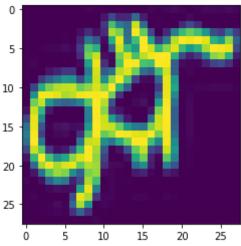
Updates and Imports

```
!sudo apt update
!sudo apt autoremove
!sudo apt upgrade
!sudo apt install python3x
!python --version
import sys
print("version:", sys.version)
!pip install —U pandas
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: pandas in
/usr/local/lib/python3.8/dist-packages (1.3.5)
Collecting pandas
 Downloading pandas-1.5.2-cp38-cp38-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (12.2 MB)
ent already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.8/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: numpy>=1.20.3 in
/usr/local/lib/python3.8/dist-packages (from pandas) (1.21.6)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.8/dist-packages (from pandas) (2022.6)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.8/dist-packages (from python-dateutil>=2.8.1-
>pandas) (1.15.0)
Installing collected packages: pandas
 Attempting uninstall: pandas
   Found existing installation: pandas 1.3.5
   Uninstalling pandas-1.3.5:
     Successfully uninstalled pandas-1.3.5
Successfully installed pandas-1.5.2
{"pip warning":{"packages":["pandas"]}}
```

```
from google.colab import drive
drive.mount('/content/drive/')
Drive already mounted at /content/drive/; to attempt to forcibly
remount, call drive.mount("/content/drive/", force_remount=True).
import seaborn as sns
import cv2
import pandas as pd
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.layers import Conv2D, MaxPooling2D,
        BatchNormalization
from tensorflow.keras.layers import Dense, Dropout, Flatten,
        Activation
from tensorflow.keras.metrics import categorical_accuracy,
        top_k_categorical_accuracy, categorical_crossentropy
from tensorflow.keras.models import Sequential
from tensorflow.keras.callbacks import EarlyStopping,
        ReduceLROnPlateau, ModelCheckpoint
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import regularizers
from tensorflow.keras.applications import MobileNet,MobileNetV2
from tensorflow.keras.applications.mobilenet import preprocess input
import matplotlib.pyplot as plt
from tensorflow.keras.utils import to_categorical
import pandas as pd
import numpy as np
from numpy import newaxis
from sklearn.model selection import train test split
import pickle
from tqdm.notebook import tqdm
import matplotlib.pyplot as plt
import cv2
from numpy import newaxis
from sklearn.model_selection import train_test_split
import pickle
from tqdm.notebook import tqdm
import matplotlib.pyplot as plt
import cv2
```

Mobilenet

reference: https://www.kaggle.com/code/sabarish2611/alexnet-vs-mobilenet-using-mnist-data#AlexNet-vs-MobileNet-:-Comparing-the-performance



```
X_train, X_test, y_train, y_test = train_test_split(X, y,
        random_state=42)
X = None
y = None
X_train.shape
(112500, 28, 28)
\# X_{re} = np.zeros((X.shape[0],32,32,3))
# for i in tqdm(range(X.shape[0])):
      temp = cv2.resize(X[i], dsize=(32, 32),
        interpolation=cv2.INTER_CUBIC)
#
      # temp = temp[:,:,newaxis]
#
      # print(temp.shape)
#
      img = np.zeros((32,32,3))
#
      # print(img.shape)
#
      img[:,:,0] = temp
#
      img[:,:,1] = temp
      img[:,:,2] = temp
#
      X_re[i] = img
X_train_re = np.zeros((X_train.shape[0],32,32,3))
for i in tqdm(range(X_train.shape[0])):
    temp = cv2.resize(X_train[i], dsize=(32, 32),
        interpolation=cv2.INTER_CUBIC)
    # temp = temp[:,:,newaxis]
    # print(temp.shape)
    img = np.zeros((32,32,3))
    # print(img.shape)
    img[:,:,0] = temp
```

```
img[:,:,1] = temp
    img[:,:,2] = temp
    X_train_re[i] = img
    X_train[i] = None
X_train = None
X_{\text{test\_re}} = \text{np.zeros}((X_{\text{test.shape}}[0],32,32,3))
for i in tqdm(range(X_test.shape[0])):
    temp = cv2.resize(X_test[i], dsize=(32, 32),
         interpolation=cv2.INTER_CUBIC)
    # temp = temp[:,:,newaxis]
    # print(temp.shape)
    img = np.zeros((32,32,3))
    # print(img.shape)
    img[:,:,0] = temp
    img[:,:,1] = temp
    img[:,:,2] = temp
    X_{\text{test\_re}[i]} = img
    X test[i] = None
X_{test} = None
{"version_major":2,"version_minor":0,"model_id":"5129e5f8573d4a298f261
         c9ecc7e3ea7"}
{"version_major":2,"version_minor":0,"model_id":"7a4f5d610cf3456fbbf29
         14b758803cb"}
X_train_re.shape
(112500, 32, 32, 3)
base_model = MobileNet(include_top=False,
         weights='imagenet',input_shape = (32,32,3), classes=100)
base_model.trainable = True
for layer in base model.layers[:50]:
    layer.trainable = False
MobileNet_model = Sequential()
MobileNet model.add(base model)
MobileNet model.add(Flatten())
MobileNet_model.add(Dense(100,activation=('softmax')))
```

```
early_stopping = EarlyStopping(min_delta = 0.001,patience =
      20, restore_best_weights = True, verbose = 0)
# Compile
MobileNet_model.compile(optimizer = "adam" , loss =
      'sparse_categorical_crossentropy' , metrics = ['accuracy'])
# Train
Mobile = MobileNet_model.fit(X_train_re, y_train, batch_size = 400,
      epochs = 50,callbacks = [early_stopping], validation_data =
      (X_test_re, y_test))
MobileNet_model.summary()
WARNING:tensorflow:`input_shape` is undefined or non-square, or `rows`
is not in [128, 160, 192, 224]. Weights for input shape (224, 224)
will be loaded as the default.
Epoch 1/50
282/282 [===============================] - 22s 34ms/step - loss:
2.3421 - accuracy: 0.4379 - val_loss: 2.2859 - val_accuracy: 0.4241
Epoch 2/50
- accuracy: 0.5846 - val_loss: 1.7769 - val_accuracy: 0.5469
Epoch 3/50
- accuracy: 0.6362 - val loss: 1.7431 - val accuracy: 0.5750
Epoch 4/50
- accuracy: 0.6715 - val loss: 1.6661 - val accuracy: 0.5821
Epoch 5/50
- accuracy: 0.7021 - val_loss: 1.7595 - val_accuracy: 0.5697
Epoch 6/50
- accuracy: 0.7280 - val_loss: 1.7388 - val_accuracy: 0.5848
Epoch 7/50
- accuracy: 0.7543 - val_loss: 1.8712 - val_accuracy: 0.5755
Epoch 8/50
- accuracy: 0.7752 - val_loss: 1.8884 - val_accuracy: 0.5788
Epoch 9/50
```

```
282/282 [============ ] - 8s 29ms/step - loss: 0.6592
- accuracy: 0.8015 - val_loss: 2.0165 - val_accuracy: 0.5817
Epoch 10/50
- accuracy: 0.8218 - val_loss: 2.1094 - val_accuracy: 0.5749
Epoch 11/50
- accuracy: 0.8446 - val_loss: 2.2363 - val_accuracy: 0.5777
Epoch 12/50
- accuracy: 0.8653 - val_loss: 2.2120 - val_accuracy: 0.5758
Epoch 13/50
- accuracy: 0.8791 - val_loss: 2.3544 - val_accuracy: 0.5704
Epoch 14/50
- accuracy: 0.8926 - val_loss: 2.3482 - val_accuracy: 0.5773
Epoch 15/50
282/282 [============ ] - 7s 26ms/step - loss: 0.2903
- accuracy: 0.9072 - val_loss: 2.4643 - val_accuracy: 0.5824
Epoch 16/50
- accuracy: 0.9130 - val_loss: 2.4808 - val_accuracy: 0.5766
Epoch 17/50
- accuracy: 0.9242 - val_loss: 2.5780 - val_accuracy: 0.5808
Epoch 18/50
- accuracy: 0.9278 - val loss: 2.6697 - val accuracy: 0.5767
Epoch 19/50
- accuracy: 0.9327 - val loss: 2.6816 - val accuracy: 0.5785
Epoch 20/50
- accuracy: 0.9373 - val loss: 2.7885 - val accuracy: 0.5827
Epoch 21/50
- accuracy: 0.9448 - val_loss: 2.7846 - val_accuracy: 0.5888
Epoch 22/50
```

```
- accuracy: 0.9436 - val_loss: 2.7298 - val_accuracy: 0.5878
Epoch 23/50
- accuracy: 0.9451 - val_loss: 2.8234 - val_accuracy: 0.5800
Epoch 24/50
- accuracy: 0.9499 - val_loss: 2.8720 - val_accuracy: 0.5853
Model: "sequential"
 Layer (type)
                        Output Shape
                                              Param #
 mobilenet_1.00_224 (Functio (None, 1, 1, 1024)
                                              3228864
 nal)
 flatten (Flatten)
                        (None, 1024)
 dense (Dense)
                        (None, 100)
                                              102500
______
Total params: 3,331,364
Trainable params: 2,766,948
Non-trainable params: 564,416
base model = MobileNet(include top=False,
       weights='imagenet',input_shape = (32,32,3), classes=100)
base model.trainable = True
for layer in base model.layers[:50]:
   layer.trainable = False
MobileNet model = Sequential()
MobileNet model.add(base model)
MobileNet model.add(Flatten())
MobileNet model.add(Dense(100,activation=('softmax')))
early_stopping = EarlyStopping(min_delta = 0.001,patience =
       20, restore_best_weights = True, verbose = 0)
# Compile
MobileNet_model.compile(optimizer = "adam" , loss =
       'sparse_categorical_crossentropy' , metrics = ['accuracy'])
```

```
# Train
Mobile = MobileNet_model.fit(X_train_re, y_train, batch_size = 400,
        epochs = 50,callbacks = [early_stopping], validation_data =
        (X_test_re, y_test))
MobileNet_model.summary()
MobileNet_model.save('/content/drive/MyDrive/AML mini
        project/mobile.h5')
# early_stopping = EarlyStopping(min_delta = 0.001,patience =
        20, restore_best_weights = True, verbose = 2)
# model = MobileNet(input_shape=(32, 32, 3), alpha=1., weights=None,
        classes=100)
# model.compile(optimizer=Adam(lr=0.002),
        loss='categorical_crossentropy',
#
               metrics=['accuracy'])
# Mobile = model.fit(X_train_re, y_train, batch_size = 400, epochs =
        50, callbacks = [early_stopping], validation_data =
        (X_test_re, y_test))
# print(model.summary())
```

LeNet

reference: https://towardsdatascience.com/going-beyond-99-mnist-handwritten-digits-recognition-cfff96337392

```
train path =
        "/content/drive/MyDrive/AMLminiproject/train100c5k v2.pkl"
test path =
        "/content/drive/MyDrive/AMLminiproject/test100c5k nolabel.pkl"
# train data = open(train path,'rb')
# test_data = open(test_path,'rb')
# df_train = pd.read_pickle(train_path)
# df test = pd.read pickle(test path)
df_train = pickle.load(open(train_path,'rb'))
df test = pickle.load(open(test path,'rb'))
# train data = df['data'].values
# sampling
#sample = df_train.groupby('target', group_keys=False).apply(lambda x:
        x.sample(frac=0.3))
sample = df train.copy()
sample['data'] = sample['data']/255
```

```
# X = np.array(list(sample['data'].values))
X = np.array([img[:,:,newaxis] for img in
         np.array(sample['data'].values)])
y = np.array(sample['target'].values)
df train = None
df_test = None
sample = None
X. shape
(500000, 28, 28, 1)
X_train, X_test, y_train, y_test = train_test_split(X, y,
         random_state=42)
X = None
y = None
X_train.shape
(375000, 28, 28, 1)
X_train.shape
(375000, 28, 28, 1)
X_{\text{train\_re}} = \text{np.pad}(X_{\text{train}}, ((0,0),(2,2),(2,2),(0,0)), 'constant')
X_{\text{test\_re}} = \text{np.pad}(X_{\text{test}}, ((0,0),(2,2),(2,2),(0,0)), 'constant')
X train = None
X \text{ test} = None
X_train_re.shape
(375000, 32, 32, 1)
y_train = to_categorical(y_train, 100)
y_test = to_categorical(y_test, 100)
```

LeNet architecture with additional hidden layers and batch normalization followed by them

```
BatchNormalization(),
# - - - - - #
Activation('relu'),
MaxPooling2D(pool_size = 2, strides = 2),
Dropout (0.25),
# - - - - - - #
Conv2D(filters = 64, kernel_size = 3, strides = 1, activation =
       'relu', kernel_regularizer=regularizers.l1_l2(l1=0,
       12=0.0005)),
# Layer 4
Conv2D(filters = 64, kernel_size = 3, strides = 1, use_bias=False),
# Laver 5
BatchNormalization(),
# - - - - - #
Activation('relu'),
MaxPooling2D(pool_size = 2, strides = 2),
Dropout(0.25),
Flatten(),
# - - - - - - #
# Layer 6
Dense(units = 256, use bias=False),
# Layer 7
BatchNormalization(),
# - - - - - #
Activation('relu').
# - - - - - - #
# Layer 8
Dense(units = 128, use_bias=False),
# Layer 9
BatchNormalization(),
# - - - - - #
Activation('relu'),
# - - - - - #
# Layer 10
Dense(units = 84, use_bias=False),
# Layer 11
BatchNormalization(),
Activation('relu'),
Dropout(0.25),
```

```
# Output
Dense(units = 100, activation = 'softmax')
])
early stopping = EarlyStopping(min delta = 0.001, patience =
     20, restore_best_weights = True, verbose = 0)
model.compile(optimizer='adam', loss='categorical_crossentropy',
     metrics=['accuracy'])
# model.fit(X_train_re, y_train, batch_size = 400, epochs =
     50, callbacks = [early_stopping], validation_data = (X_{test_re}, X_{test_re})
     y_test))
history = model.fit(X_train_re, y_train, epochs = 50, batch_size =
     100, callbacks = [early_stopping], validation_data =
     (X_test_re, y_test))
Epoch 1/50
2.2783 - accuracy: 0.4449 - val_loss: 1.6516 - val_accuracy: 0.5801
Epoch 2/50
1.6669 - accuracy: 0.5811 - val_loss: 1.4732 - val_accuracy: 0.6205
Epoch 3/50
1.5325 - accuracy: 0.6130 - val_loss: 1.3022 - val_accuracy: 0.6662
Epoch 4/50
1.4575 - accuracy: 0.6315 - val loss: 1.2603 - val accuracy: 0.6777
Epoch 5/50
1.4107 - accuracy: 0.6435 - val loss: 1.2330 - val accuracy: 0.6849
Epoch 6/50
1.3774 - accuracy: 0.6511 - val_loss: 1.2859 - val_accuracy: 0.6710
Epoch 7/50
1.3474 - accuracy: 0.6589 - val_loss: 1.1728 - val_accuracy: 0.6997
Epoch 8/50
1.3262 - accuracy: 0.6645 - val_loss: 1.1501 - val_accuracy: 0.7063
Epoch 9/50
1.3089 - accuracy: 0.6690 - val_loss: 1.2101 - val_accuracy: 0.6926
```

```
Epoch 10/50
1.2971 - accuracy: 0.6720 - val_loss: 1.2375 - val_accuracy: 0.6868
Epoch 11/50
1.2832 - accuracy: 0.6750 - val_loss: 1.1592 - val_accuracy: 0.7046
Epoch 12/50
1.2681 - accuracy: 0.6789 - val_loss: 1.1577 - val_accuracy: 0.7052
Epoch 13/50
1.2565 - accuracy: 0.6821 - val_loss: 1.1342 - val_accuracy: 0.7117
Epoch 14/50
1.2473 - accuracy: 0.6844 - val_loss: 1.1447 - val_accuracy: 0.7090
Epoch 15/50
3750/3750 [============== ] - 32s 9ms/step - loss:
1.2405 - accuracy: 0.6861 - val_loss: 1.1253 - val_accuracy: 0.7134
Epoch 16/50
1.2326 - accuracy: 0.6877 - val loss: 1.1250 - val accuracy: 0.7139
Epoch 17/50
1.2237 - accuracy: 0.6898 - val loss: 1.0995 - val accuracy: 0.7190
Epoch 18/50
1.2178 - accuracy: 0.6915 - val_loss: 1.1277 - val_accuracy: 0.7145
Epoch 19/50
1.2120 - accuracy: 0.6925 - val_loss: 1.0959 - val_accuracy: 0.7211
Epoch 20/50
1.2063 - accuracy: 0.6940 - val_loss: 1.0966 - val_accuracy: 0.7214
Epoch 21/50
1.2006 - accuracy: 0.6961 - val_loss: 1.1016 - val_accuracy: 0.7194
Epoch 22/50
1.1943 - accuracy: 0.6963 - val loss: 1.1236 - val accuracy: 0.7140
Epoch 23/50
```

```
1.1898 - accuracy: 0.6979 - val_loss: 1.1178 - val_accuracy: 0.7157
Epoch 24/50
1.1842 - accuracy: 0.6994 - val_loss: 1.0987 - val_accuracy: 0.7211
Epoch 25/50
1.1826 - accuracy: 0.6997 - val_loss: 1.0938 - val_accuracy: 0.7225
Epoch 26/50
1.1776 - accuracy: 0.7012 - val_loss: 1.0939 - val_accuracy: 0.7221
Epoch 27/50
1.1742 - accuracy: 0.7020 - val_loss: 1.0851 - val_accuracy: 0.7240
Epoch 28/50
1.1715 - accuracy: 0.7027 - val_loss: 1.0933 - val_accuracy: 0.7220
Epoch 29/50
1.1690 - accuracy: 0.7031 - val_loss: 1.0715 - val_accuracy: 0.7274
Epoch 30/50
1.1622 - accuracy: 0.7045 - val_loss: 1.0896 - val_accuracy: 0.7241
Epoch 31/50
1.1633 - accuracy: 0.7047 - val_loss: 1.0927 - val_accuracy: 0.7245
Epoch 32/50
1.1583 - accuracy: 0.7061 - val loss: 1.0938 - val accuracy: 0.7230
Epoch 33/50
1.1554 - accuracy: 0.7065 - val loss: 1.0898 - val accuracy: 0.7233
Epoch 34/50
1.1521 - accuracy: 0.7068 - val loss: 1.0800 - val accuracy: 0.7269
Epoch 35/50
1.1514 - accuracy: 0.7075 - val_loss: 1.0962 - val_accuracy: 0.7238
Epoch 36/50
```

```
1.1505 - accuracy: 0.7074 - val_loss: 1.1167 - val_accuracy: 0.7165
Epoch 37/50
1.1466 - accuracy: 0.7085 - val_loss: 1.0998 - val_accuracy: 0.7219
Epoch 38/50
1.1423 - accuracy: 0.7099 - val_loss: 1.0994 - val_accuracy: 0.7205
Epoch 39/50
3750/3750 [============== ] - 33s 9ms/step - loss:
1.1412 - accuracy: 0.7095 - val_loss: 1.0968 - val_accuracy: 0.7220
Epoch 40/50
1.1361 - accuracy: 0.7107 - val_loss: 1.0621 - val_accuracy: 0.7308
Epoch 41/50
1.1384 - accuracy: 0.7110 - val_loss: 1.0644 - val_accuracy: 0.7309
Epoch 42/50
1.1306 - accuracy: 0.7119 - val_loss: 1.0785 - val_accuracy: 0.7276
Epoch 43/50
1.1335 - accuracy: 0.7110 - val_loss: 1.0780 - val_accuracy: 0.7275
Epoch 44/50
1.1282 - accuracy: 0.7127 - val loss: 1.1323 - val accuracy: 0.7139
Epoch 45/50
1.1290 - accuracy: 0.7122 - val loss: 1.0585 - val accuracy: 0.7326
Epoch 46/50
1.1273 - accuracy: 0.7128 - val_loss: 1.0745 - val_accuracy: 0.7280
Epoch 47/50
1.1273 - accuracy: 0.7129 - val_loss: 1.0550 - val_accuracy: 0.7332
Epoch 48/50
1.1233 - accuracy: 0.7137 - val_loss: 1.0631 - val_accuracy: 0.7302
Epoch 49/50
1.1224 - accuracy: 0.7137 - val_loss: 1.0843 - val_accuracy: 0.7255
```

Model: "sequential"

Layer (type)	Output Shape	 Param #
conv2d (Conv2D)	(None, 28, 28, 32)	832
conv2d_1 (Conv2D)	(None, 24, 24, 32)	25600
<pre>batch_normalization (BatchN ormalization)</pre>	(None, 24, 24, 32)	128
activation (Activation)	(None, 24, 24, 32)	0
<pre>max_pooling2d (MaxPooling2D)</pre>	(None, 12, 12, 32)	0
dropout (Dropout)	(None, 12, 12, 32)	0
conv2d_2 (Conv2D)	(None, 10, 10, 64)	18496
conv2d_3 (Conv2D)	(None, 8, 8, 64)	36864
<pre>batch_normalization_1 (Batc hNormalization)</pre>	(None, 8, 8, 64)	256
<pre>activation_1 (Activation)</pre>	(None, 8, 8, 64)	0
<pre>max_pooling2d_1 (MaxPooling 2D)</pre>	(None, 4, 4, 64)	0

dropout_1 (Dropout)	(None, 4, 4, 64)	0
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 256)	262144
<pre>batch_normalization_2 (Batc hNormalization)</pre>	(None, 256)	1024
activation_2 (Activation)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32768
<pre>batch_normalization_3 (Batc hNormalization)</pre>	(None, 128)	512
activation_3 (Activation)	(None, 128)	0
dense_2 (Dense)	(None, 84)	10752
<pre>batch_normalization_4 (Batc hNormalization)</pre>	(None, 84)	336
activation_4 (Activation)	(None, 84)	0
dropout_2 (Dropout)	(None, 84)	0
dense_3 (Dense)	(None, 100)	8500

Total params: 398,212

Trainable params: 397,084 Non-trainable params: 1,128

history = model.fit(X_train_re, y_train, epochs = 50, batch_size =

```
100, callbacks = [early_stopping], validation_data =
     (X_test_re, y_test))
Epoch 1/50
1.1188 - accuracy: 0.7156 - val_loss: 1.0998 - val_accuracy: 0.7250
Epoch 2/50
1.1188 - accuracy: 0.7154 - val_loss: 1.0536 - val_accuracy: 0.7333
Epoch 3/50
1.1176 - accuracy: 0.7152 - val_loss: 1.0578 - val_accuracy: 0.7320
Epoch 4/50
1.1138 - accuracy: 0.7159 - val_loss: 1.0859 - val_accuracy: 0.7266
Epoch 5/50
3750/3750 [============== ] - 32s 9ms/step - loss:
1.1124 - accuracy: 0.7159 - val_loss: 1.0568 - val_accuracy: 0.7334
Epoch 6/50
1.1119 - accuracy: 0.7168 - val_loss: 1.0853 - val_accuracy: 0.7261
Epoch 7/50
1.1092 - accuracy: 0.7173 - val loss: 1.0525 - val accuracy: 0.7336
Epoch 8/50
1.1099 - accuracy: 0.7166 - val_loss: 1.0811 - val_accuracy: 0.7275
Epoch 9/50
1.1091 - accuracy: 0.7174 - val_loss: 1.0553 - val_accuracy: 0.7328
Epoch 10/50
1.1065 - accuracy: 0.7175 - val_loss: 1.0673 - val_accuracy: 0.7310
Epoch 11/50
1.1051 - accuracy: 0.7182 - val_loss: 1.0560 - val_accuracy: 0.7336
Epoch 12/50
1.1051 - accuracy: 0.7188 - val loss: 1.0638 - val accuracy: 0.7315
```

```
Epoch 13/50
1.1011 - accuracy: 0.7195 - val_loss: 1.0767 - val_accuracy: 0.7279
Epoch 14/50
1.1019 - accuracy: 0.7186 - val_loss: 1.0484 - val_accuracy: 0.7347
Epoch 15/50
1.1014 - accuracy: 0.7193 - val_loss: 1.0647 - val_accuracy: 0.7318
Epoch 16/50
1.0990 - accuracy: 0.7199 - val_loss: 1.0630 - val_accuracy: 0.7326
Epoch 17/50
1.0970 - accuracy: 0.7200 - val_loss: 1.0759 - val_accuracy: 0.7294
Epoch 18/50
3750/3750 [============= ] - 34s 9ms/step - loss:
1.0971 - accuracy: 0.7206 - val_loss: 1.0858 - val_accuracy: 0.7267
Epoch 19/50
1.0967 - accuracy: 0.7205 - val loss: 1.0699 - val accuracy: 0.7298
Epoch 20/50
1.0963 - accuracy: 0.7207 - val loss: 1.0471 - val accuracy: 0.7356
Epoch 21/50
1.0961 - accuracy: 0.7209 - val_loss: 1.0690 - val_accuracy: 0.7310
Epoch 22/50
1.0943 - accuracy: 0.7215 - val_loss: 1.0556 - val_accuracy: 0.7338
Epoch 23/50
1.0939 - accuracy: 0.7212 - val_loss: 1.0651 - val_accuracy: 0.7323
Epoch 24/50
1.0921 - accuracy: 0.7212 - val_loss: 1.0574 - val_accuracy: 0.7337
Epoch 25/50
1.0924 - accuracy: 0.7207 - val loss: 1.0836 - val accuracy: 0.7282
Epoch 26/50
```

```
1.0929 - accuracy: 0.7214 - val_loss: 1.0697 - val_accuracy: 0.7306
Epoch 27/50
1.0901 - accuracy: 0.7218 - val_loss: 1.0572 - val_accuracy: 0.7345
Epoch 28/50
1.0885 - accuracy: 0.7227 - val_loss: 1.0650 - val_accuracy: 0.7323
Epoch 29/50
1.0878 - accuracy: 0.7228 - val_loss: 1.0554 - val_accuracy: 0.7341
Epoch 30/50
1.0869 - accuracy: 0.7233 - val_loss: 1.0543 - val_accuracy: 0.7348
Epoch 31/50
1.0873 - accuracy: 0.7232 - val_loss: 1.0550 - val_accuracy: 0.7342
Epoch 32/50
1.0871 - accuracy: 0.7227 - val_loss: 1.0521 - val_accuracy: 0.7358
Epoch 33/50
1.0861 - accuracy: 0.7234 - val_loss: 1.0510 - val_accuracy: 0.7351
Epoch 34/50
1.0860 - accuracy: 0.7228 - val_loss: 1.0557 - val_accuracy: 0.7346
Epoch 35/50
1.0829 - accuracy: 0.7234 - val_loss: 1.0761 - val_accuracy: 0.7296
Epoch 36/50
1.0814 - accuracy: 0.7245 - val loss: 1.0670 - val accuracy: 0.7321
Epoch 37/50
1.0833 - accuracy: 0.7238 - val loss: 1.0397 - val accuracy: 0.7382
Epoch 38/50
1.0814 - accuracy: 0.7232 - val_loss: 1.0523 - val_accuracy: 0.7361
Epoch 39/50
```

```
1.0819 - accuracy: 0.7242 - val_loss: 1.0573 - val_accuracy: 0.7328
Epoch 40/50
3750/3750 [================] - 35s 9ms/step - loss:
1.0786 - accuracy: 0.7248 - val_loss: 1.0673 - val_accuracy: 0.7314
Epoch 41/50
3750/3750 [============= ] - 32s 9ms/step - loss:
1.0809 - accuracy: 0.7241 - val_loss: 1.0668 - val_accuracy: 0.7325
Epoch 42/50
3750/3750 [============== ] - 32s 9ms/step - loss:
1.0780 - accuracy: 0.7249 - val_loss: 1.0547 - val_accuracy: 0.7353
Epoch 43/50
1.0772 - accuracy: 0.7252 - val_loss: 1.0579 - val_accuracy: 0.7352
Epoch 44/50
1.0773 - accuracy: 0.7251 - val_loss: 1.0533 - val_accuracy: 0.7353
Epoch 45/50
1.0762 - accuracy: 0.7252 - val_loss: 1.0487 - val_accuracy: 0.7371
Epoch 46/50
1.0765 - accuracy: 0.7251 - val_loss: 1.0524 - val_accuracy: 0.7354
Epoch 47/50
1.0748 - accuracy: 0.7252 - val loss: 1.0475 - val accuracy: 0.7381
Epoch 48/50
1.0743 - accuracy: 0.7253 - val loss: 1.0653 - val accuracy: 0.7329
Epoch 49/50
1.0733 - accuracy: 0.7259 - val_loss: 1.0532 - val_accuracy: 0.7353
Epoch 50/50
1.0739 - accuracy: 0.7252 - val_loss: 1.0760 - val_accuracy: 0.7325
save path = '/content/drive/MyDrive/AML mini project/lenet 100e.h5'
model.save(save_path,save_format='tf')
save_path = '/content/drive/MyDrive/AML mini project/lenet.h5'
model = tf.keras.models.load_model(save_path)
```

```
f1f4ff09984b43529cbae8637c55a1df
# we can see that the best fit is around 75 epochs, hence we will
        train the 50 epoch model for mre 25 epochs total of 75
history = model.fit(X_train_re, y_train, epochs = 25, batch_size =
        100, validation_data = (X_test_re, y_test))
                                           Traceback (most recent call
NameError
last)
<ipython-input-17-2bf365c77103> in <module>
      1 # we can see that the best fit is around 75 epochs, hence we
will train the 50 epoch model for mre 25 epochs total of 75
----> 2 history = model.fit(X_train_re, y_train, epochs = 25,
batch_size = 100, validation_data = (X_test_re, y_test))
NameError: name 'model' is not defined
save_path = '/content/drive/MyDrive/AML mini project/lenet_75e.h5'
model.save(save_path,save_format='tf')
```

	data
o	[[0, 0, 0, 4, 4, 0, 0, 3, 5, 2, 0, 0, 11, 0, 0
1	[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
2	[[0, 3, 0, 0, 101, 128, 21, 0, 10, 4, 3, 2, 2,
3	[[0, 12, 55, 101, 116, 98, 79, 66, 52, 39, 30,
4	[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0

df_test['data'] = df_test['data']/255

df test.head()

```
df_test['data'] = df_test['data']/255

df_test.head()

-----
AttributeError Traceback (most recent call
last)
<ipython-input-27-711c74f5b217> in <module>
----> 1 df_test.head()
```

```
AttributeError: 'NoneType' object has no attribute 'head'
test_data = np.array([img[:,:,newaxis] for img in
        np.array(df_test['data'].values)])
test_data.shape
(100000, 28, 28, 1)
X_{\text{test\_data}} = np.pad(\text{test\_data}, ((0,0),(2,2),(2,2),(0,0)), 'constant')
X_test_data.shape
(100000, 32, 32, 1)
save_path = '/content/drive/MyDrive/AML mini project/lenet_75e.h5'
model = tf.keras.models.load_model(save_path)
X_test_data[0].shape
(32, 32, 1)
y_pred = model.predict(X_test_data)
results = np.argmax(y pred,axis = 1)
results
array([77, 50, 80, ..., 63, 0, 22])
```

Trying modifying LeNet architecture

Increase batch size

```
Dropout (0.25),
# - - - - - #
# Layer 3
Conv2D(filters = 64, kernel_size = 3, strides = 1, activation =
      'relu', kernel_regularizer=regularizers.l1_l2(l1=0,
      12=0.0005)).
# Layer 4
Conv2D(filters = 64, kernel_size = 3, strides = 1, use_bias=False),
# Layer 5
BatchNormalization(),
# - - - - - #
Activation('relu'),
MaxPooling2D(pool_size = 2, strides = 2),
Dropout (0.25),
Flatten(),
# - - - - - #
# Layer 6
Dense(units = 320, use_bias=False),
# Layer 7
BatchNormalization(),
# - - - - - #
Activation('relu'),
# - - - - - #
# Laver 8
Dense(units = 160, use_bias=False),
# Layer 9
BatchNormalization(),
# - - - - - #
Activation('relu'),
# - - - - - #
# Layer 10
Dense(units = 128, use_bias=False),
# Layer 11
BatchNormalization(),
# - - - - - #
Activation('relu'),
Dropout(0.25),
# - - - - - #
# Output
Dense(units = 100, activation = 'softmax')
1)
```

```
early stopping = EarlyStopping(min delta = 0.001, patience =
     20, restore_best_weights = True, verbose = 0)
model.compile(optimizer='adam', loss='categorical_crossentropy',
     metrics=['accuracy'])
# model.fit(X_train_re, y_train, batch_size = 400, epochs =
     50, callbacks = [early_stopping], validation_data = (X_test_re,
     y_test))
history = model.fit(X_train_re, y_train, epochs = 50, batch_size =
     150, callbacks = [early stopping], validation data =
     (X_test_re, y_test))
Epoch 1/50
2.2116 - accuracy: 0.4587 - val_loss: 1.5957 - val_accuracy: 0.5915
Epoch 2/50
1.5810 - accuracy: 0.5981 - val_loss: 1.3743 - val_accuracy: 0.6450
Epoch 3/50
1.4423 - accuracy: 0.6323 - val_loss: 1.2739 - val_accuracy: 0.6710
Epoch 4/50
1.3668 - accuracy: 0.6505 - val_loss: 1.1954 - val_accuracy: 0.6905
Epoch 5/50
1.3173 - accuracy: 0.6633 - val_loss: 1.2172 - val_accuracy: 0.6856
Epoch 6/50
1.2796 - accuracy: 0.6715 - val_loss: 1.1713 - val_accuracy: 0.6970
Epoch 7/50
1.2501 - accuracy: 0.6787 - val_loss: 1.1428 - val_accuracy: 0.7053
Epoch 8/50
1.2269 - accuracy: 0.6847 - val_loss: 1.1322 - val_accuracy: 0.7077
Epoch 9/50
1.2061 - accuracy: 0.6898 - val loss: 1.1290 - val accuracy: 0.7090
Epoch 10/50
1.1898 - accuracy: 0.6943 - val_loss: 1.0969 - val_accuracy: 0.7168
Epoch 11/50
```

```
1.1772 - accuracy: 0.6967 - val_loss: 1.1215 - val_accuracy: 0.7130
Epoch 12/50
1.1615 - accuracy: 0.7003 - val_loss: 1.0929 - val_accuracy: 0.7197
Epoch 13/50
1.1515 - accuracy: 0.7030 - val_loss: 1.0917 - val_accuracy: 0.7193
Epoch 14/50
1.1431 - accuracy: 0.7050 - val_loss: 1.0779 - val_accuracy: 0.7221
Epoch 15/50
1.1311 - accuracy: 0.7085 - val_loss: 1.0904 - val_accuracy: 0.7206
Epoch 16/50
1.1220 - accuracy: 0.7108 - val_loss: 1.0715 - val_accuracy: 0.7239
Epoch 17/50
1.1153 - accuracy: 0.7110 - val_loss: 1.0677 - val_accuracy: 0.7280
Epoch 18/50
1.1077 - accuracy: 0.7131 - val_loss: 1.0531 - val_accuracy: 0.7295
Epoch 19/50
1.1004 - accuracy: 0.7154 - val_loss: 1.0938 - val_accuracy: 0.7196
Epoch 20/50
1.0953 - accuracy: 0.7169 - val_loss: 1.0504 - val_accuracy: 0.7322
Epoch 21/50
1.0891 - accuracy: 0.7175 - val loss: 1.0610 - val accuracy: 0.7271
Epoch 22/50
1.0817 - accuracy: 0.7195 - val loss: 1.0567 - val accuracy: 0.7311
Epoch 23/50
1.0790 - accuracy: 0.7194 - val_loss: 1.0614 - val_accuracy: 0.7284
Epoch 24/50
```

```
1.0723 - accuracy: 0.7222 - val_loss: 1.0620 - val_accuracy: 0.7291
Epoch 25/50
1.0685 - accuracy: 0.7226 - val_loss: 1.0496 - val_accuracy: 0.7308
Epoch 26/50
1.0643 - accuracy: 0.7239 - val_loss: 1.0525 - val_accuracy: 0.7322
Epoch 27/50
2500/2500 [============== ] - 29s 12ms/step - loss:
1.0615 - accuracy: 0.7247 - val_loss: 1.0622 - val_accuracy: 0.7284
Epoch 28/50
1.0564 - accuracy: 0.7258 - val_loss: 1.0464 - val_accuracy: 0.7344
Epoch 29/50
1.0523 - accuracy: 0.7264 - val_loss: 1.0464 - val_accuracy: 0.7329
Epoch 30/50
1.0504 - accuracy: 0.7274 - val_loss: 1.0430 - val_accuracy: 0.7353
Epoch 31/50
1.0470 - accuracy: 0.7276 - val_loss: 1.0809 - val_accuracy: 0.7252
Epoch 32/50
2500/2500 [=============== ] - 30s 12ms/step - loss:
1.0410 - accuracy: 0.7291 - val loss: 1.0540 - val accuracy: 0.7315
Epoch 33/50
1.0401 - accuracy: 0.7293 - val loss: 1.0729 - val accuracy: 0.7264
Epoch 34/50
1.0361 - accuracy: 0.7307 - val_loss: 1.0624 - val_accuracy: 0.7309
Epoch 35/50
1.0335 - accuracy: 0.7311 - val_loss: 1.0749 - val_accuracy: 0.7274
Epoch 36/50
1.0308 - accuracy: 0.7319 - val_loss: 1.0504 - val_accuracy: 0.7331
Epoch 37/50
2500/2500 [=============== ] - 30s 12ms/step - loss:
1.0275 - accuracy: 0.7329 - val_loss: 1.0430 - val_accuracy: 0.7358
```

```
Epoch 38/50
1.0257 - accuracy: 0.7324 - val_loss: 1.0396 - val_accuracy: 0.7358
Epoch 39/50
1.0230 - accuracy: 0.7340 - val_loss: 1.0398 - val_accuracy: 0.7369
Epoch 40/50
1.0236 - accuracy: 0.7333 - val_loss: 1.0351 - val_accuracy: 0.7371
Epoch 41/50
1.0172 - accuracy: 0.7352 - val_loss: 1.0561 - val_accuracy: 0.7349
Epoch 42/50
1.0153 - accuracy: 0.7355 - val_loss: 1.0379 - val_accuracy: 0.7378
Epoch 43/50
1.0141 - accuracy: 0.7355 - val_loss: 1.0442 - val_accuracy: 0.7354
Epoch 44/50
1.0114 - accuracy: 0.7354 - val loss: 1.0383 - val accuracy: 0.7360
Epoch 45/50
1.0093 - accuracy: 0.7362 - val loss: 1.0398 - val accuracy: 0.7371
Epoch 46/50
1.0104 - accuracy: 0.7360 - val_loss: 1.0411 - val_accuracy: 0.7377
Epoch 47/50
1.0043 - accuracy: 0.7384 - val_loss: 1.0775 - val_accuracy: 0.7279
Epoch 48/50
1.0028 - accuracy: 0.7380 - val_loss: 1.0375 - val_accuracy: 0.7366
Epoch 49/50
1.0010 - accuracy: 0.7383 - val_loss: 1.0387 - val_accuracy: 0.7370
Epoch 50/50
1.0015 - accuracy: 0.7386 - val loss: 1.0338 - val accuracy: 0.7378
```

Trying to change neurons in hidden layers

```
model = Sequential([
# Laver 1
Conv2D(filters = 32, kernel_size = 5, strides = 1, activation =
       'relu', input_shape = (32,32,1),
       kernel_regularizer=regularizers.l1_l2(l1=0, l2=0.0005)),
# Layer 2
Conv2D(filters = 32, kernel_size = 5, strides = 1, use_bias=False),
# Laver 3
BatchNormalization(),
# - - - - - - #
Activation('relu'),
MaxPooling2D(pool_size = 2, strides = 2),
Dropout (0.25),
# - - - - - - #
# Layer 3
Conv2D(filters = 64, kernel_size = 3, strides = 1, activation =
       'relu', kernel_regularizer=regularizers.l1_l2(l1=0,
       12=0.0005)),
# Layer 4
Conv2D(filters = 64, kernel size = 3, strides = 1, use bias=False),
# Layer 5
BatchNormalization(),
# - - - - - #
Activation('relu'),
MaxPooling2D(pool_size = 2, strides = 2),
Dropout(0.25),
Flatten(),
# - - - - - - #
# Layer 6
Dense(units = 256, use_bias=False),
# Layer 7
BatchNormalization(),
# - - - - - #
Activation('relu'),
# - - - - - #
# Layer 10
Dense(units = 128, use_bias=False),
# Layer 11
BatchNormalization(),
# - - - - - #
```

```
Activation('relu'),
Dropout (0.25),
# - - - - - - #
# Output
Dense(units = 100, activation = 'softmax')
])
early_stopping = EarlyStopping(min_delta = 0.001,patience =
      20, restore_best_weights = True, verbose = 0)
model.compile(optimizer='adam', loss='categorical_crossentropy',
      metrics=['accuracy'])
# model.fit(X_train_re, y_train, batch_size = 400, epochs =
      50, callbacks = [early_stopping], validation_data = (X_test_re,
      y_test))
history = model.fit(X_train_re, y_train, epochs = 50, batch_size =
      150, callbacks = [early_stopping], validation_data =
      (X_test_re, y_test))
Epoch 1/50
2500/2500 [============== ] - 31s 12ms/step - loss:
2.2103 - accuracy: 0.4587 - val_loss: 1.6014 - val_accuracy: 0.5920
Epoch 2/50
1.5995 - accuracy: 0.5932 - val loss: 1.3521 - val accuracy: 0.6519
Epoch 3/50
1.4686 - accuracy: 0.6246 - val loss: 1.3037 - val accuracy: 0.6650
Epoch 4/50
1.3992 - accuracy: 0.6420 - val_loss: 1.3229 - val_accuracy: 0.6599
Epoch 5/50
1.3533 - accuracy: 0.6536 - val_loss: 1.2024 - val_accuracy: 0.6896
Epoch 6/50
1.3196 - accuracy: 0.6615 - val_loss: 1.1897 - val_accuracy: 0.6926
Epoch 7/50
1.2899 - accuracy: 0.6685 - val_loss: 1.1597 - val_accuracy: 0.7022
Epoch 8/50
1.2709 - accuracy: 0.6730 - val loss: 1.1717 - val accuracy: 0.6966
```

```
Epoch 9/50
1.2518 - accuracy: 0.6780 - val_loss: 1.1402 - val_accuracy: 0.7075
Epoch 10/50
1.2366 - accuracy: 0.6815 - val_loss: 1.1636 - val_accuracy: 0.7006
Epoch 11/50
2500/2500 [============= ] - 28s 11ms/step - loss:
1.2245 - accuracy: 0.6843 - val_loss: 1.1111 - val_accuracy: 0.7146
Epoch 12/50
1.2137 - accuracy: 0.6867 - val_loss: 1.1004 - val_accuracy: 0.7170
Epoch 13/50
1.2040 - accuracy: 0.6897 - val_loss: 1.1071 - val_accuracy: 0.7157
Epoch 14/50
2500/2500 [============== ] - 28s 11ms/step - loss:
1.1941 - accuracy: 0.6921 - val_loss: 1.1185 - val_accuracy: 0.7122
Epoch 15/50
1.1865 - accuracy: 0.6937 - val loss: 1.1260 - val accuracy: 0.7110
Epoch 16/50
1.1797 - accuracy: 0.6949 - val loss: 1.1019 - val accuracy: 0.7187
Epoch 17/50
1.1733 - accuracy: 0.6971 - val_loss: 1.0888 - val_accuracy: 0.7215
Epoch 18/50
1.1659 - accuracy: 0.6986 - val_loss: 1.1507 - val_accuracy: 0.7043
Epoch 19/50
1.1612 - accuracy: 0.7001 - val_loss: 1.0709 - val_accuracy: 0.7264
Epoch 20/50
1.1545 - accuracy: 0.7015 - val_loss: 1.0786 - val_accuracy: 0.7232
Epoch 21/50
1.1490 - accuracy: 0.7021 - val loss: 1.0697 - val accuracy: 0.7243
Epoch 22/50
```

```
1.1475 - accuracy: 0.7032 - val_loss: 1.1085 - val_accuracy: 0.7174
Epoch 23/50
1.1388 - accuracy: 0.7055 - val_loss: 1.0930 - val_accuracy: 0.7198
Epoch 24/50
1.1383 - accuracy: 0.7050 - val_loss: 1.0703 - val_accuracy: 0.7261
Epoch 25/50
1.1337 - accuracy: 0.7065 - val_loss: 1.0836 - val_accuracy: 0.7227
Epoch 26/50
1.1295 - accuracy: 0.7073 - val_loss: 1.0606 - val_accuracy: 0.7294
Epoch 27/50
1.1251 - accuracy: 0.7086 - val_loss: 1.0879 - val_accuracy: 0.7215
Epoch 28/50
1.1241 - accuracy: 0.7083 - val_loss: 1.0568 - val_accuracy: 0.7302
Epoch 29/50
1.1203 - accuracy: 0.7097 - val_loss: 1.0652 - val_accuracy: 0.7285
Epoch 30/50
1.1182 - accuracy: 0.7096 - val_loss: 1.1191 - val_accuracy: 0.7119
Epoch 31/50
1.1151 - accuracy: 0.7108 - val_loss: 1.0513 - val_accuracy: 0.7318
Epoch 32/50
1.1112 - accuracy: 0.7114 - val loss: 1.0834 - val accuracy: 0.7229
Epoch 33/50
1.1097 - accuracy: 0.7122 - val loss: 1.0634 - val accuracy: 0.7276
Epoch 34/50
1.1073 - accuracy: 0.7128 - val_loss: 1.0734 - val_accuracy: 0.7251
Epoch 35/50
```

```
1.1040 - accuracy: 0.7125 - val_loss: 1.0718 - val_accuracy: 0.7261
Epoch 36/50
1.1036 - accuracy: 0.7127 - val_loss: 1.0558 - val_accuracy: 0.7292
Epoch 37/50
1.1017 - accuracy: 0.7144 - val_loss: 1.1079 - val_accuracy: 0.7157
Epoch 38/50
1.0992 - accuracy: 0.7150 - val_loss: 1.0574 - val_accuracy: 0.7302
Epoch 39/50
1.0958 - accuracy: 0.7158 - val_loss: 1.0509 - val_accuracy: 0.7309
Epoch 40/50
1.0946 - accuracy: 0.7155 - val_loss: 1.1161 - val_accuracy: 0.7151
Epoch 41/50
1.0942 - accuracy: 0.7159 - val_loss: 1.0506 - val_accuracy: 0.7329
Epoch 42/50
1.0900 - accuracy: 0.7163 - val_loss: 1.0706 - val_accuracy: 0.7265
Epoch 43/50
1.0888 - accuracy: 0.7164 - val loss: 1.0460 - val accuracy: 0.7339
Epoch 44/50
1.0866 - accuracy: 0.7170 - val loss: 1.0615 - val accuracy: 0.7298
Epoch 45/50
1.0852 - accuracy: 0.7171 - val_loss: 1.0690 - val_accuracy: 0.7258
Epoch 46/50
1.0855 - accuracy: 0.7179 - val_loss: 1.0500 - val_accuracy: 0.7329
Epoch 47/50
1.0812 - accuracy: 0.7188 - val_loss: 1.0631 - val_accuracy: 0.7292
Epoch 48/50
1.0832 - accuracy: 0.7182 - val_loss: 1.0621 - val_accuracy: 0.7305
```

Reduce batch size back to 100, with new architecture(modified hidden layers)

```
model = Sequential([
# Laver 1
Conv2D(filters = 32, kernel_size = 5, strides = 1, activation =
        'relu', input_shape = (32,32,1),
       kernel_regularizer=regularizers.l1_l2(l1=0, l2=0.0005)),
# Laver 2
Conv2D(filters = 32, kernel_size = 5, strides = 1, use_bias=False),
# Layer 3
BatchNormalization(),
# - - - - - #
Activation('relu'),
MaxPooling2D(pool_size = 2, strides = 2),
Dropout(0.25),
# - - - - - - #
# Layer 3
Conv2D(filters = 64, kernel_size = 3, strides = 1, activation =
       'relu', kernel_regularizer=regularizers.l1_l2(l1=0,
       12=0.0005)).
# Layer 4
Conv2D(filters = 64, kernel_size = 3, strides = 1, use_bias=False),
# Layer 5
BatchNormalization(),
# - - - - - #
Activation('relu'),
MaxPooling2D(pool size = 2, strides = 2),
Dropout(0.25),
Flatten(),
# - - - - - #
# Laver 6
```

```
Dense(units = 256, use_bias=False),
# Laver 7
BatchNormalization().
# - - - - - - #
Activation('relu'),
# - - - - - #
# Laver 10
Dense(units = 128, use_bias=False),
# Layer 11
BatchNormalization(),
# - - - - - #
Activation('relu'),
Dropout (0.25),
# - - - - - #
# Output
Dense(units = 100, activation = 'softmax')
1)
early_stopping = EarlyStopping(min_delta = 0.001,patience =
      20, restore_best_weights = True, verbose = 0)
model.compile(optimizer='adam', loss='categorical crossentropy',
      metrics=['accuracy'])
# model.fit(X train re, y train, batch size = 400, epochs =
      50, callbacks = [early_stopping], validation_data = (X_{t})
      y test))
history = model.fit(X train re, y train, epochs = 50, batch size =
      100, callbacks = [early stopping], validation data =
      (X_test_re, y_test))
Epoch 1/50
3750/3750 [============== ] - 43s 9ms/step - loss:
2.1532 - accuracy: 0.4711 - val loss: 1.5326 - val accuracy: 0.6105
Epoch 2/50
1.6008 - accuracy: 0.5934 - val loss: 1.3645 - val accuracy: 0.6505
Epoch 3/50
1.4787 - accuracy: 0.6228 - val loss: 1.2879 - val accuracy: 0.6712
Epoch 4/50
1.4118 - accuracy: 0.6392 - val_loss: 1.2095 - val_accuracy: 0.6888
Epoch 5/50
```

```
3750/3750 [============= ] - 33s 9ms/step - loss:
1.3690 - accuracy: 0.6508 - val_loss: 1.1964 - val_accuracy: 0.6921
Epoch 6/50
1.3377 - accuracy: 0.6578 - val_loss: 1.1704 - val_accuracy: 0.6999
Epoch 7/50
1.3142 - accuracy: 0.6641 - val_loss: 1.1578 - val_accuracy: 0.7024
Epoch 8/50
1.2944 - accuracy: 0.6688 - val_loss: 1.1562 - val_accuracy: 0.7045
Epoch 9/50
1.2781 - accuracy: 0.6729 - val_loss: 1.1708 - val_accuracy: 0.6998
Epoch 10/50
1.2610 - accuracy: 0.6775 - val_loss: 1.1177 - val_accuracy: 0.7135
Epoch 11/50
1.2495 - accuracy: 0.6789 - val_loss: 1.1286 - val_accuracy: 0.7114
Epoch 12/50
1.2407 - accuracy: 0.6816 - val_loss: 1.1106 - val_accuracy: 0.7158
Epoch 13/50
1.2291 - accuracy: 0.6844 - val_loss: 1.1114 - val_accuracy: 0.7157
Epoch 14/50
1.2231 - accuracy: 0.6861 - val loss: 1.1042 - val accuracy: 0.7178
Epoch 15/50
1.2136 - accuracy: 0.6883 - val loss: 1.0939 - val accuracy: 0.7197
Epoch 16/50
1.2075 - accuracy: 0.6899 - val loss: 1.1110 - val accuracy: 0.7162
Epoch 17/50
1.1975 - accuracy: 0.6922 - val_loss: 1.1220 - val_accuracy: 0.7115
Epoch 18/50
```

```
1.1949 - accuracy: 0.6927 - val_loss: 1.0900 - val_accuracy: 0.7219
Epoch 19/50
1.1884 - accuracy: 0.6938 - val_loss: 1.0867 - val_accuracy: 0.7224
Epoch 20/50
1.1837 - accuracy: 0.6952 - val_loss: 1.0910 - val_accuracy: 0.7215
Epoch 21/50
3750/3750 [============== ] - 33s 9ms/step - loss:
1.1786 - accuracy: 0.6965 - val_loss: 1.0993 - val_accuracy: 0.7205
Epoch 22/50
1.1745 - accuracy: 0.6973 - val_loss: 1.0767 - val_accuracy: 0.7240
Epoch 23/50
1.1700 - accuracy: 0.6984 - val_loss: 1.0681 - val_accuracy: 0.7272
Epoch 24/50
1.1681 - accuracy: 0.6988 - val_loss: 1.1138 - val_accuracy: 0.7176
Epoch 25/50
3750/3750 [============= ] - 32s 8ms/step - loss:
1.1628 - accuracy: 0.7006 - val_loss: 1.0797 - val_accuracy: 0.7258
Epoch 26/50
1.1576 - accuracy: 0.7022 - val loss: 1.0691 - val accuracy: 0.7264
Epoch 27/50
1.1582 - accuracy: 0.7014 - val loss: 1.0788 - val accuracy: 0.7257
Epoch 28/50
1.1535 - accuracy: 0.7026 - val_loss: 1.0734 - val_accuracy: 0.7254
Epoch 29/50
1.1483 - accuracy: 0.7038 - val_loss: 1.0970 - val_accuracy: 0.7198
Epoch 30/50
1.1466 - accuracy: 0.7040 - val_loss: 1.0746 - val_accuracy: 0.7260
Epoch 31/50
1.1456 - accuracy: 0.7052 - val_loss: 1.0736 - val_accuracy: 0.7265
```

```
Epoch 32/50
1.1435 - accuracy: 0.7048 - val_loss: 1.0736 - val_accuracy: 0.7256
Epoch 33/50
1.1372 - accuracy: 0.7068 - val_loss: 1.0707 - val_accuracy: 0.7278
Epoch 34/50
1.1367 - accuracy: 0.7071 - val_loss: 1.0758 - val_accuracy: 0.7268
Epoch 35/50
1.1344 - accuracy: 0.7072 - val_loss: 1.0673 - val_accuracy: 0.7304
Epoch 36/50
1.1315 - accuracy: 0.7078 - val_loss: 1.0574 - val_accuracy: 0.7305
Epoch 37/50
1.1320 - accuracy: 0.7083 - val_loss: 1.0718 - val_accuracy: 0.7268
Epoch 38/50
1.1276 - accuracy: 0.7085 - val loss: 1.0619 - val accuracy: 0.7291
Epoch 39/50
1.1264 - accuracy: 0.7093 - val loss: 1.0466 - val accuracy: 0.7337
Epoch 40/50
1.1259 - accuracy: 0.7098 - val_loss: 1.0781 - val_accuracy: 0.7258
Epoch 41/50
1.1213 - accuracy: 0.7106 - val_loss: 1.0522 - val_accuracy: 0.7309
Epoch 42/50
1.1213 - accuracy: 0.7106 - val_loss: 1.0706 - val_accuracy: 0.7276
Epoch 43/50
1.1195 - accuracy: 0.7111 - val_loss: 1.0562 - val_accuracy: 0.7310
Epoch 44/50
1.1164 - accuracy: 0.7110 - val loss: 1.0514 - val accuracy: 0.7319
Epoch 45/50
```

```
3750/3750 [============= ] - 33s 9ms/step - loss:
1.1146 - accuracy: 0.7119 - val_loss: 1.0632 - val_accuracy: 0.7295
Epoch 46/50
1.1143 - accuracy: 0.7117 - val_loss: 1.0546 - val_accuracy: 0.7326
Epoch 47/50
1.1110 - accuracy: 0.7132 - val_loss: 1.0881 - val_accuracy: 0.7243
Epoch 48/50
3750/3750 [============= ] - 33s 9ms/step - loss:
1.1132 - accuracy: 0.7127 - val_loss: 1.0584 - val_accuracy: 0.7306
Epoch 49/50
1.1096 - accuracy: 0.7133 - val_loss: 1.0570 - val_accuracy: 0.7328
Epoch 50/50
3750/3750 [============== ] - 31s 8ms/step - loss:
1.1082 - accuracy: 0.7135 - val_loss: 1.0591 - val_accuracy: 0.7299
save_path = '/content/drive/MyDrive/AML mini
      project/lenet_50e_100b_1.h5'
model.save(save_path,save_format='tf')
```

Adding one more hidden layer

```
model = Sequential([
# Layer 1
Conv2D(filters = 32, kernel size = 5, strides = 1, activation =
        'relu', input shape = (32,32,1),
        kernel_regularizer=regularizers.l1_l2(l1=0, l2=0.0005)),
# Layer 2
Conv2D(filters = 32, kernel size = 5, strides = 1, use bias=False),
# Layer 3
BatchNormalization(),
# - - - - - #
Activation('relu'),
MaxPooling2D(pool_size = 2, strides = 2),
Dropout (0.25),
# - - - - - #
# Laver 3
Conv2D(filters = 64, kernel size = 3, strides = 1, activation =
        'relu', kernel_regularizer=regularizers.l1_l2(l1=0,
       12=0.0005)),
# Laver 4
```

```
Conv2D(filters = 64, kernel_size = 3, strides = 1, use_bias=False),
# Layer 5
BatchNormalization(),
# - - - - - #
Activation('relu'),
MaxPooling2D(pool_size = 2, strides = 2),
Dropout(0.25),
Flatten(),
# - - - - - - #
# Layer 6
Dense(units = 256, use_bias=False),
# Layer 7
BatchNormalization(),
# - - - - - #
Activation('relu'),
# - - - - - #
# Layer 8
Dense(units = 186, use_bias=False),
# Layer 9
BatchNormalization(),
# - - - - - #
Activation('relu'),
# - - - - - #
# Layer 10
Dense(units = 128, use bias=False),
# Layer 11
BatchNormalization(),
# - - - - - - -
Activation('relu'),
# - - - - - #
# Layer 12
Dense(units = 84, use bias=False),
# Layer 13
BatchNormalization(),
# - - - - - #
Activation('relu'),
Dropout(0.25),
# - - - - - #
# Output
```

```
Dense(units = 100, activation = 'softmax')
])
early_stopping = EarlyStopping(min_delta = 0.001,patience =
              20, restore_best_weights = True, verbose = 0)
model.compile(optimizer='adam', loss='categorical_crossentropy',
              metrics=['accuracy'])
# model.fit(X train re, y train, batch size = 400, epochs =
              50, callbacks = [early_stopping], validation_data = (X_{test_re}, X_{test_re}, 
              y_test))
history = model.fit(X_train_re, y_train, epochs = 50, batch_size =
              100, callbacks = [early_stopping], validation_data =
              (X test re, y test))
Epoch 1/50
2.3009 - accuracy: 0.4401 - val_loss: 1.5902 - val_accuracy: 0.5925
Epoch 2/50
1.6725 - accuracy: 0.5796 - val_loss: 1.4001 - val_accuracy: 0.6415
Epoch 3/50
1.5302 - accuracy: 0.6150 - val_loss: 1.3544 - val_accuracy: 0.6550
Epoch 4/50
1.4518 - accuracy: 0.6347 - val_loss: 1.3184 - val_accuracy: 0.6616
Epoch 5/50
1.3979 - accuracy: 0.6478 - val loss: 1.2264 - val accuracy: 0.6860
Epoch 6/50
1.3604 - accuracy: 0.6581 - val_loss: 1.1936 - val_accuracy: 0.6949
Epoch 7/50
1.3326 - accuracy: 0.6646 - val loss: 1.1751 - val accuracy: 0.6995
Epoch 8/50
3750/3750 [============== ] - 34s 9ms/step - loss:
1.3076 - accuracy: 0.6700 - val_loss: 1.1685 - val_accuracy: 0.7021
Epoch 9/50
1.2868 - accuracy: 0.6753 - val_loss: 1.1796 - val_accuracy: 0.6988
Epoch 10/50
```

```
1.2699 - accuracy: 0.6797 - val_loss: 1.2019 - val_accuracy: 0.6948
Epoch 11/50
1.2514 - accuracy: 0.6844 - val_loss: 1.1396 - val_accuracy: 0.7086
Epoch 12/50
1.2419 - accuracy: 0.6866 - val_loss: 1.1343 - val_accuracy: 0.7117
Epoch 13/50
3750/3750 [============== ] - 35s 9ms/step - loss:
1.2315 - accuracy: 0.6892 - val_loss: 1.1484 - val_accuracy: 0.7083
Epoch 14/50
1.2181 - accuracy: 0.6925 - val_loss: 1.1194 - val_accuracy: 0.7162
Epoch 15/50
1.2098 - accuracy: 0.6940 - val_loss: 1.1274 - val_accuracy: 0.7134
Epoch 16/50
1.2026 - accuracy: 0.6949 - val_loss: 1.1141 - val_accuracy: 0.7166
Epoch 17/50
1.1927 - accuracy: 0.6979 - val_loss: 1.1511 - val_accuracy: 0.7071
Epoch 18/50
1.1854 - accuracy: 0.6999 - val loss: 1.1378 - val accuracy: 0.7115
Epoch 19/50
1.1802 - accuracy: 0.7009 - val loss: 1.1031 - val accuracy: 0.7220
Epoch 20/50
1.1708 - accuracy: 0.7042 - val_loss: 1.1022 - val_accuracy: 0.7199
Epoch 21/50
1.1653 - accuracy: 0.7049 - val_loss: 1.0740 - val_accuracy: 0.7275
Epoch 22/50
1.1634 - accuracy: 0.7052 - val_loss: 1.0928 - val_accuracy: 0.7229
Epoch 23/50
1.1569 - accuracy: 0.7069 - val_loss: 1.0736 - val_accuracy: 0.7268
```

```
Epoch 24/50
1.1520 - accuracy: 0.7077 - val_loss: 1.1143 - val_accuracy: 0.7171
Epoch 25/50
1.1458 - accuracy: 0.7092 - val_loss: 1.0754 - val_accuracy: 0.7287
Epoch 26/50
1.1428 - accuracy: 0.7105 - val_loss: 1.0879 - val_accuracy: 0.7255
Epoch 27/50
1.1373 - accuracy: 0.7119 - val_loss: 1.0776 - val_accuracy: 0.7280
Epoch 28/50
1.1334 - accuracy: 0.7128 - val_loss: 1.1104 - val_accuracy: 0.7176
Epoch 29/50
1.1299 - accuracy: 0.7135 - val_loss: 1.0899 - val_accuracy: 0.7256
Epoch 30/50
1.1269 - accuracy: 0.7135 - val loss: 1.0791 - val accuracy: 0.7266
Epoch 31/50
1.1211 - accuracy: 0.7158 - val loss: 1.0641 - val accuracy: 0.7316
Epoch 32/50
1.1197 - accuracy: 0.7160 - val_loss: 1.0664 - val_accuracy: 0.7300
Epoch 33/50
1.1164 - accuracy: 0.7164 - val_loss: 1.0599 - val_accuracy: 0.7322
Epoch 34/50
1.1124 - accuracy: 0.7172 - val_loss: 1.0841 - val_accuracy: 0.7273
Epoch 35/50
1.1100 - accuracy: 0.7181 - val_loss: 1.0623 - val_accuracy: 0.7311
Epoch 36/50
1.1069 - accuracy: 0.7182 - val loss: 1.0741 - val accuracy: 0.7282
Epoch 37/50
```

```
3750/3750 [============= ] - 33s 9ms/step - loss:
1.1046 - accuracy: 0.7196 - val_loss: 1.0906 - val_accuracy: 0.7242
Epoch 38/50
1.1035 - accuracy: 0.7191 - val_loss: 1.0509 - val_accuracy: 0.7352
Epoch 39/50
1.0988 - accuracy: 0.7205 - val_loss: 1.0595 - val_accuracy: 0.7326
Epoch 40/50
3750/3750 [=================] - 34s 9ms/step - loss:
1.0981 - accuracy: 0.7206 - val_loss: 1.0623 - val_accuracy: 0.7338
Epoch 41/50
1.0954 - accuracy: 0.7216 - val_loss: 1.1022 - val_accuracy: 0.7211
Epoch 42/50
1.0918 - accuracy: 0.7229 - val_loss: 1.0681 - val_accuracy: 0.7300
Epoch 43/50
1.0909 - accuracy: 0.7227 - val_loss: 1.0713 - val_accuracy: 0.7307
Epoch 44/50
3750/3750 [============= ] - 34s 9ms/step - loss:
1.0886 - accuracy: 0.7242 - val_loss: 1.0763 - val_accuracy: 0.7291
Epoch 45/50
3750/3750 [============= ] - 35s 9ms/step - loss:
1.0854 - accuracy: 0.7228 - val_loss: 1.0581 - val_accuracy: 0.7340
Epoch 46/50
1.0844 - accuracy: 0.7244 - val loss: 1.0536 - val accuracy: 0.7346
Epoch 47/50
1.0824 - accuracy: 0.7244 - val loss: 1.0541 - val accuracy: 0.7357
Epoch 48/50
1.0825 - accuracy: 0.7242 - val loss: 1.0521 - val accuracy: 0.7361
Epoch 49/50
1.0792 - accuracy: 0.7255 - val_loss: 1.0494 - val_accuracy: 0.7356
Epoch 50/50
```

Predictions

```
df_test = pickle.load(open(test_path,'rb'))
df_test['data'] = df_test['data']/255
df_test.head()
```

	data
o	[[0.0, 0.0, 0.0, 0.01568627450980392, 0.015686
1	[[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0
2	[[0.0, 0.011764705882352941, 0.0, 0.0, 0.39607
3	[[0.0, 0.047058823529411764, 0.215686274509803
4	[[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0

```
array([77, 50, 80, ..., 63, 0, 22])
with open('/content/drive/MyDrive/AMLminiproject/project_rsheta.txt',
        'w') as file: # edit here as your username
   file.write('\n'.join(map(str, results)))
   file.flush()
y_pred = model.predict(X_test_re)
3907/3907 [============ ] - 10s 2ms/step
results = np.argmax(y_pred,axis = 1)
results.shape
(125000,)
y_test_new = np.argmax(y_test,axis = 1)
y_test_new.shape
(125000,)
from sklearn.metrics import accuracy_score
accuracy_score(y_test_new, results)
0.731992
y_test_new[:5]
array([20, 39, 28, 26, 81])
results[:5]
array([51, 39, 28, 26, 81])
```