value=32, max_value=512, step=32),
9                             activation=hp.Choice('activation', values=['relu', 'tanh', 'sigmoid']),
10                            input_dim=X_train.shape[1]))
11     for i in range(hp.Int('num_layers', 1, 3)):
12         model.add(Dense(units=hp.Int(f'units_{i}', min_value=32, max_value=512, step=32),
13                             activation=hp.Choice(f'activation_{i}', values=['relu', 'tanh', 'sigmoid']))))
14     model.add(Dense(1, activation='linear'))
15     model.compile(
16         optimizer=hp.Choice('optimizer', values=['adam', 'sgd', 'rmsprop']),
17         loss='mean_squared_error',
18         metrics=['mae'])
19     )
20     return model
21
22 tuner = kt.Hyperband(
23     build_model,
24     objective='val_mae',
25     max_epochs=10,
26     hyperband_iterations=2,
27     directory='my_dir',
28     project_name='keras_tuner_demo'
29 )
30
31 # Поиск гиперпараметров
32 tuner.search(X_train, y_train, epochs=50, validation_split=0.2, verbose=1)
33
34 # Получение оптимальных гиперпараметров
35 best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]
36 print(f"Лучшие гиперпараметры: {best_hps.values}")
37

```

↻ Reloading Tuner from my\_dir/keras\_tuner\_demo/tuner0.json  
 Лучшие гиперпараметры: {'units': 256, 'activation': 'tanh', 'num\_layers': 3, 'units\_0': 416, 'activation\_0': 'tanh', 'optimizer': 'r

1

```

1 # Обучение модели с оптимальными гиперпараметрами
2 model = tuner.hypermodel.build(best_hps)
3 history = model.fit(X_train, y_train, epochs=50, validation_split=0.2, verbose=0)
4
5 # Оценка лучшей модели
6 eval_result = model.evaluate(X_test, y_test)
7 print("[test loss, test mae]:", eval_result)

```

↻ 93/93 [=====] - 0s 3ms/step - loss: 0.0156 - mae: 0.0764  
 [test loss, test mae]: [0.015587517991662025, 0.0763791874051094]

```

1 # Сохранение визуализации архитектуры модели в файл
2 plot_model(model, to_file='model_best.png', show_shapes=True, show_layer_names=True)
3
4 # Отображение изображения архитектуры модели
5 img = mpimg.imread('model_best.png')
6 plt.figure(figsize=(10, 10))
7 plt.imshow(img)
8 plt.axis('off') # Скрыть оси
9 plt.show()
10

```



dense_27_input	input:	[(None, 8)]
InputLayer	output:	[(None, 8)]



dense_27	input:	(None, 8)
Dense	output:	(None, 256)



dense_28	input:	(None, 256)
Dense	output:	(None, 416)



dense_29	input:	(None, 416)
Dense	output:	(None, 448)



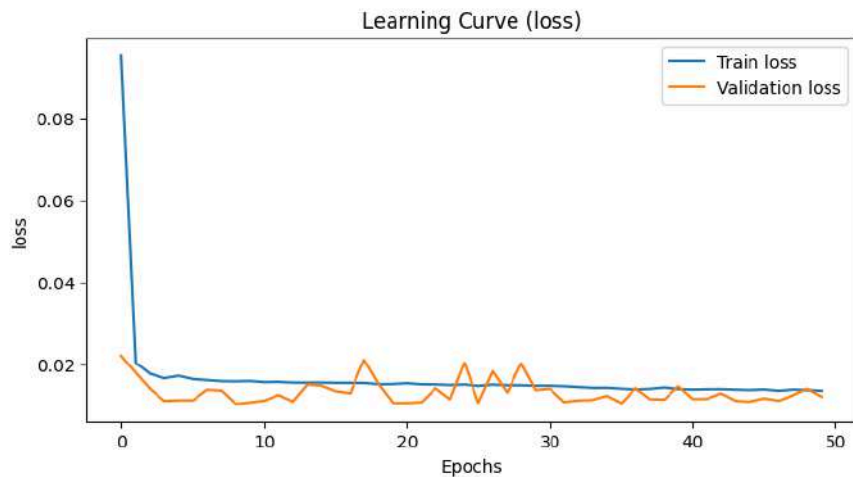
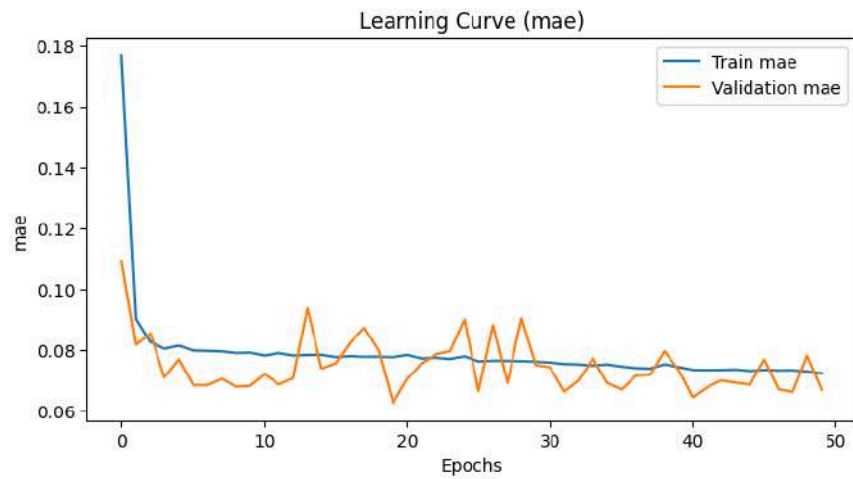
dense_30	input:	(None, 448)
Dense	output:	(None, 32)



dense_31	input:	(None, 32)
Dense	output:	(None, 1)

```
1 import matplotlib.pyplot as plt
2
3 def plot_learning_curve(history, metric):
4     plt.figure(figsize=(8, 4))
5     plt.plot(history.history[metric], label=f'Train {metric}')
6     plt.plot(history.history[f'val_{metric}'], label=f'Validation {metric}')
7     plt.title(f'Learning Curve ({metric})')
8     plt.xlabel('Epochs')
9     plt.ylabel(metric)
10    plt.legend()
11    plt.show()
12
13
14 plot_learning_curve(history, 'mae')
15 plot_learning_curve(history, 'loss')
16
17
```





## ✓ 2) Задача классификации с помощью нейронных сетей

```
1 from keras.models import Sequential
2 from keras.layers import Dense, Dropout
3 from keras.optimizers import Adam

1 X_train = train[["tBodyAcc-max()-X", "tBodyAccMag-mean()", "tBodyGyroJerk-mad()-X", "tGravityAcc-min()-X", "fBodyAcc-bandsEnergy()-1,8.2", "angle(X,gr
2 X_test = test[["tBodyAcc-max()-X", "tBodyAccMag-mean()", "tBodyGyroJerk-mad()-X", "tGravityAcc-min()-X", "fBodyAcc-bandsEnergy()-1,8.2", "angle(X,gr
3
4 y_train = train["Activity"]
5 y_test = test["Activity"]

1 from sklearn.preprocessing import LabelEncoder
2 from keras.utils import to_categorical
3 # Создание экземпляра LabelEncoder
4 label_encoder = LabelEncoder()
5
6 # Обучение энкодера и преобразование меток
7 y_train_encoded = label_encoder.fit_transform(y_train)
8 y_test_encoded = label_encoder.transform(y_test)
9
10 # Теперь преобразование числовых меток в категориальный формат
11 y_train_categorical = to_categorical(y_train_encoded)
12 y_test_categorical = to_categorical(y_test_encoded)
13

1 # Архитектура 1: Простая полносвязная сеть
2 model_1 = Sequential([
3     Dense(64, input_shape=(X_train.shape[1],), activation='relu'),
4     Dense(64, activation='relu'),
5     Dense(y_train_categorical.shape[1], activation='softmax')
6 ])
7 model_1.compile(optimizer=Adam(lr=0.001), loss='categorical_crossentropy', metrics=['accuracy'])
8 history_1 = model_1.fit(X_train, y_train_categorical, epochs=30, batch_size=32, validation_split=0.2)
```

```

WARNING:abs1:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use the legacy optimizer, e.g.,tf.keras.optimi
Epoch 1/30
184/184 [=====] - 4s 11ms/step - loss: 0.8929 - accuracy: 0.6854 - val_loss: 0.4422 - val_accuracy: 0.88
Epoch 2/30
184/184 [=====] - 2s 11ms/step - loss: 0.4231 - accuracy: 0.8340 - val_loss: 0.3305 - val_accuracy: 0.96
Epoch 3/30
184/184 [=====] - 2s 9ms/step - loss: 0.3318 - accuracy: 0.8594 - val_loss: 0.3382 - val_accuracy: 0.86
Epoch 4/30
184/184 [=====] - 1s 5ms/step - loss: 0.2896 - accuracy: 0.8781 - val_loss: 0.3191 - val_accuracy: 0.88
Epoch 5/30
184/184 [=====] - 1s 5ms/step - loss: 0.2664 - accuracy: 0.8888 - val_loss: 0.3359 - val_accuracy: 0.88
Epoch 6/30
184/184 [=====] - 1s 5ms/step - loss: 0.2545 - accuracy: 0.8896 - val_loss: 0.3247 - val_accuracy: 0.88
Epoch 7/30
184/184 [=====] - 1s 5ms/step - loss: 0.2472 - accuracy: 0.8953 - val_loss: 0.3153 - val_accuracy: 0.89
Epoch 8/30
184/184 [=====] - 1s 5ms/step - loss: 0.2383 - accuracy: 0.8956 - val_loss: 0.3185 - val_accuracy: 0.88
Epoch 9/30
184/184 [=====] - 1s 5ms/step - loss: 0.2316 - accuracy: 0.9004 - val_loss: 0.3167 - val_accuracy: 0.88
Epoch 10/30
184/184 [=====] - 0s 3ms/step - loss: 0.2278 - accuracy: 0.9022 - val_loss: 0.3184 - val_accuracy: 0.89
Epoch 11/30
184/184 [=====] - 0s 3ms/step - loss: 0.2230 - accuracy: 0.9036 - val_loss: 0.3088 - val_accuracy: 0.89
Epoch 12/30
184/184 [=====] - 0s 2ms/step - loss: 0.2177 - accuracy: 0.9075 - val_loss: 0.3090 - val_accuracy: 0.88
Epoch 13/30
184/184 [=====] - 1s 3ms/step - loss: 0.2139 - accuracy: 0.9072 - val_loss: 0.3034 - val_accuracy: 0.88
Epoch 14/30
184/184 [=====] - 0s 3ms/step - loss: 0.2116 - accuracy: 0.9112 - val_loss: 0.3078 - val_accuracy: 0.89
Epoch 15/30
184/184 [=====] - 1s 3ms/step - loss: 0.2107 - accuracy: 0.9099 - val_loss: 0.3263 - val_accuracy: 0.87
Epoch 16/30
184/184 [=====] - 1s 3ms/step - loss: 0.2047 - accuracy: 0.9104 - val_loss: 0.3100 - val_accuracy: 0.89
Epoch 17/30
184/184 [=====] - 1s 3ms/step - loss: 0.2016 - accuracy: 0.9145 - val_loss: 0.2991 - val_accuracy: 0.89
Epoch 18/30
184/184 [=====] - 1s 3ms/step - loss: 0.1988 - accuracy: 0.9174 - val_loss: 0.2957 - val_accuracy: 0.89
Epoch 19/30
184/184 [=====] - 0s 3ms/step - loss: 0.1987 - accuracy: 0.9158 - val_loss: 0.2897 - val_accuracy: 0.90
Epoch 20/30
184/184 [=====] - 1s 3ms/step - loss: 0.1962 - accuracy: 0.9160 - val_loss: 0.3031 - val_accuracy: 0.89
Epoch 21/30
184/184 [=====] - 1s 3ms/step - loss: 0.1934 - accuracy: 0.9186 - val_loss: 0.3005 - val_accuracy: 0.89
Epoch 22/30
184/184 [=====] - 1s 3ms/step - loss: 0.1902 - accuracy: 0.9197 - val_loss: 0.2918 - val_accuracy: 0.89
Epoch 23/30
184/184 [=====] - 1s 3ms/step - loss: 0.1884 - accuracy: 0.9175 - val_loss: 0.3076 - val_accuracy: 0.89
Epoch 24/30
184/184 [=====] - 0s 3ms/step - loss: 0.1886 - accuracy: 0.9180 - val_loss: 0.3022 - val_accuracy: 0.89
Epoch 25/30
184/184 [=====] - 0s 3ms/step - loss: 0.1857 - accuracy: 0.9214 - val_loss: 0.3179 - val_accuracy: 0.88
Epoch 26/30
184/184 [=====] - 0s 3ms/step - loss: 0.1877 - accuracy: 0.9203 - val_loss: 0.2945 - val_accuracy: 0.89
Epoch 27/30
184/184 [=====] - 0s 3ms/step - loss: 0.1869 - accuracy: 0.9199 - val_loss: 0.2899 - val_accuracy: 0.89
Epoch 28/30
184/184 [=====] - 1s 4ms/step - loss: 0.1852 - accuracy: 0.9174 - val_loss: 0.2761 - val_accuracy: 0.90

```

```

1 # Архитектура 2: Полносвязная сеть с Dropout
2 model_2 = Sequential([
3     Dense(128, input_shape=(X_train.shape[1],), activation='relu'),
4     Dropout(0.5),
5     Dense(128, activation='relu'),
6     Dropout(0.5),
7     Dense(y_train_categorical.shape[1], activation='softmax')
8 ])
9 model_2.compile(optimizer=Adam(lr=0.0005), loss='categorical_crossentropy', metrics=['accuracy'])
10 history_2 = model_2.fit(X_train, y_train_categorical, epochs=30, batch_size=64, validation_split=0.2)
11

```

```


WARNING:abs1:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use the legacy optimizer, e.g.,tf.keras.optimi
Epoch 1/30
92/92 [=====] - 1s 6ms/step - loss: 1.1251 - accuracy: 0.5322 - val_loss: 0.5898 - val_accuracy: 0.8736
Epoch 2/30
92/92 [=====] - 0s 4ms/step - loss: 0.6755 - accuracy: 0.6970 - val_loss: 0.4415 - val_accuracy: 0.8804
Epoch 3/30
92/92 [=====] - 0s 4ms/step - loss: 0.5533 - accuracy: 0.7613 - val_loss: 0.3627 - val_accuracy: 0.9028
Epoch 4/30
92/92 [=====] - 0s 5ms/step - loss: 0.4909 - accuracy: 0.7909 - val_loss: 0.3336 - val_accuracy: 0.8939
Epoch 5/30
92/92 [=====] - 0s 4ms/step - loss: 0.4455 - accuracy: 0.8121 - val_loss: 0.3232 - val_accuracy: 0.8865
Epoch 6/30
92/92 [=====] - 0s 4ms/step - loss: 0.4025 - accuracy: 0.8332 - val_loss: 0.3191 - val_accuracy: 0.8810
Epoch 7/30
92/92 [=====] - 0s 4ms/step - loss: 0.3779 - accuracy: 0.8371 - val_loss: 0.3087 - val_accuracy: 0.8804
Epoch 8/30
92/92 [=====] - 0s 4ms/step - loss: 0.3557 - accuracy: 0.8556 - val_loss: 0.3370 - val_accuracy: 0.8729
Epoch 9/30

```

```
92/92 [=====] - 0s 4ms/step - loss: 0.3426 - accuracy: 0.8643 - val_loss: 0.3089 - val_accuracy: 0.8817
Epoch 10/30
92/92 [=====] - 0s 4ms/step - loss: 0.3292 - accuracy: 0.8711 - val_loss: 0.3077 - val_accuracy: 0.8878
Epoch 11/30
92/92 [=====] - 0s 4ms/step - loss: 0.3189 - accuracy: 0.8723 - val_loss: 0.3123 - val_accuracy: 0.8919
Epoch 12/30
92/92 [=====] - 0s 4ms/step - loss: 0.3126 - accuracy: 0.8742 - val_loss: 0.3118 - val_accuracy: 0.8844
Epoch 13/30
92/92 [=====] - 0s 3ms/step - loss: 0.3071 - accuracy: 0.8737 - val_loss: 0.3151 - val_accuracy: 0.8892
Epoch 14/30
92/92 [=====] - 0s 4ms/step - loss: 0.3037 - accuracy: 0.8810 - val_loss: 0.3070 - val_accuracy: 0.8926
Epoch 15/30
92/92 [=====] - 1s 6ms/step - loss: 0.2971 - accuracy: 0.8832 - val_loss: 0.3053 - val_accuracy: 0.8878
Epoch 16/30
92/92 [=====] - 0s 4ms/step - loss: 0.2837 - accuracy: 0.8854 - val_loss: 0.3039 - val_accuracy: 0.8858
Epoch 17/30
92/92 [=====] - 0s 4ms/step - loss: 0.2772 - accuracy: 0.8885 - val_loss: 0.3129 - val_accuracy: 0.8919
Epoch 18/30
92/92 [=====] - 0s 4ms/step - loss: 0.2741 - accuracy: 0.8876 - val_loss: 0.3059 - val_accuracy: 0.8926
Epoch 19/30
92/92 [=====] - 0s 4ms/step - loss: 0.2695 - accuracy: 0.8905 - val_loss: 0.3118 - val_accuracy: 0.8926
Epoch 20/30
92/92 [=====] - 0s 4ms/step - loss: 0.2602 - accuracy: 0.8941 - val_loss: 0.2993 - val_accuracy: 0.8939
Epoch 21/30
92/92 [=====] - 1s 6ms/step - loss: 0.2574 - accuracy: 0.8953 - val_loss: 0.3097 - val_accuracy: 0.8831
Epoch 22/30
92/92 [=====] - 1s 7ms/step - loss: 0.2575 - accuracy: 0.8978 - val_loss: 0.3013 - val_accuracy: 0.8899
Epoch 23/30
92/92 [=====] - 1s 7ms/step - loss: 0.2616 - accuracy: 0.8961 - val_loss: 0.2933 - val_accuracy: 0.8933
Epoch 24/30
92/92 [=====] - 1s 8ms/step - loss: 0.2499 - accuracy: 0.8978 - val_loss: 0.3005 - val_accuracy: 0.8933
Epoch 25/30
92/92 [=====] - 1s 6ms/step - loss: 0.2507 - accuracy: 0.8995 - val_loss: 0.2966 - val_accuracy: 0.8939
Epoch 26/30
92/92 [=====] - 1s 7ms/step - loss: 0.2473 - accuracy: 0.9019 - val_loss: 0.3174 - val_accuracy: 0.8906
Epoch 27/30
92/92 [=====] - 1s 7ms/step - loss: 0.2417 - accuracy: 0.9034 - val_loss: 0.3135 - val_accuracy: 0.8946
Epoch 28/30
92/92 [=====] - 1s 6ms/step - loss: 0.2410 - accuracy: 0.9012 - val_loss: 0.3032 - val_accuracy: 0.8939
```

1 # Архитектура 3: Глубокая полносвязная сеть

```
2 model_3 = Sequential([
3     Dense(256, input_shape=(X_train.shape[1],), activation='relu'),
4     Dense(256, activation='relu'),
5     Dense(256, activation='relu'),
6     Dense(256, activation='relu'),
7     Dense(256, activation='relu'),
8     Dense(256, activation='relu'),
9     Dense(y_train_categorical.shape[1], activation='softmax')
10 ])
11 model_3.compile(optimizer=Adam(lr=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])
12 history_3 = model_3.fit(X_train, y_train_categorical, epochs=30, batch_size=128, validation_split=0.2)
13
```

 WARNING: `absl:lr` is deprecated in Keras optimizer, please use `learning\_rate` or use the legacy optimizer, e.g., `tf.keras.optimizers.Adam(lr=0.0001)`

```
Epoch 1/30
46/46 [=====] - 2s 21ms/step - loss: 0.7686 - accuracy: 0.6910 - val_loss: 0.3338 - val_accuracy: 0.8892
Epoch 2/30
46/46 [=====] - 1s 16ms/step - loss: 0.3431 - accuracy: 0.8485 - val_loss: 0.4094 - val_accuracy: 0.8555
Epoch 3/30
46/46 [=====] - 1s 16ms/step - loss: 0.2748 - accuracy: 0.8845 - val_loss: 0.3307 - val_accuracy: 0.8851
Epoch 4/30
46/46 [=====] - 1s 14ms/step - loss: 0.2477 - accuracy: 0.8908 - val_loss: 0.3162 - val_accuracy: 0.8858
Epoch 5/30
46/46 [=====] - 1s 16ms/step - loss: 0.2247 - accuracy: 0.9078 - val_loss: 0.2970 - val_accuracy: 0.8986
Epoch 6/30
46/46 [=====] - 1s 16ms/step - loss: 0.2114 - accuracy: 0.9114 - val_loss: 0.3116 - val_accuracy: 0.8824
Epoch 7/30
46/46 [=====] - 1s 21ms/step - loss: 0.2126 - accuracy: 0.9097 - val_loss: 0.3118 - val_accuracy: 0.8782
Epoch 8/30
46/46 [=====] - 1s 26ms/step - loss: 0.2236 - accuracy: 0.9061 - val_loss: 0.3125 - val_accuracy: 0.8776
Epoch 9/30
46/46 [=====] - 1s 25ms/step - loss: 0.1990 - accuracy: 0.9220 - val_loss: 0.2955 - val_accuracy: 0.8895
Epoch 10/30
46/46 [=====] - 1s 27ms/step - loss: 0.1770 - accuracy: 0.9243 - val_loss: 0.3117 - val_accuracy: 0.8865
Epoch 11/30
46/46 [=====] - 1s 27ms/step - loss: 0.1768 - accuracy: 0.9277 - val_loss: 0.3025 - val_accuracy: 0.8915
Epoch 12/30
46/46 [=====] - 1s 29ms/step - loss: 0.1775 - accuracy: 0.9265 - val_loss: 0.3005 - val_accuracy: 0.8926
Epoch 13/30
46/46 [=====] - 1s 16ms/step - loss: 0.1642 - accuracy: 0.9308 - val_loss: 0.3627 - val_accuracy: 0.8796
Epoch 14/30
46/46 [=====] - 1s 15ms/step - loss: 0.1594 - accuracy: 0.9337 - val_loss: 0.3481 - val_accuracy: 0.8872
Epoch 15/30
46/46 [=====] - 1s 15ms/step - loss: 0.1774 - accuracy: 0.9245 - val_loss: 0.3728 - val_accuracy: 0.8804
Epoch 16/30
46/46 [=====] - 1s 16ms/step - loss: 0.1583 - accuracy: 0.9323 - val_loss: 0.3657 - val_accuracy: 0.8796
Epoch 17/30
```

```

46/46 [=====] - 1s 16ms/step - loss: 0.1470 - accuracy: 0.9347 - val_loss: 0.4045 - val_accuracy: 0.8745
Epoch 18/30
46/46 [=====] - 1s 15ms/step - loss: 0.1470 - accuracy: 0.9350 - val_loss: 0.3850 - val_accuracy: 0.8906
Epoch 19/30
46/46 [=====] - 1s 15ms/step - loss: 0.1419 - accuracy: 0.9373 - val_loss: 0.3895 - val_accuracy: 0.8634
Epoch 20/30
46/46 [=====] - 1s 16ms/step - loss: 0.1384 - accuracy: 0.9356 - val_loss: 0.3401 - val_accuracy: 0.8776
Epoch 21/30
46/46 [=====] - 1s 20ms/step - loss: 0.1399 - accuracy: 0.9405 - val_loss: 0.3775 - val_accuracy: 0.8917
Epoch 22/30
46/46 [=====] - 1s 26ms/step - loss: 0.1274 - accuracy: 0.9410 - val_loss: 0.3968 - val_accuracy: 0.8831
Epoch 23/30
46/46 [=====] - 1s 24ms/step - loss: 0.1222 - accuracy: 0.9444 - val_loss: 0.3850 - val_accuracy: 0.8865
Epoch 24/30
46/46 [=====] - 1s 27ms/step - loss: 0.1287 - accuracy: 0.9420 - val_loss: 0.4216 - val_accuracy: 0.8851
Epoch 25/30
46/46 [=====] - 1s 32ms/step - loss: 0.1212 - accuracy: 0.9442 - val_loss: 0.4838 - val_accuracy: 0.8646
Epoch 26/30
46/46 [=====] - 1s 32ms/step - loss: 0.1222 - accuracy: 0.9442 - val_loss: 0.4150 - val_accuracy: 0.8715
Epoch 27/30
46/46 [=====] - 1s 32ms/step - loss: 0.1189 - accuracy: 0.9480 - val_loss: 0.3874 - val_accuracy: 0.8707
Epoch 28/30

```

```

1 # Оценка моделей
2 score_1 = model_1.evaluate(X_test, y_test_categorical, verbose=1)
3 score_2 = model_2.evaluate(X_test, y_test_categorical, verbose=1)
4 score_3 = model_3.evaluate(X_test, y_test_categorical, verbose=1)
5
6 print(f'Модель 1 - Точность: {score_1[1]:.4f}')
7 print(f'Модель 2 - Точность: {score_2[1]:.4f}')
8 print(f'Модель 3 - Точность: {score_3[1]:.4f}')

```

```

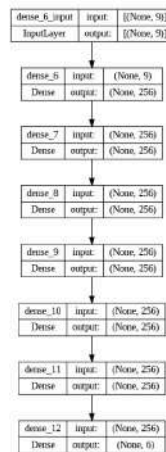
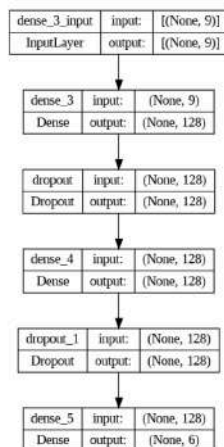
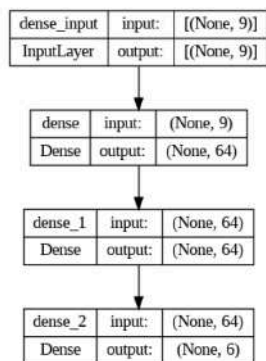
93/93 [=====] - 0s 3ms/step - loss: 0.5275 - accuracy: 0.8208
93/93 [=====] - 0s 3ms/step - loss: 0.4783 - accuracy: 0.8347
93/93 [=====] - 1s 6ms/step - loss: 1.2838 - accuracy: 0.8056
Модель 1 - Точность: 0.8208
Модель 2 - Точность: 0.8347
Модель 3 - Точность: 0.8056

```

```

1 from tensorflow.keras.utils import plot_model
2 from IPython.display import Image
3 import matplotlib.image as mpimg
4
5 # Сохранение визуализаций архитектур моделей в файлы
6 plot_model(model_1, to_file='model_1_c1.png', show_shapes=True, show_layer_names=True)
7 plot_model(model_2, to_file='model_2_c1.png', show_shapes=True, show_layer_names=True)
8 plot_model(model_3, to_file='model_3_c1.png', show_shapes=True, show_layer_names=True)
9
10 # Отображение изображений архитектур моделей на одном plot
11 fig, axs = plt.subplots(1, 3, figsize=(20, 10))
12
13 # Отображение модели 1
14 img_1 = mpimg.imread('model_1_c1.png')
15 axs[0].imshow(img_1)
16 axs[0].axis('off') # Скрыть оси
17
18 # Отображение модели 2
19 img_2 = mpimg.imread('model_2_c1.png')
20 axs[1].imshow(img_2)
21 axs[1].axis('off')
22
23 # Отображение модели 3
24 img_3 = mpimg.imread('model_3_c1.png')
25 axs[2].imshow(img_3)
26 axs[2].axis('off')
27
28 plt.show()
29
30

```



```

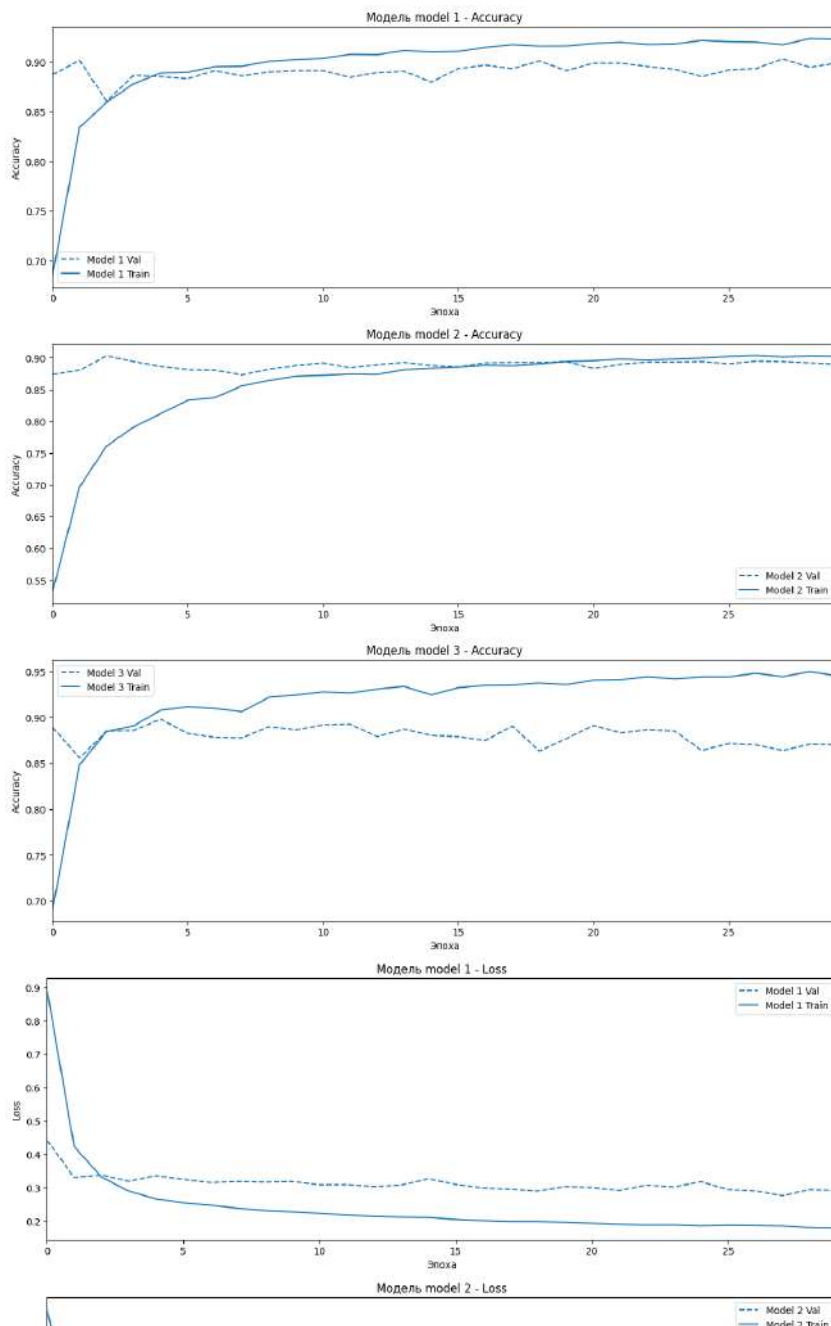
1 def plot_history(history, name, key='accuracy'):
2     plt.figure(figsize=(15, 5))
3
4     val = plt.plot(history.epoch, history.history['val_'+key],
5                    '--', label=name.title()+' Val')
6     plt.plot(history.epoch, history.history[key], color=val[0].get_color(),
7             label=name.title()+' Train')
8
9     plt.title(f'Модель {name} - {key.replace("_", " ").title()}')
10    plt.xlabel('Эпоха')
11    plt.ylabel(key.replace('_', ' ').title())
12    plt.legend()
13    plt.xlim([0, max(history.epoch)])
14    plt.show()

```

```

1 plot_history(history_1, 'model 1', key='accuracy')
2 plot_history(history_2, 'model 2', key='accuracy')
3 plot_history(history_3, 'model 3', key='accuracy')
4
5 # Построение графика потерь для каждой модели
6 plot_history(history_1, 'model 1', key='loss')
7 plot_history(history_2, 'model 2', key='loss')
8 plot_history(history_3, 'model 3', key='loss')

```



```
1 !pip install keras-tuner --upgrade
```



```
Collecting keras-tuner
  Downloading keras_tuner-1.4.7-py3-none-any.whl (129 kB)
    129.1/129.1 kB 4.2 MB/s eta 0:00:00
Requirement already satisfied: keras in /usr/local/lib/python3.10/dist-packages (from keras-tuner) (2.15.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from keras-tuner) (24.1)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from keras-tuner) (2.31.0)
Collecting kt-legacy (from keras-tuner)
  Downloading kt_legacy-1.0.5-py3-none-any.whl (9.6 kB)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (2024.6.2)
Installing collected packages: kt-legacy, keras-tuner
Successfully installed keras-tuner-1.4.7 kt-legacy-1.0.5
```

```
1 from kerastuner import RandomSearch
2 from kerastuner.engine.hyperparameters import HyperParameters
3 import tensorflow as tf
4 from tensorflow.keras import Sequential
5 from keras.layers import Dense, Dropout
6 from keras.optimizers import Adam
```



```
<ipython-input-21-b0a47e0e0420>:1: DeprecationWarning: `import kerastuner` is deprecated, please use `import keras_tuner`.
  from kerastuner import RandomSearch
```

```

1 # Функция создания модели с гиперпараметрами
2 def build_model(hp):
3     model = Sequential()
4     model.add(Dense(hp.Int('input_units', min_value=32, max_value=256, step=32),
5                       input_shape=(X_train.shape[1],), activation='relu'))
6     model.add(Dropout(hp.Float('dropout_1', min_value=0.0, max_value=0.5, default=0.25, step=0.05)))
7     model.add(Dense(hp.Int('dense_1_units', min_value=32, max_value=256, step=32), activation='relu'))
8     model.add(Dropout(hp.Float('dropout_2', min_value=0.0, max_value=0.5, default=0.25, step=0.05)))
9     model.add(Dense(y_train_categorical.shape[1], activation='softmax'))
10
11     model.compile(optimizer=Adam(hp.Choice('learning_rate', values=[1e-2, 1e-3, 1e-4])),
12                  loss='categorical_crossentropy',
13                  metrics=['accuracy'])
14     return model
15
16 # Создание объекта RandomSearch
17 tuner = RandomSearch(
18     build_model,
19     objective='val_accuracy',
20     max_trials=5, # Количество вариантов гиперпараметров для пробы
21     executions_per_trial=3, # Количество повторений каждого эксперимента
22     directory='my_dir', # Директория для сохранения логов
23     project_name='hparam_tuning'
24 )
25
26

```

```

1 # Запуск поиска
2 tuner.search(X_train, y_train_categorical,
3             epochs=10,
4             batch_size=64,
5             validation_split=0.2)
6
7 # Получение наилучших гиперпараметров
8 best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

```

```

Trial 5 Complete [00h 00m 25s]
val_accuracy: 0.8991615573565165

Best val_accuracy So Far: 0.905733068784078
Total elapsed time: 00h 02m 40s

```

1

```

1 # Загрузка лучшей модели
2 best_model = tuner.get_best_models(num_models=1)[0]

```

```

1 # Получение значений гиперпараметров с проверкой на их наличие
2 epochs = best_hps.get('epochs') if 'epochs' in best_hps.values else 40
3 batch_size = best_hps.get('batch_size') if 'batch_size' in best_hps.values else 64
4
5 # Обучение модели с лучшими гиперпараметрами
6 history = best_model.fit(X_train, y_train_categorical,
7                          epochs=epochs,
8                          batch_size=batch_size,
9                          validation_split=0.2)
10
11
12

```

```

Epoch 1/40
92/92 [=====] - 2s 10ms/step - loss: 0.5372 - accuracy: 0.7856 - val_loss: 0.4287 - val_accuracy: 0.8975
Epoch 2/40
92/92 [=====] - 1s 7ms/step - loss: 0.5205 - accuracy: 0.7905 - val_loss: 0.4065 - val_accuracy: 0.9021
Epoch 3/40
92/92 [=====] - 1s 7ms/step - loss: 0.4935 - accuracy: 0.7960 - val_loss: 0.3891 - val_accuracy: 0.9103
Epoch 4/40
92/92 [=====] - 1s 7ms/step - loss: 0.4731 - accuracy: 0.8118 - val_loss: 0.3753 - val_accuracy: 0.9028
Epoch 5/40
92/92 [=====] - 1s 7ms/step - loss: 0.4657 - accuracy: 0.8107 - val_loss: 0.3644 - val_accuracy: 0.9075
Epoch 6/40
92/92 [=====] - 1s 8ms/step - loss: 0.4498 - accuracy: 0.8158 - val_loss: 0.3563 - val_accuracy: 0.8906
Epoch 7/40
92/92 [=====] - 1s 8ms/step - loss: 0.4428 - accuracy: 0.8206 - val_loss: 0.3476 - val_accuracy: 0.9048
Epoch 8/40
92/92 [=====] - 0s 4ms/step - loss: 0.4288 - accuracy: 0.8225 - val_loss: 0.3434 - val_accuracy: 0.8892
Epoch 9/40
92/92 [=====] - 0s 4ms/step - loss: 0.4216 - accuracy: 0.8208 - val_loss: 0.3381 - val_accuracy: 0.8946
Epoch 10/40
92/92 [=====] - 0s 4ms/step - loss: 0.4127 - accuracy: 0.8271 - val_loss: 0.3348 - val_accuracy: 0.8804
Epoch 11/40
92/92 [=====] - 0s 5ms/step - loss: 0.3952 - accuracy: 0.8385 - val_loss: 0.3363 - val_accuracy: 0.8729
Epoch 12/40
92/92 [=====] - 0s 4ms/step - loss: 0.3998 - accuracy: 0.8312 - val_loss: 0.3290 - val_accuracy: 0.8878
Epoch 13/40

```

```

92/92 [=====] - 0s 4ms/step - loss: 0.3878 - accuracy: 0.8381 - val_loss: 0.3269 - val_accuracy: 0.8810
Epoch 14/40
92/92 [=====] - 0s 4ms/step - loss: 0.3763 - accuracy: 0.8473 - val_loss: 0.3258 - val_accuracy: 0.8865
Epoch 15/40
92/92 [=====] - 0s 4ms/step - loss: 0.3786 - accuracy: 0.8398 - val_loss: 0.3256 - val_accuracy: 0.8810
Epoch 16/40
92/92 [=====] - 0s 4ms/step - loss: 0.3742 - accuracy: 0.8432 - val_loss: 0.3272 - val_accuracy: 0.8722
Epoch 17/40
92/92 [=====] - 0s 4ms/step - loss: 0.3661 - accuracy: 0.8415 - val_loss: 0.3236 - val_accuracy: 0.8797
Epoch 18/40
92/92 [=====] - 0s 4ms/step - loss: 0.3599 - accuracy: 0.8478 - val_loss: 0.3221 - val_accuracy: 0.8797
Epoch 19/40
92/92 [=====] - 0s 5ms/step - loss: 0.3552 - accuracy: 0.8459 - val_loss: 0.3225 - val_accuracy: 0.8770
Epoch 20/40
92/92 [=====] - 0s 4ms/step - loss: 0.3466 - accuracy: 0.8533 - val_loss: 0.3238 - val_accuracy: 0.8736
Epoch 21/40
92/92 [=====] - 0s 5ms/step - loss: 0.3433 - accuracy: 0.8587 - val_loss: 0.3252 - val_accuracy: 0.8736
Epoch 22/40
92/92 [=====] - 0s 4ms/step - loss: 0.3388 - accuracy: 0.8558 - val_loss: 0.3219 - val_accuracy: 0.8790
Epoch 23/40
92/92 [=====] - 0s 4ms/step - loss: 0.3342 - accuracy: 0.8607 - val_loss: 0.3236 - val_accuracy: 0.8756
Epoch 24/40
92/92 [=====] - 0s 4ms/step - loss: 0.3369 - accuracy: 0.8599 - val_loss: 0.3269 - val_accuracy: 0.8708
Epoch 25/40
92/92 [=====] - 0s 4ms/step - loss: 0.3307 - accuracy: 0.8609 - val_loss: 0.3231 - val_accuracy: 0.8763
Epoch 26/40
92/92 [=====] - 0s 5ms/step - loss: 0.3268 - accuracy: 0.8606 - val_loss: 0.3221 - val_accuracy: 0.8776
Epoch 27/40
92/92 [=====] - 0s 4ms/step - loss: 0.3239 - accuracy: 0.8587 - val_loss: 0.3267 - val_accuracy: 0.8729
Epoch 28/40
92/92 [=====] - 0s 4ms/step - loss: 0.3245 - accuracy: 0.8631 - val_loss: 0.3234 - val_accuracy: 0.8756
Epoch 29/40

```

```

1 from sklearn.metrics import classification_report, confusion_matrix
2
3 # Оценка модели на тестовых данных
4 test_loss, test_accuracy = best_model.evaluate(X_test, y_test_categorical)
5 print(f"Тестовая потеря: {test_loss}")
6 print(f"Тестовая точность: {test_accuracy}")
7

```

```

93/93 [=====] - 0s 2ms/step - loss: 0.4183 - accuracy: 0.8351
Тестовая потеря: 0.41826650500297546
Тестовая точность: 0.8350865244865417

```

```

1 # Предсказания на тестовых данных
2 y_pred = best_model.predict(X_test)
3 y_pred_classes = np.argmax(y_pred, axis=1)
4 y_true = np.argmax(y_test_categorical, axis=1)
5

```

```

93/93 [=====] - 0s 2ms/step

```

```

1
2 # Вывод отчета о классификации
3 print(classification_report(y_true, y_pred_classes))

```

```

precision    recall  f1-score   support

0           1.00      0.99      1.00       537
1           0.86      0.75      0.80       491
2           0.79      0.89      0.84       532
3           0.80      0.86      0.83       496
4           0.81      0.75      0.78       420
5           0.74      0.73      0.73       471

accuracy          0.84       2947
macro avg         0.83      0.83      0.83       2947
weighted avg      0.84      0.84      0.83       2947

```

```

1 # Вывод матрицы ошибок
2 print(confusion_matrix(y_true, y_pred_classes))

```

```

[[533  0  4  0  0  0]
 [  0 369 119  0  0  3]
 [  0  60 471  0  0  1]
 [  0  0  0 427 34 35]
 [  0  0  0 19 316 85]
 [  0  0  0 86 40 345]]

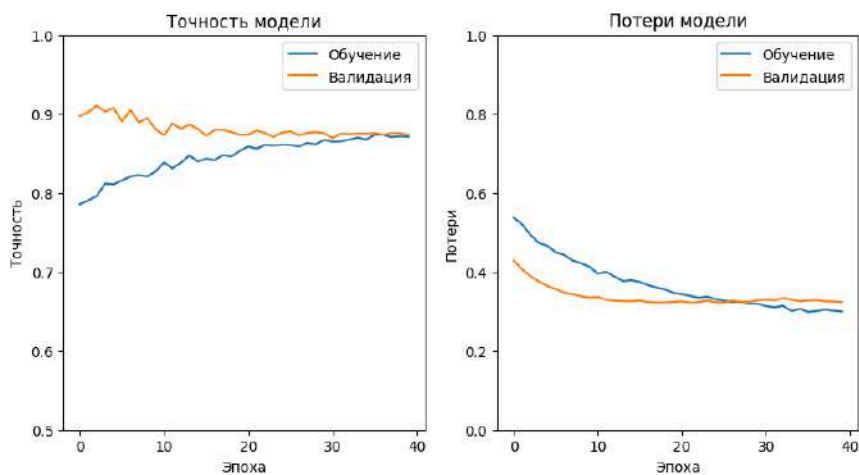
```



```

1 # Установка размера фигуры для более детального просмотра
2 plt.figure(figsize=(10, 5))
3
4 # Построение графика точности
5 plt.subplot(1, 2, 1)
6 plt.plot(history.history['accuracy'], label='Обучение')
7 plt.plot(history.history['val_accuracy'], label='Валидация')
8 plt.title('Точность модели')
9 plt.xlabel('Эпоха')
10 plt.ylabel('Точность')
11 plt.legend()
12
13 # Установка пределов для оси Y, чтобы увидеть более мелкие изменения
14 plt.ylim(0.5, 1) # Например, если вы хотите видеть изменения от 50% до 100%
15
16 # Построение графика потерь
17 plt.subplot(1, 2, 2)
18 plt.plot(history.history['loss'], label='Обучение')
19 plt.plot(history.history['val_loss'], label='Валидация')
20 plt.title('Потери модели')
21 plt.xlabel('Эпоха')
22 plt.ylabel('Потери')
23 plt.legend()
24
25 # Установка пределов для оси Y, чтобы увидеть более мелкие изменения
26 plt.ylim(0, 1) # Например, если вы хотите видеть изменения от 0 до 1
27
28 plt.show()
29

```



1

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 # Предсказание классов для тестового набора данных
5 y_pred = best_model.predict(X_test)
6 y_pred_classes = np.argmax(y_pred, axis=1)
7
8 # Вывод реальных и предсказанных классов
9 for i in range(70, 90):
10     print(f'Пример {i+1}: Реальный класс - {y_true[i]}, Предсказанный класс - {y_pred_classes[i]}')
11

```



```

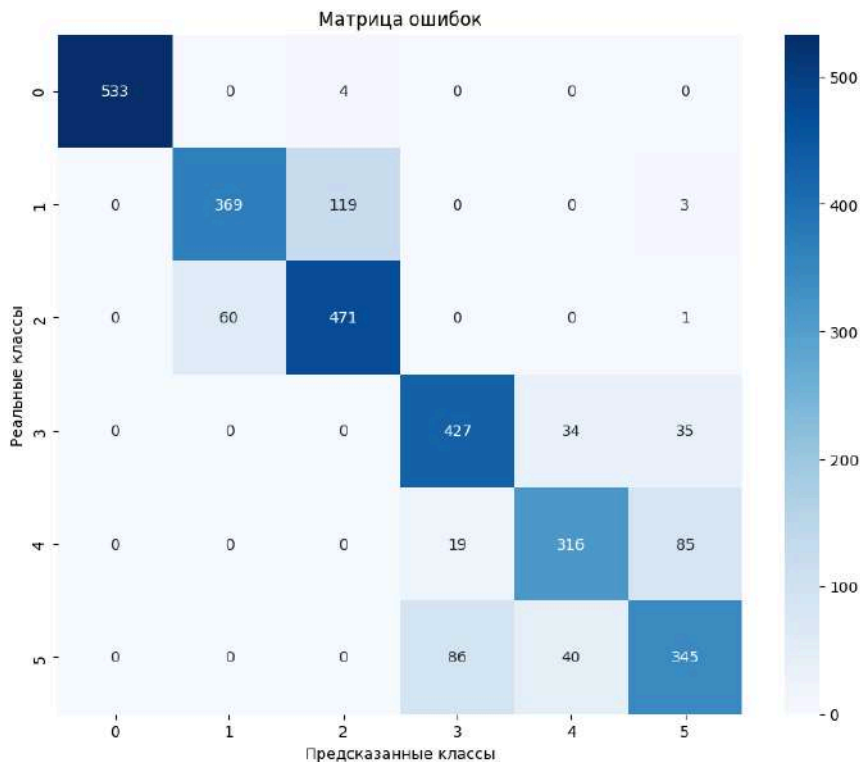
93/93 [=====] - 0s 3ms/step
Пример 71: Реальный класс - 0, Предсказанный класс - 0
Пример 72: Реальный класс - 0, Предсказанный класс - 0
Пример 73: Реальный класс - 0, Предсказанный класс - 0
Пример 74: Реальный класс - 0, Предсказанный класс - 0
Пример 75: Реальный класс - 0, Предсказанный класс - 0
Пример 76: Реальный класс - 0, Предсказанный класс - 0
Пример 77: Реальный класс - 0, Предсказанный класс - 0
Пример 78: Реальный класс - 0, Предсказанный класс - 0
Пример 79: Реальный класс - 0, Предсказанный класс - 0
Пример 80: Реальный класс - 3, Предсказанный класс - 3
Пример 81: Реальный класс - 3, Предсказанный класс - 3
Пример 82: Реальный класс - 3, Предсказанный класс - 3
Пример 83: Реальный класс - 3, Предсказанный класс - 3
Пример 84: Реальный класс - 3, Предсказанный класс - 3
Пример 85: Реальный класс - 3, Предсказанный класс - 3

```

Пример 86: Реальный класс - 3, Предсказанный класс - 3  
 Пример 87: Реальный класс - 3, Предсказанный класс - 3  
 Пример 88: Реальный класс - 3, Предсказанный класс - 3  
 Пример 89: Реальный класс - 3, Предсказанный класс - 3  
 Пример 90: Реальный класс - 3, Предсказанный класс - 3

```
1 import matplotlib.pyplot as plt
2 import seaborn as sns
3 from sklearn.metrics import confusion_matrix
4
5 # Предсказания на тестовых данных
6 y_pred = best_model.predict(X_test)
7 y_pred_classes = np.argmax(y_pred, axis=1)
8 y_true = np.argmax(y_test_categorical, axis=1)
9
10 # Визуализация матрицы ошибок
11 plt.figure(figsize=(10, 8))
12 cm = confusion_matrix(y_true, y_pred_classes)
13 sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
14 plt.title('Матрица ошибок')
15 plt.xlabel('Предсказанные классы')
16 plt.ylabel('Реальные классы')
17 plt.show()
18
19
20 plt.show()
21
```

93/93 [=====] - 0s 4ms/step



1

### 3) AutoKeras

3) Возьмите датасет или изображений, или видео, или текстов, или звуковых/речевых данных, которые связаны с вашим проектом и нужны для решения задач проекта или создания нового умного функционала продукта/сервиса проекта.

Проведите обработку взятых данных с помощью нейронных сетей (аналогично предыдущим пунктам).

Выполните п.3, используя AutoKeras.

\*Если ваш проект связан с рекомендательными системами или обучением с подкреплением, то можно адаптировать/изменить п.3 для решения такой задачи.

```
1 import os
2 import numpy as np
3 import pandas as pd
4 import tensorflow as tf
5
6 from tensorflow import io
7 from tensorflow import data as tfd
8 from tensorflow import image as tfi
9 from tensorflow.keras.preprocessing.image import ImageDataGenerator
10
11 import plotly.express as px
12 import matplotlib.pyplot as plt
```

```
1 from google.colab import drive
2 drive.mount('/content/drive')
3
```

↗ Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force\_remount=True).

```
1 train_path = "/content/drive/MyDrive/landscape/Training Data/"
2 test_path = "/content/drive/MyDrive/landscape/Testing Data/"
3 valid_path = "/content/drive/MyDrive/landscape/Validation Data/"
```

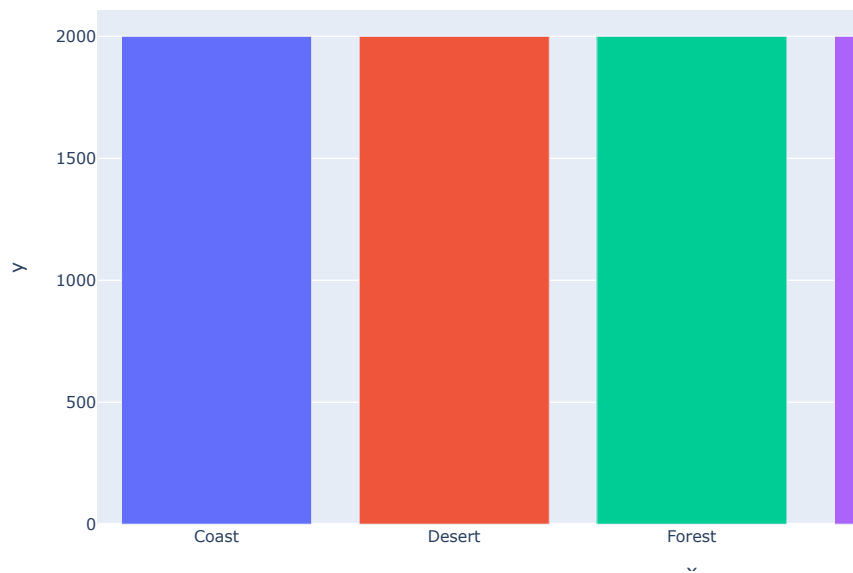
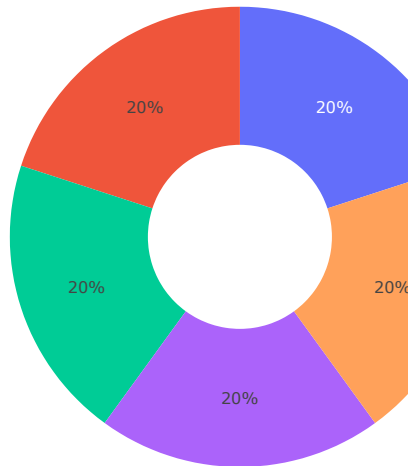
```
1 # Class Names
2 class_names = sorted(os.listdir(train_path))
3 n_classes = len(class_names)
4
5 # Show
6 print(f"Number of Classes : {n_classes}\nClass names : {class_names}")
```

↗ Number of Classes : 5  
Class names : ['Coast', 'Desert', 'Forest', 'Glacier', 'Mountain']

```
1 # Class Distribution
2 class_dis = [len(os.listdir(train_path + name)) for name in class_names]
3
4
5 # Visualize
6 fig = px.pie(names=class_names, values=class_dis, title="Training Class Distribution", hole=0.4)
7 fig.update_layout({'title':{'x':0.5}})
8 fig.show()
9
10 fig = px.bar(x=class_names, y=class_dis, color=class_names)
11 fig.show()
```



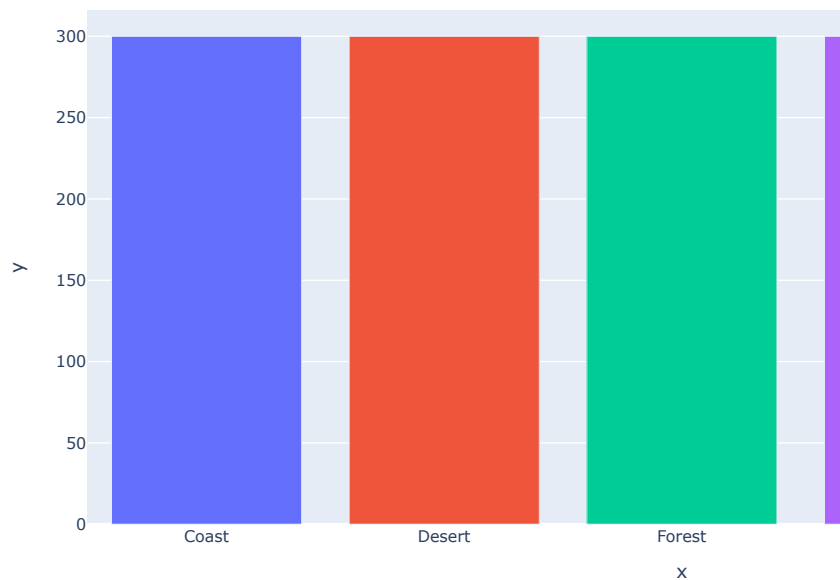
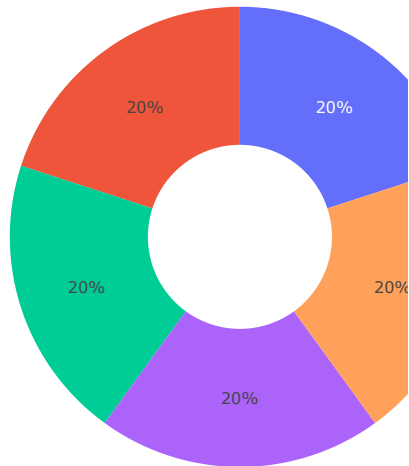
Training Class Distributio



```
1 # Class Distribution
2 class_dis = [len(os.listdir(valid_path + name)) for name in class_names]
3
4
5 # Visualize
6 fig = px.pie(names=class_names, values=class_dis, title="Validation Class Distribution", hole=0.4)
7 fig.update_layout({'title': {'x': 0.5}})
8 fig.show()
9
10 fig = px.bar(x=class_names, y=class_dis, color=class_names)
11 fig.show()
```



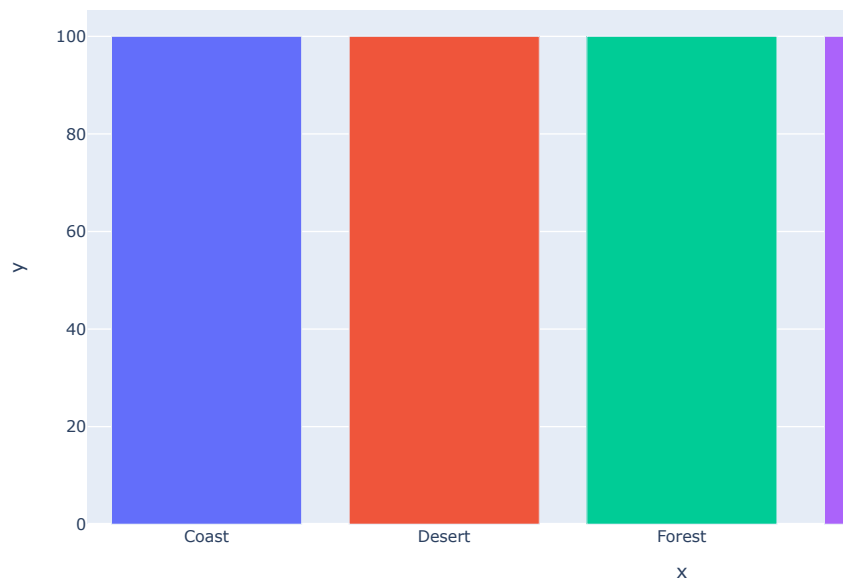
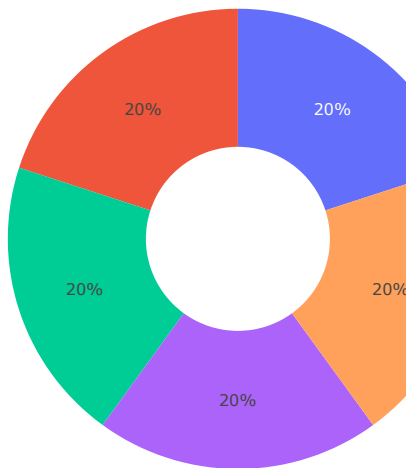
Validation Class Distribution



```
1 # Class Distribution
2 class_dis = [len(os.listdir(test_path + name)) for name in class_names]
3
4
5 # Visualize
6 fig = px.pie(names=class_names, values=class_dis, title="Testing Class Distribution", hole=0.4)
7 fig.update_layout({'title':{'x':0.5}})
8 fig.show()
9
10 fig = px.bar(x=class_names, y=class_dis, color=class_names)
11 fig.show()
```



## Testing Class Distribution



1

```
1 # List all TFRecords Paths
2 tfr_train = "/content/drive/MyDrive/landscape/TFrecords/Train/"
3 tfr_valid = "/content/drive/MyDrive/landscape/TFrecords/Valid/"
4 tfr_test = "/content/drive/MyDrive/landscape/TFrecords/Test/"

1 print(f"Train TFRecords : {len(os.listdir(tfr_train))} = {len(os.listdir(tfr_train))/5} X 5")
2 print(f"Valid TFRecords : {len(os.listdir(tfr_valid))} = {len(os.listdir(tfr_valid))/5} X 5")
3 print(f"Test TFRecords : {len(os.listdir(tfr_test))} = {len(os.listdir(tfr_test))/5} X 5")
```



Train TFRecords : 10000 = 2000 X 5  
Valid TFRecords : 1500 = 300 X 5  
Test TFRecords : 500 = 100 X 5

```
1 def decode_image(image):
2     image = tfi.decode_jpeg(image, channels=3)
3     # image = tfi.resize(image, (256,256))
4     # Apply any augmentations here.
5     image = tf.cast(image, tf.float32)
6     image = image/255.
7     return image
8
9 def decode_data(example):
10     features = {
```

```

10     features = {
11         'image':io.FixedLenFeature([], tf.string),
12         'label':io.FixedLenFeature([], tf.int64)
13     }
14
15     example = io.parse_single_example(example, features)
16     image, label = example['image'], example['label']
17     image = decode_image(image)
18     return image, label
19
20 def load_data(file_dir, BATCH_SIZE=32, BUFFER=1000):
21     AUTOTUNE = tfd.AUTOTUNE
22     file_dir = file_dir + "/*.tfrecord"
23     files = tfd.Dataset.list_files(file_dir)
24     data = tfd.TFRecordDataset(files, num_parallel_reads=AUTOTUNE)
25     data = data.map(decode_data, num_parallel_calls=AUTOTUNE)
26     data = data.shuffle(BUFFER).batch(BATCH_SIZE, drop_remainder=True)
27     data = data.prefetch(AUTOTUNE)
28     return data
29
30 train_ds = load_data(file_dir=tfr_train)
31 valid_ds = load_data(file_dir=tfr_valid)
32 test_ds = load_data(file_dir=tfr_test, BATCH_SIZE=1, BUFFER=500)

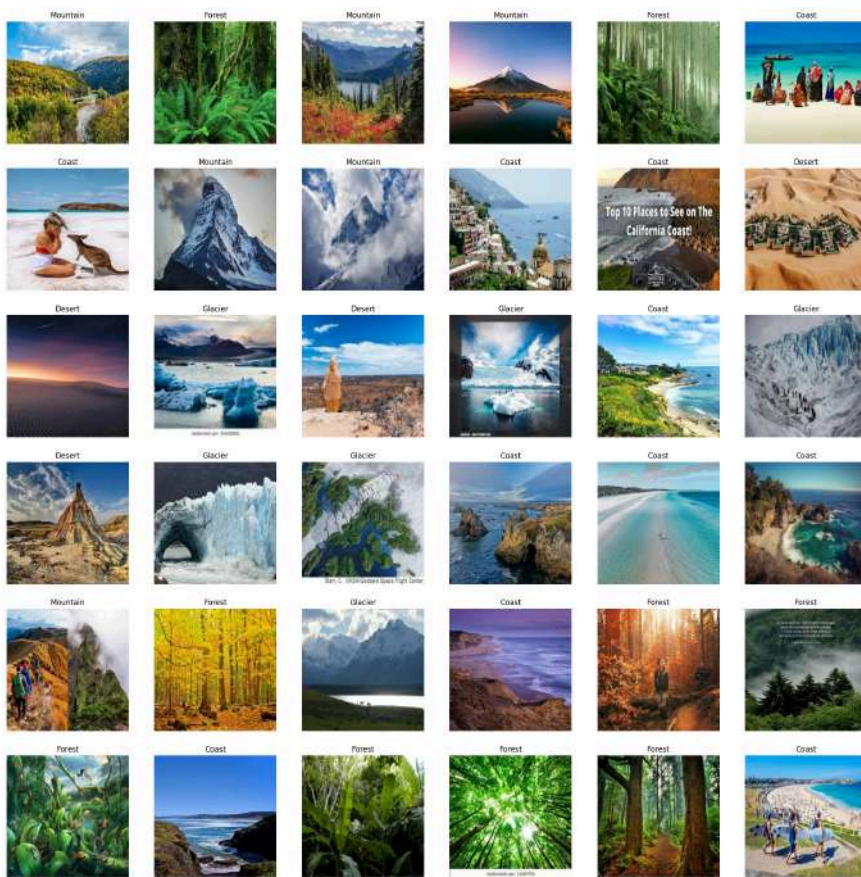
```

1

```

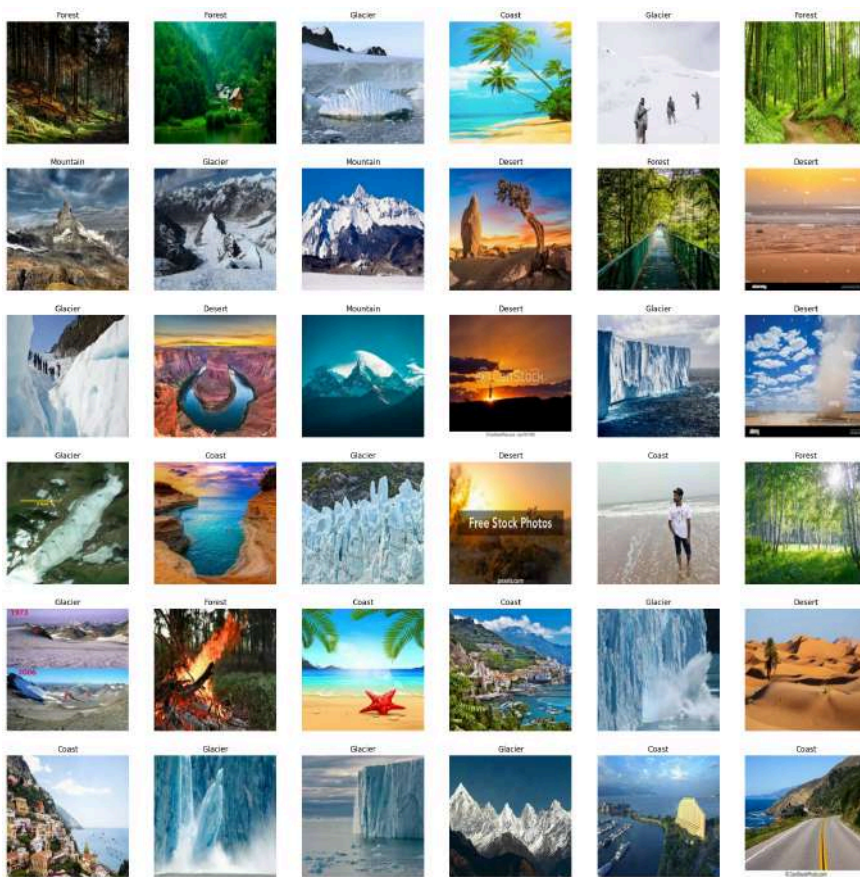
1 def show_images(data, class_names=class_names, model=None, SIZE=(25,25), GRID=[6,6]):
2
3     # Plot Configuration
4     n_rows, n_cols = GRID
5     n_images = n_rows * n_cols
6     plt.figure(figsize=SIZE)
7
8     # Iterate through the data
9     i=1
10    for images, labels in iter(data):
11
12        # Select some items randomly
13        id = np.random.randint(len(images))
14        image, label = tf.expand_dims(images[id], axis=0), class_names[int(labels[id])]
15
16        # Make Prediction
17        if model is not None:
18            pred = model.predict(image)[0]
19            score = np.round(max(pred),2)
20            pred_class = class_names[np.argmax(pred)]
21
22            title = f"True : {label}\nPred : {pred_class}\n Score : {score}"
23        else:
24            title = label
25
26        # plot Images
27        plt.subplot(n_rows, n_cols, i)
28        plt.imshow(image[0])
29        plt.axis('off')
30        plt.title(title)
31
32        # Break Loop
33        i+=1
34        if i>n_images:
35            break
36
37    # Final Show
38    plt.show()
39 show_images(train_ds)

```



```
1 show_images(valid_ds)
```





1

## Model Architecture

1 pip install autokeras



```
Requirement already satisfied: autokeras in /usr/local/lib/python3.10/dist-packages (2.0.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from autokeras) (24.1)
Requirement already satisfied: keras-tuner>=1.4.0 in /usr/local/lib/python3.10/dist-packages (from autokeras) (1.4.7)
Requirement already satisfied: keras-nlp>=0.8.0 in /usr/local/lib/python3.10/dist-packages (from autokeras) (0.12.1)
Collecting keras>=3.0.0 (from autokeras)
  Using cached keras-3.3.3-py3-none-any.whl (1.1 MB)
Requirement already satisfied: dm-tree in /usr/local/lib/python3.10/dist-packages (from autokeras) (0.1.8)
Requirement already satisfied: absl-py in /usr/local/lib/python3.10/dist-packages (from keras>=3.0.0->autokeras) (1.4.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from keras>=3.0.0->autokeras) (1.25.2)
Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-packages (from keras>=3.0.0->autokeras) (13.7.1)
Requirement already satisfied: namex in /usr/local/lib/python3.10/dist-packages (from keras>=3.0.0->autokeras) (0.0.8)
Requirement already satisfied: h5py in /usr/local/lib/python3.10/dist-packages (from keras>=3.0.0->autokeras) (3.11.0)
Requirement already satisfied: optree in /usr/local/lib/python3.10/dist-packages (from keras>=3.0.0->autokeras) (0.11.0)
Requirement already satisfied: ml-dtypes in /usr/local/lib/python3.10/dist-packages (from keras>=3.0.0->autokeras) (0.3.2)
Requirement already satisfied: keras-core in /usr/local/lib/python3.10/dist-packages (from keras-nlp>=0.8.0->autokeras) (0.1.7)
Requirement already satisfied: regex in /usr/local/lib/python3.10/dist-packages (from keras-nlp>=0.8.0->autokeras) (2024.5.15)
Requirement already satisfied: kagglehub in /usr/local/lib/python3.10/dist-packages (from keras-nlp>=0.8.0->autokeras) (0.2.6)
```

Requirement already satisfied: tensorflow-text in /usr/local/lib/python3.10/dist-packages (from keras-nlp>=0.8.0->autokeras) (2.17.0)

Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from keras-tuner>=1.4.0->autokeras) (2.31.0)

Requirement already satisfied: kt-legacy in /usr/local/lib/python3.10/dist-packages (from keras-tuner>=1.4.0->autokeras) (1.0.5)

Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from kagglehub->keras-nlp>=0.8.0->autokeras) (4.66.0)

Requirement already satisfied: typing-extensions>=4.0.0 in /usr/local/lib/python3.10/dist-packages (from optree->keras>=3.0.0->autokeras) (4.11.0)

Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner>=1.4.0->autokeras) (3.3.2)

Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner>=1.4.0->autokeras) (3.10.1)

Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner>=1.4.0->autokeras) (2.2.3)

Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner>=1.4.0->autokeras) (2024.7.4)

Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.10/dist-packages (from rich->keras>=3.0.0->autokeras) (3.0.0)

Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.10/dist-packages (from rich->keras>=3.0.0->autokeras) (2.18.0)

Collecting tensorflow<2.17,>=2.16.1 (from tensorflow-text->keras-nlp>=0.8.0->autokeras)

Using cached tensorflow-2.16.1-cp310-cp310-manylinux\_2\_17\_x86\_64.manylinux2014\_x86\_64.whl (589.8 MB)

Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.10/dist-packages (from markdown-it-py>=2.2.0->rich->keras>=3.0.0->autokeras) (0.1.2)

Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (1.6.0)

Requirement already satisfied: flatbuffers>=23.5.26 in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (24.3.25)

Requirement already satisfied: gast!=0.5.0,!0.5.1,!0.5.2,>=0.2.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (0.6.0)

Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (0.2.0)

Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (16.0.6)

Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (3.3.0)

Requirement already satisfied: protobuf!=4.21.0,!4.21.1,!4.21.2,!4.21.3,!4.21.4,!4.21.5,<5.0.0dev,>=3.20.3 in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (4.25.3)

Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (3.2.0)

Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (1.17.0)

Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (2.4.0)

Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (1.16.0)

Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (1.64.0)

Collecting tensorboard<2.17,>=2.16 (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras)

Using cached tensorboard-2.16.2-py3-none-any.whl (5.5 MB)

Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow<2.17,>=2.16.1->tensorflow-text->keras-nlp>=0.8.0->autokeras) (0.37.0)

Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.10/dist-packages (from astunparse>=1.6.0->tensorflow-text->keras-nlp>=0.8.0->autokeras) (0.44.0)

Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.17,>=2.16->tensorflow-text->keras-nlp>=0.8.0->autokeras) (3.7.0)

Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.17,>=2.16->tensorflow-text->keras-nlp>=0.8.0->autokeras) (0.17.0)

Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.17,>=2.16->tensorflow-text->keras-nlp>=0.8.0->autokeras) (3.0.6)

Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.10/dist-packages (from werkzeug>=1.0.1->tensorboard<2.17,>=2.16->tensorflow-text->keras-nlp>=0.8.0->autokeras) (3.0.2)

Installing collected packages: tensorboard, keras, tensorflow

Attempting uninstall: tensorboard

Found existing installation: tensorboard 2.15.2

Uninstalling tensorboard-2.15.2:

Successfully uninstalled tensorboard-2.15.2

Attempting uninstall: keras

1 pip install tensorflow-hub

```

Requirement already satisfied: tensorflow-hub in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: numpy>=1.12.0 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: protobuf>=3.19.6 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: tf-keras>=2.14.1 in /usr/local/lib/python3.10/dist-pac
Collecting tensorflow<2.16,>=2.15 (from tf-keras>=2.14.1->tensorflow-hub)
  Using cached tensorflow-2.15.1-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: flatbuffers>=23.5.26 in /usr/local/lib/python3.10/dist
Requirement already satisfied: gast!=0.5.0,!0.5.1,!0.5.2,>=0.2.1 in /usr/local/lib/
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.10/dist-
Requirement already satisfied: h5py>=2.9.0 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: ml-dtypes<=0.3.1 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python3.10/
Requirement already satisfied: wrapt<1.15,>=1.11.0 in /usr/local/lib/python3.10/dist-
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.10/dist-
Collecting tensorboard<2.16,>=2.15 (from tensorflow<2.16,>=2.15->tf-keras>=2.14.1->te
  Using cached tensorboard-2.15.2-py3-none-any.whl (5.5 MB)
Requirement already satisfied: tensorflow-estimator<2.16,>=2.15.0 in /usr/local/lib/p
Collecting keras<2.16,>=2.15.0 (from tensorflow<2.16,>=2.15->tf-keras>=2.14.1->tensor
  Using cached keras-2.15.0-py3-none-any.whl (1.7 MB)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: google-auth<3,>=1.6.3 in /usr/local/lib/python3.10/dis
Requirement already satisfied: google-auth-oauthlib<2,>=0.5 in /usr/local/lib/python3
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.10/dist-pack
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.10/dist-
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/li
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.10/dist-pack
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /usr/local/lib/python3.10/di
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.10/dis
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python3.10/
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: pyasn1<0.7.0,>=0.4.6 in /usr/local/lib/python3.10/dist
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.10/dist-pack
Installing collected packages: keras, tensorboard, tensorflow
Attempting uninstall: keras
  Found existing installation: keras 3.3.3
  Uninstalling keras-3.3.3:
    Successfully uninstalled keras-3.3.3
Attempting uninstall: tensorboard
  Found existing installation: tensorboard 2.16.2
  Uninstalling tensorboard-2.16.2:
    Successfully uninstalled tensorboard-2.16.2
Attempting uninstall: tensorflow
  Found existing installation: tensorflow 2.16.1
  Uninstalling tensorflow-2.16.1:
    Successfully uninstalled tensorflow-2.16.1
ERROR: pip's dependency resolver does not currently take into account all the package
autokeras 2.0.0 requires keras>=3.0.0, but you have keras 2.15.0 which is incompatibl
tensorflow-text 2.16.1 requires tensorflow<2.17,>=2.16.1; platform_machine != "arm64"
Successfully installed keras-2.15.0 tensorboard-2.15.2 tensorflow-2.15.1

```

```

1 import tensorflow_hub as hub
2 from keras.models import load_model

```

```

1 import autokeras as ak
2 import numpy as np
3 import pandas as pd
4 from sklearn.preprocessing import LabelEncoder, normalize
5 from sklearn.model_selection import train_test_split
6 from tensorflow.keras import utils
7 import matplotlib.pyplot as plt
8 from PIL import Image
9 import os

```

```

1 # Папка с папками картинок, рассортированных по категориям
2 IMAGE_PATH = '/content/drive/MyDrive/landscape/Training Data/'
3 # Получение списка папок, находящегося по адресу в скобках
4 os.listdir(IMAGE_PATH)

```

```

1 # просмотр примеров изображений из разных классов
2 categories = os.listdir(IMAGE_PATH)
3
4 plt.figure(figsize=(6,12))
5
6 for i, category in enumerate(categories):
7     # все имена файлов из папки
8     file_names = os.listdir(os.path.join(IMAGE_PATH, category))
9
10    # открываем первое изображение
11    img_path = os.path.join(IMAGE_PATH, category, file_names[0])
12    img = Image.open(img_path)
13
14    # отображаем содержимое файла
15    plt.subplot(4,2,i+1)
16    plt.title(category)
17    plt.imshow(img)
18
19 plt.tight_layout()
20 plt.show()

1 train_data = ak.image_dataset_from_directory(
2     IMAGE_PATH,
3     image_size = (192,108),
4     seed = 111,
5     validation_split = 0.2,
6     subset = 'training'
7 )
8
9 test_data = ak.image_dataset_from_directory(
10     IMAGE_PATH,
11     image_size = (192,108),
12     seed = 111,
13     validation_split = 0.2,
14     subset = 'validation'
15 )

1 clf1 = ak.ImageClassifier(max_trials=5,
2                             max_model_size=42545288,
3                             loss='categorical_crossentropy',
4                             metrics=['accuracy'],
5                             tuner='hyperband',
6                             objective='val_accuracy')
7 hist = clf1.fit(train_data, epochs=2, validation_split=0.2)

1 bit = hub.KerasLayer("https://tfhub.dev/google/bit/m-r50x1/1")
2 model_path = '/content/drive/MyDrive/landscape/Bit-LR-91-83.h5'
3 model = load_model(model_path, custom_objects={"KerasLayer":bit})
4

```

```
1 model.summary()
```

🔗 Model: "sequential"

Layer (type)	Output Shape	Param #
keras_layer (KerasLayer)	(32, 2048)	23500352
dense (Dense)	(32, 5)	10245
Total params: 23510597 (89.69 MB)		
Trainable params: 10245 (40.02 KB)		
Non-trainable params: 23500352 (89.65 MB)		

```
1 model.evaluate(train_ds)
```

🔗 312/312 [=====] - 4865s 14s/step - loss: 1.4098 - accuracy: 0.9122  
[1.4097508192062378, 0.9121594429016113]

```
1 model.evaluate(valid_ds)
```

🔗 46/46 [=====] - 767s 14s/step - loss: 3.0030 - accuracy: 0.8417  
[3.003037452697754, 0.8417119383811951]

```
1 model.evaluate(test_ds)
```

🔗 500/500 [=====] - 309s 445ms/step - loss: 1.8340 - accuracy: 0.9140  
[1.833951711654663, 0.9139999747276306]

```
1 # Model Predictions
2 show_images(test_ds, class_names=class_names, model=model, SIZE=(25,30))
```



1/1 [=====] - 2s 2s/step  
1/1 [=====] - 1s 612ms/step  
1/1 [=====] - 1s 539ms/step  
1/1 [=====] - 0s 410ms/step  
1/1 [=====] - 0s 386ms/step  
1/1 [=====] - 0s 410ms/step  
1/1 [=====] - 0s 412ms/step  
1/1 [=====] - 0s 400ms/step  
1/1 [=====] - 0s 396ms/step  
1/1 [=====] - 0s 410ms/step  
1/1 [=====] - 0s 390ms/step  
1/1 [=====] - 0s 421ms/step  
1/1 [=====] - 0s 399ms/step  
1/1 [=====] - 0s 406ms/step  
1/1 [=====] - 0s 389ms/step  
1/1 [=====] - 0s 396ms/step  
1/1 [=====] - 0s 397ms/step  
1/1 [=====] - 0s 394ms/step  
1/1 [=====] - 0s 426ms/step  
1/1 [=====] - 0s 396ms/step  
1/1 [=====] - 0s 411ms/step  
1/1 [=====] - 0s 403ms/step  
1/1 [=====] - 0s 412ms/step  
1/1 [=====] - 1s 553ms/step  
1/1 [=====] - 1s 604ms/step  
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1/1 [=====] - 1s 603ms/step  
1/1 [=====] - 1s 611ms/step  
1/1 [=====] - 1s 627ms/step  
1/1 [=====] - 0s 483ms/step  
1/1 [=====] - 0s 401ms/step  
1/1 [=====] - 0s 402ms/step  
1/1 [=====] - 0s 395ms/step  
1/1 [=====] - 0s 391ms/step  
1/1 [=====] - 0s 383ms/step

