

In this notebook we will evaluate performance of different models to classify the images of Kazakh language cyrillic alphabet

```
#load data and libraries
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
import tensorflow as tf
```

```
#load images from directory and split them into train and test sets
train_dir = 'Cyrillic/'
IMG_SIZE = 278
```

```
#I want to make scv file with all the images and their labels
#so I will use ImageDataGenerator to load images and their labels
```

```
import csv
import os
import random
from shutil import copyfile
def create_csv_file():
    with open('images.csv', 'w', newline='') as file:
        writer = csv.writer(file)
        writer.writerow(["filename", "label"])
        #make list of all the folders in the directory
        folders = os.listdir(train_dir)
        #write all the images and their labels to the csv file, where
label is the name of the folder maximum 20 images per folder
        for folder in folders:
            images = os.listdir(train_dir + folder)
            random.shuffle(images)
            for image in images[:20]:
                writer.writerow([train_dir + folder + '/' + image,
folder])
create_csv_file()
tf.config.run_functions_eagerly(True)

df = pd.read_csv('images.csv', encoding='windows-1251')
df.head()
```

	filename	label
0	Cyrillic/I/58c112a5ce550.png	I
1	Cyrillic/I/58befb0d1017a.png	I
2	Cyrillic/I/58bf01a4195b7.png	I
3	Cyrillic/I/58bf1b1bad929.png	I
4	Cyrillic/I/58c1d7e02ffc7.png	I

```
#show one image for every letter
```

```
import matplotlib.pyplot as plt
```

```

import matplotlib.image as mpimg
length = len(df['label'].unique())
#print all labels
print(df['label'].unique())
fig = plt.figure(figsize=(20, 20))
for i in range(length):
    img = mpimg.imread(df[df['label'] == df['label'].unique()[i]]
['filename'].iloc[0])
    fig.add_subplot(1, length, i+1)
    plt.imshow(img)
    plt.title(df['label'].unique()[i])
    plt.axis('off')

['I' 'K1' 'Y1' 'Y2' 'Ё' 'А' 'А1' 'Б' 'В' 'Г' 'Г1' 'Д' 'Е' 'Ж' 'З' 'И'
'Й'
'К' 'Л' 'М' 'Н' 'Н1' 'О' 'О1' 'П' 'Р' 'С' 'Т' 'У' 'Ф' 'Х' 'Ц' 'Ч' 'Ш'
'Щ'
'Ъ' 'Ы' 'Ь' 'Э' 'Ю' 'Я']

```

I K1 Y1 Y2 E A A1 B B Г Г1 Д Е Ж З И Й К Л М Н Н1 О О1 П Р С Т У Ф Х Ц Ч Ш Щ Ъ Ы Ь Э Ю Я
I K1 Y1 Y2 E A A1 B B Г Г1 Д Е Ж З И Й К Л М Н Н1 О О1 П Р С Т У Ф Х Ц Ч Ш Щ Ъ Ы Ь Э Ю Я

#here we preprocess the images

```

from tensorflow.keras.preprocessing.image import ImageDataGenerator
#we will use ImageDataGenerator to load images and their labels
#we will use rescale to normalize the images
#we will use validation_split to split the data into train and test
sets

```

```

train_datagen = ImageDataGenerator(rescale=1./255,
validation_split=0.2)
train_generator = train_datagen.flow_from_dataframe(
    dataframe=df,
    x_col="filename",
    y_col="label",
    target_size=(IMG_SIZE, IMG_SIZE),
    batch_size=32,
    class_mode="categorical",
    subset='training',
    shuffle=True
)

validation_generator = train_datagen.flow_from_dataframe(
    dataframe=df,
    x_col="filename",
    y_col="label",
    target_size=(IMG_SIZE, IMG_SIZE),
    batch_size=32,
    class_mode="categorical",
    subset='validation',

```

```
        shuffle=True
    )
```

```
Found 656 validated image filenames belonging to 41 classes.
Found 164 validated image filenames belonging to 41 classes.
```

```
train_generator.class_indices
```

```
{'I': 0,
 'K1': 1,
 'Y1': 2,
 'Y2': 3,
 'Ё': 4,
 'А': 5,
 'А1': 6,
 'Б': 7,
 'В': 8,
 'Г': 9,
 'Г1': 10,
 'Д': 11,
 'Е': 12,
 'Ж': 13,
 'З': 14,
 'И': 15,
 'Й': 16,
 'К': 17,
 'Л': 18,
 'М': 19,
 'Н': 20,
 'О': 21,
 'О1': 22,
 'П': 23,
 'Р': 24,
 'С': 25,
 'Т': 26,
 'У': 27,
 'Ф': 28,
 'Х': 29,
 'Ц': 30,
 'Ч': 31,
 'Ш': 32,
 'Щ': 33,
 'Ъ': 34,
 'Ы': 35,
 'Ь': 36,
 'Э': 37,
 'Ю': 38,
 'Я': 39,
 'н1': 40}
```

```

#here we will create a linear model
linModel = tf.keras.models.Sequential([
    tf.keras.layers.Flatten(input_shape=(IMG_SIZE, IMG_SIZE, 3)),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(41, activation='softmax')
])

linModel.compile(optimizer='adam',
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])

linModel.summary()

```

Model: "sequential_7"

Layer (type)	Output Shape	Param #
flatten_7 (Flatten)	(None, 231852)	0
dense_20 (Dense)	(None, 128)	29677184
dense_21 (Dense)	(None, 41)	5289
Total params: 29,682,473		
Trainable params: 29,682,473		
Non-trainable params: 0		

```

#here we will train the model and save everything to the LinModHistory
LinModHistory = linModel.fit(
    train_generator,
    validation_data=validation_generator,
    epochs=10
)

```

```

Epoch 1/10
21/21 [=====] - 18s 840ms/step - loss: 25.6811 - accuracy: 0.0290 - val_loss: 297.6140 - val_accuracy: 0.0000e+00
Epoch 2/10
21/21 [=====] - 11s 514ms/step - loss: 6.1667 - accuracy: 0.0488 - val_loss: 479.9029 - val_accuracy: 0.0000e+00
Epoch 3/10
21/21 [=====] - 12s 558ms/step - loss: 9.2877 - accuracy: 0.0595 - val_loss: 578.8351 - val_accuracy: 0.0000e+00
Epoch 4/10
21/21 [=====] - 10s 493ms/step - loss: 8.8683 - accuracy: 0.0655 - val_loss: 614.8513 - val_accuracy: 0.0000e+00

```

```

Epoch 5/10
21/21 [=====] - 11s 499ms/step - loss: 9.0525
- accuracy: 0.0671 - val_loss: 528.8709 - val_accuracy: 0.0000e+00
Epoch 6/10
21/21 [=====] - 13s 644ms/step - loss: 4.7850
- accuracy: 0.0823 - val_loss: 557.3412 - val_accuracy: 0.0000e+00
Epoch 7/10
21/21 [=====] - 9s 441ms/step - loss: 5.8816
- accuracy: 0.0762 - val_loss: 597.4167 - val_accuracy: 0.0000e+00
Epoch 8/10
21/21 [=====] - 10s 480ms/step - loss: 4.3194
- accuracy: 0.0869 - val_loss: 641.0949 - val_accuracy: 0.0000e+00
Epoch 9/10
21/21 [=====] - 12s 568ms/step - loss: 5.4576
- accuracy: 0.0686 - val_loss: 669.9567 - val_accuracy: 0.0000e+00
Epoch 10/10
21/21 [=====] - 12s 559ms/step - loss: 5.1323
- accuracy: 0.0762 - val_loss: 639.2811 - val_accuracy: 0.0000e+00

```

#here we will create a Sequential model

```

SeqMod = tf.keras.models.Sequential()
SeqMod.add(tf.keras.layers.Conv2D(32, (3, 3), activation='relu',
input_shape=(IMG_SIZE, IMG_SIZE, 3)))
SeqMod.add(tf.keras.layers.MaxPooling2D(2, 2))
SeqMod.add(tf.keras.layers.Conv2D(64, (3, 3), activation='relu'))
SeqMod.add(tf.keras.layers.MaxPooling2D(2, 2))
SeqMod.add(tf.keras.layers.Conv2D(128, (3, 3), activation='relu'))
SeqMod.add(tf.keras.layers.MaxPooling2D(2, 2))
SeqMod.add(tf.keras.layers.Flatten())
SeqMod.add(tf.keras.layers.Dropout(0.5))
SeqMod.add(tf.keras.layers.Dense(41, activation='softmax'))

```

```

SeqMod.compile(optimizer='adam',
               loss='categorical_crossentropy',
               metrics=['accuracy'])

```

```
SeqMod.summary()
```

Model: "sequential_14"

Layer (type)	Output Shape	Param #
conv2d_15 (Conv2D)	(None, 276, 276, 32)	896
max_pooling2d_15 (MaxPoolin g2D)	(None, 138, 138, 32)	0
conv2d_16 (Conv2D)	(None, 136, 136, 64)	18496
max_pooling2d_16 (MaxPoolin	(None, 68, 68, 64)	0

g2D)

conv2d_17 (Conv2D)	(None, 66, 66, 128)	73856
max_pooling2d_17 (MaxPoolin g2D)	(None, 33, 33, 128)	0
flatten_14 (Flatten)	(None, 139392)	0
dropout_3 (Dropout)	(None, 139392)	0
dense_31 (Dense)	(None, 41)	5715113

```
=====
Total params: 5,808,361
Trainable params: 5,808,361
Non-trainable params: 0
```

#here we will train the model and save everything to the SeqModHistory

```
SeqModHistory = SeqMod.fit(
    train_generator,
    validation_data=validation_generator,
    epochs=10
)
```

Epoch 1/10

21/21 [=====] - 181s 8s/step - loss: 3.4267 - accuracy: 0.0473 - val_loss: 7.3359 - val_accuracy: 0.0000e+00

Epoch 2/10

21/21 [=====] - 179s 8s/step - loss: 3.1932 - accuracy: 0.0976 - val_loss: 14.0701 - val_accuracy: 0.0000e+00

Epoch 3/10

21/21 [=====] - 153s 7s/step - loss: 3.1366 - accuracy: 0.1067 - val_loss: 18.0838 - val_accuracy: 0.0000e+00

Epoch 4/10

21/21 [=====] - 171s 8s/step - loss: 3.1200 - accuracy: 0.1113 - val_loss: 23.1211 - val_accuracy: 0.0000e+00

Epoch 5/10

21/21 [=====] - 153s 7s/step - loss: 3.1112 - accuracy: 0.1220 - val_loss: 22.6159 - val_accuracy: 0.0000e+00

Epoch 6/10

21/21 [=====] - 128s 6s/step - loss: 3.1137 - accuracy: 0.1021 - val_loss: 23.1690 - val_accuracy: 0.0000e+00

Epoch 7/10

21/21 [=====] - 122s 6s/step - loss: 3.1092 - accuracy: 0.1174 - val_loss: 23.6593 - val_accuracy: 0.0000e+00

Epoch 8/10

21/21 [=====] - 125s 6s/step - loss: 3.1109 - accuracy: 0.1143 - val_loss: 23.7144 - val_accuracy: 0.0000e+00

Epoch 9/10

```
21/21 [=====] - 120s 6s/step - loss: 3.1066 -  
accuracy: 0.1128 - val_loss: 24.4580 - val_accuracy: 0.0000e+00  
Epoch 10/10  
21/21 [=====] - 123s 6s/step - loss: 3.1069 -  
accuracy: 0.1128 - val_loss: 24.4360 - val_accuracy: 0.0000e+00
```

```
#load all images from imagedatagenerator to x as np.array and all  
labels to y as np.array
```

```
x = np.array(train_generator[0][0])  
y = np.array(train_generator[0][1])  
for i in range(1, len(train_generator)):  
    x = np.concatenate((x, np.array(train_generator[i][0])))  
    y = np.concatenate((y, np.array(train_generator[i][1])))
```

```
#import naive bayes model
```

```
from sklearn.naive_bayes import GaussianNB
```

```
#reshape x to 2d array
```

```
x = x.reshape(x.shape[0], -1)
```

```
#reshape y to 1d array
```

```
y = y.argmax(axis=1)
```

```
#train the model
```

```
gnb = GaussianNB()
```

```
gnb.fit(x, y)
```

```
GaussianNB()
```

```
#show accuracy with x_val, y_val
```

```
x_val = np.array(validation_generator[0][0])
```

```
y_val = np.array(validation_generator[0][1])
```

```
for i in range(1, len(validation_generator)):  
    x_val = np.concatenate((x_val, np.array(validation_generator[i]  
[0])))
```

```
    y_val = np.concatenate((y_val, np.array(validation_generator[i]  
[1])))
```

```
x_val = x_val.reshape(x_val.shape[0], -1)
```

```
y_val = y_val.argmax(axis=1)
```

```
print(gnb.score(x_val, y_val))
```

```
0.15154847
```

```
#here we will create a support vector machines model
```

```
from sklearn import svm
```

```
clf = svm.SVC()
```

```
clf.fit(x, y)
```

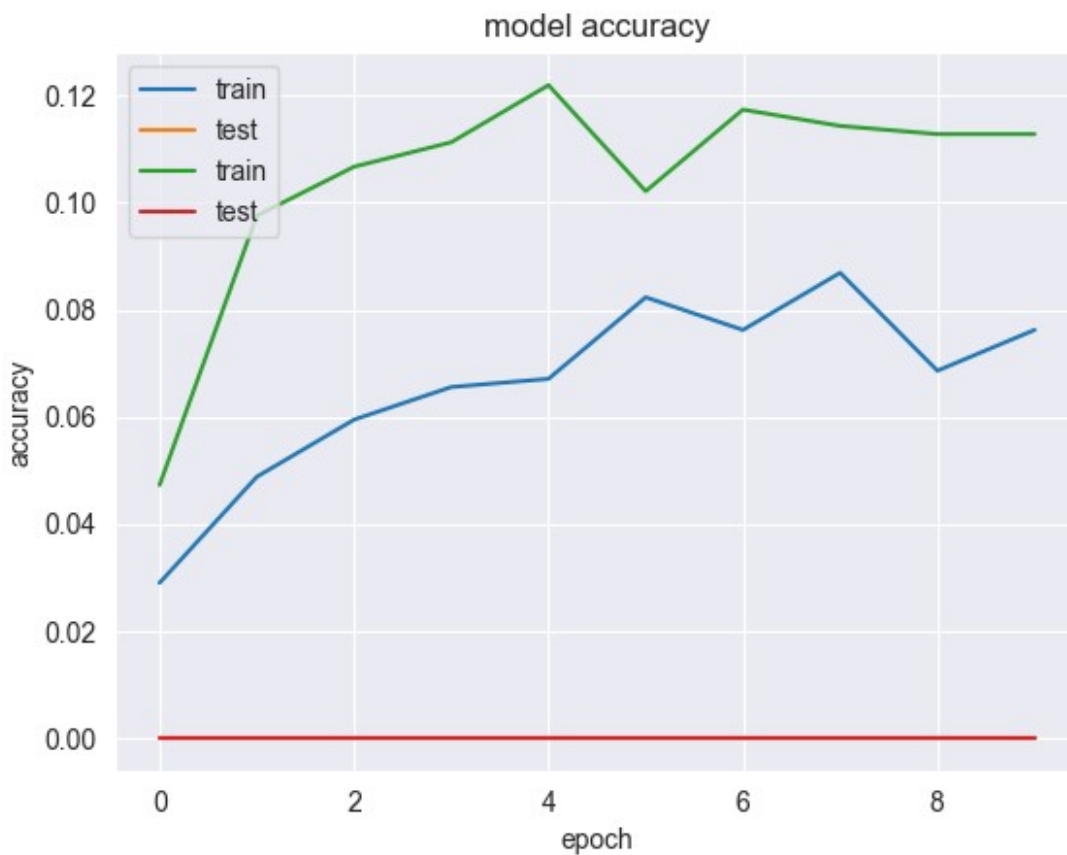
```
SVC()
```

```
#output accuracy with x_val, y_val
print(clf.score(x_val, y_val))
```

92.848474

```
#plot the accuracy of the models over the epochs for the linear model
and the sequential model
```

```
plt.plot(LinModHistory.history['accuracy'])
plt.plot(LinModHistory.history['val_accuracy'])
plt.plot(SeqModHistory.history['accuracy'])
plt.plot(SeqModHistory.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test', 'train', 'test'], loc='upper left')
plt.show()
```

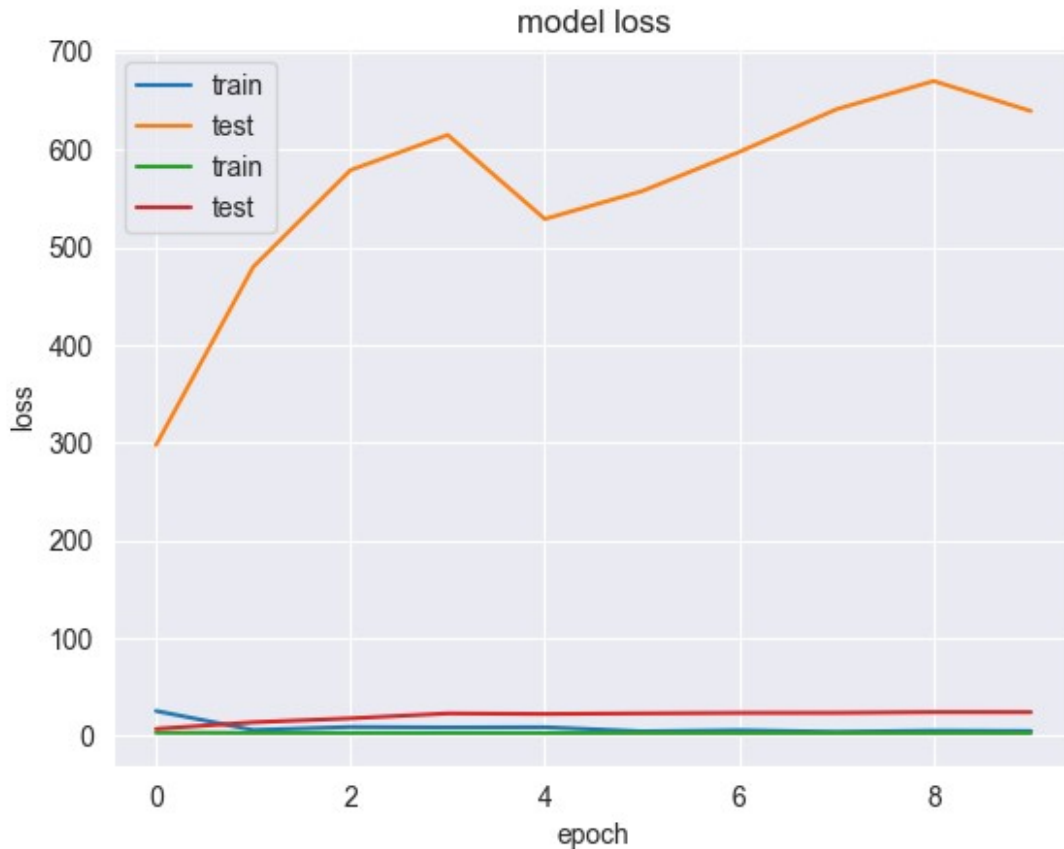


```
#plot the loss of the models over the epochs for the linear model and
the sequential model
```

```
plt.plot(LinModHistory.history['loss'])
plt.plot(LinModHistory.history['val_loss'])
plt.plot(SeqModHistory.history['loss'])
plt.plot(SeqModHistory.history['val_loss'])
plt.title('model loss')
```



```
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test', 'train', 'test'], loc='upper left')
plt.show()
```



As we can see the simplest Linear model cannot even achieve 10% accuracy, while Sequential model is able to achieve 12% accuracy. Naive Bayes and SVM models are able to achieve much higher results. This is not a good result, but it is better than random guessing. We can try to improve the accuracy by using more complex models, but it will take a lot of time and resources. We can also try to use transfer learning, but it will also take a lot of time and resources. So, we will use the Sequential model for the final model. We can understand, that complex methods even show effectiveness as this Kazakhs MNIST is, where not over 20 images of each class are available. So, we will use the Sequential model for the final model.