

01_deep_learning_for_nlp

March 12, 2024

```
[16]: # tensorflow or pytorch?
      # here, tensorflow
      import tensorflow as tf
      # import models and layers from tensorflow.keras
      from tensorflow.keras import models, layers
      import tensorflow_datasets as tfds
      import numpy as np
      import matplotlib.pyplot as plt
```

```
[17]: (dataset_train_original, dataset_validate_original, dataset_test_original),
      ↪info = tfds.load(
          "mnist",
          split = ["train", "test[:50%]", "test[50%:]"], # 60,000 for stochastic
          ↪gradient descent, 5,000 for test, 5,000 for validation
          as_supervised = True, # to use inputs and outputs for training, returns
          ↪tuples, not dictionaries
          with_info = True,
      )
      info
```

```
[17]: tfds.core.DatasetInfo(
      name='mnist',
      full_name='mnist/3.0.1',
      description="""
      The MNIST database of handwritten digits.
      """,
      homepage='http://yann.lecun.com/exdb/mnist/',
      data_dir='/home/solaris/tensorflow_datasets/mnist/3.0.1',
      file_format=tfrecord,
      download_size=11.06 MiB,
      dataset_size=21.00 MiB,
      features=FeaturesDict({
          'image': Image(shape=(28, 28, 1), dtype=uint8),
          'label': ClassLabel(shape=(), dtype=int64, num_classes=10),
      }),
      supervised_keys=('image', 'label'),
      disable_shuffling=False,
```

```

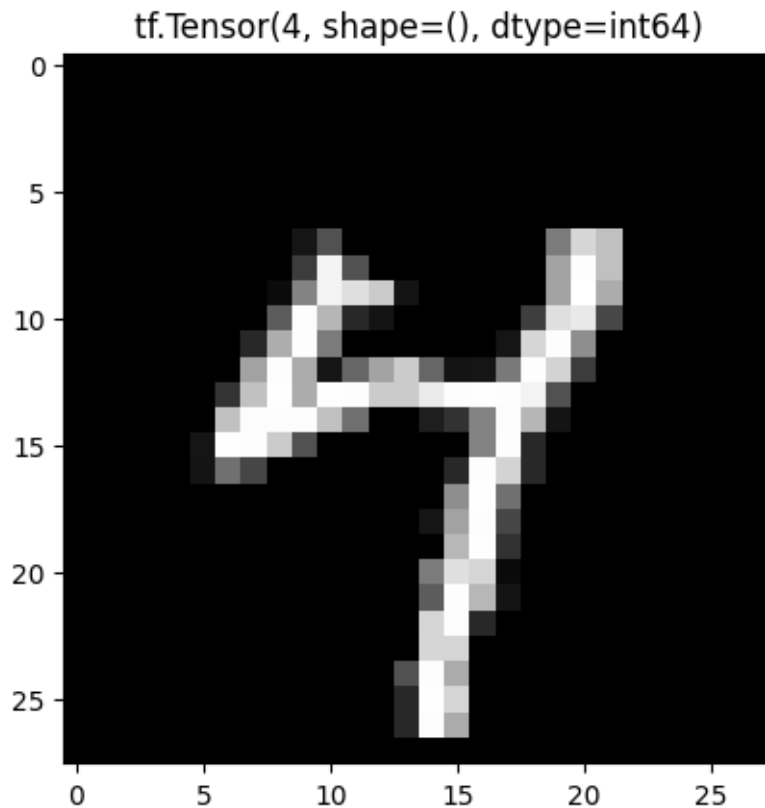
splits={
    'test': <SplitInfo num_examples=10000, num_shards=1>,
    'train': <SplitInfo num_examples=60000, num_shards=1>,
},
citation="""@article{lecun2010mnist,
    title={MNIST handwritten digit database},
    author={LeCun, Yann and Cortes, Corinna and Burges, CJ},
    journal={ATT Labs [Online]. Available: http://yann.lecun.com/exdb/mnist},
    volume={2},
    year={2010}
}""",
)

```

```

[18]: # inspect data
      # takes a sample of the dataset
      # use snake case with _
      # use chain to use sub commands with .
      for x, y in dataset_train_original.shuffle(60_000).take(1):
          plt.imshow(x, cmap="gray")
          plt.title(str(y))

```



```
[19]: # normalise dataset
def encode(image, label):
    # encodes data
    image = tf.image.convert_image_dtype(image, dtype=tf.float32)
    return image, label

# lambda is an anonymous function; .map applies to multiple data types; apply
    ↪ encode to each data point
#dataset = dataset_train_original.map(lambda image, label: encode(image,
    ↪ label))
dataset = dataset_train_original.map(encode)

for image, label in dataset.take(1):
    print(image.dtype, image.shape)
    print(label)
```

```
<dtype: 'float32'> (28, 28, 1)
tf.Tensor(4, shape=(), dtype=int64)
```

```
[20]: dataset_train = dataset_train_original.map(encode).cache().shuffle(60_000).
    ↪ batch(128)
dataset_validate = dataset_validate_original.map(encode).cache().batch(128)
dataset_test = dataset_test_original.map(encode).cache().batch(128)
```

```
[21]: # define architecture of model
# this defines a model in tensorflow
# stackable API is .Sequential()
# produces 200175 trainable parameters

# 1. Build Neural Network

# starts with low activation scores
model = models.Sequential()
# sets dimensions of input
model.add(layers.Flatten(input_shape=(28, 28, 1)))
# add input layer with 255 units and
model.add(layers.Dense(units=255, activation="relu"))
# add hidden layer with 128 units
model.add(layers.Dense(units=128, activation="relu"))
# add output layer, linear, then softmax activation (probability 0-1 of output
    ↪ being category)
model.add(layers.Dense(units=10, activation="softmax"))
model.summary()

# 2. Train model

model.compile(
```

```

# gradient descent optimization
# adam is influenced by stochastic gradient descent
optimizer="adam",
# distance between expected and observed values
# we're predicting 10 categories
loss="sparse_categorical_crossentropy",
# add evaluation
# we need metrics to show accuracy
# easier to interpret than probability scores
metrics=["accuracy"]
)

model.fit(
    dataset_train,
    epochs=100,
    validation_data=dataset_validate
)
# backpropagation

```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
flatten_5 (Flatten)	(None, 784)	0
dense_15 (Dense)	(None, 255)	200175
dense_16 (Dense)	(None, 128)	32768
dense_17 (Dense)	(None, 10)	1290

```

=====
Total params: 234233 (914.97 KB)
Trainable params: 234233 (914.97 KB)
Non-trainable params: 0 (0.00 Byte)
=====

```

```

-----
Epoch 1/100
469/469 [=====] - 2s 2ms/step - loss: 0.2757 -
accuracy: 0.9208 - val_loss: 0.1281 - val_accuracy: 0.9604
Epoch 2/100
469/469 [=====] - 1s 2ms/step - loss: 0.1038 -
accuracy: 0.9688 - val_loss: 0.0956 - val_accuracy: 0.9706
Epoch 3/100
469/469 [=====] - 1s 2ms/step - loss: 0.0672 -
accuracy: 0.9789 - val_loss: 0.0827 - val_accuracy: 0.9762
Epoch 4/100
469/469 [=====] - 1s 2ms/step - loss: 0.0475 -
accuracy: 0.9850 - val_loss: 0.0760 - val_accuracy: 0.9762

```

Epoch 5/100
469/469 [=====] - 1s 2ms/step - loss: 0.0368 -
accuracy: 0.9882 - val_loss: 0.0743 - val_accuracy: 0.9760
Epoch 6/100
469/469 [=====] - 1s 2ms/step - loss: 0.0292 -
accuracy: 0.9909 - val_loss: 0.0660 - val_accuracy: 0.9796
Epoch 7/100
469/469 [=====] - 1s 2ms/step - loss: 0.0195 -
accuracy: 0.9938 - val_loss: 0.0672 - val_accuracy: 0.9820
Epoch 8/100
469/469 [=====] - 1s 2ms/step - loss: 0.0186 -
accuracy: 0.9942 - val_loss: 0.0885 - val_accuracy: 0.9746
Epoch 9/100
469/469 [=====] - 1s 2ms/step - loss: 0.0159 -
accuracy: 0.9949 - val_loss: 0.0686 - val_accuracy: 0.9806
Epoch 10/100
469/469 [=====] - 1s 2ms/step - loss: 0.0127 -
accuracy: 0.9959 - val_loss: 0.0851 - val_accuracy: 0.9788
Epoch 11/100
469/469 [=====] - 1s 2ms/step - loss: 0.0110 -
accuracy: 0.9963 - val_loss: 0.0893 - val_accuracy: 0.9764
Epoch 12/100
469/469 [=====] - 1s 2ms/step - loss: 0.0137 -
accuracy: 0.9954 - val_loss: 0.0950 - val_accuracy: 0.9754
Epoch 13/100
469/469 [=====] - 1s 2ms/step - loss: 0.0094 -
accuracy: 0.9969 - val_loss: 0.0722 - val_accuracy: 0.9830
Epoch 14/100
469/469 [=====] - 1s 2ms/step - loss: 0.0093 -
accuracy: 0.9967 - val_loss: 0.0973 - val_accuracy: 0.9762
Epoch 15/100
469/469 [=====] - 1s 2ms/step - loss: 0.0053 -
accuracy: 0.9982 - val_loss: 0.1126 - val_accuracy: 0.9774
Epoch 16/100
469/469 [=====] - 1s 2ms/step - loss: 0.0116 -
accuracy: 0.9960 - val_loss: 0.0873 - val_accuracy: 0.9814
Epoch 17/100
469/469 [=====] - 1s 2ms/step - loss: 0.0071 -
accuracy: 0.9976 - val_loss: 0.0846 - val_accuracy: 0.9820
Epoch 18/100
469/469 [=====] - 1s 2ms/step - loss: 0.0093 -
accuracy: 0.9969 - val_loss: 0.0939 - val_accuracy: 0.9798
Epoch 19/100
469/469 [=====] - 1s 2ms/step - loss: 0.0035 -
accuracy: 0.9989 - val_loss: 0.0839 - val_accuracy: 0.9840
Epoch 20/100
469/469 [=====] - 1s 2ms/step - loss: 0.0029 -
accuracy: 0.9991 - val_loss: 0.0928 - val_accuracy: 0.9816

Epoch 21/100
469/469 [=====] - 1s 2ms/step - loss: 0.0128 -
accuracy: 0.9960 - val_loss: 0.1016 - val_accuracy: 0.9806
Epoch 22/100
469/469 [=====] - 1s 2ms/step - loss: 0.0071 -
accuracy: 0.9976 - val_loss: 0.0919 - val_accuracy: 0.9796
Epoch 23/100
469/469 [=====] - 1s 2ms/step - loss: 0.0049 -
accuracy: 0.9986 - val_loss: 0.0827 - val_accuracy: 0.9848
Epoch 24/100
469/469 [=====] - 1s 2ms/step - loss: 0.0029 -
accuracy: 0.9991 - val_loss: 0.0785 - val_accuracy: 0.9828
Epoch 25/100
469/469 [=====] - 1s 2ms/step - loss: 0.0070 -
accuracy: 0.9975 - val_loss: 0.0856 - val_accuracy: 0.9818
Epoch 26/100
469/469 [=====] - 1s 2ms/step - loss: 0.0046 -
accuracy: 0.9985 - val_loss: 0.0956 - val_accuracy: 0.9820
Epoch 27/100
469/469 [=====] - 1s 2ms/step - loss: 0.0066 -
accuracy: 0.9978 - val_loss: 0.0972 - val_accuracy: 0.9816
Epoch 28/100
469/469 [=====] - 1s 2ms/step - loss: 0.0066 -
accuracy: 0.9980 - val_loss: 0.1097 - val_accuracy: 0.9798
Epoch 29/100
469/469 [=====] - 1s 2ms/step - loss: 0.0049 -
accuracy: 0.9983 - val_loss: 0.0869 - val_accuracy: 0.9842
Epoch 30/100
469/469 [=====] - 1s 2ms/step - loss: 0.0048 -
accuracy: 0.9984 - val_loss: 0.1010 - val_accuracy: 0.9808
Epoch 31/100
469/469 [=====] - 1s 2ms/step - loss: 0.0044 -
accuracy: 0.9987 - val_loss: 0.1042 - val_accuracy: 0.9810
Epoch 32/100
469/469 [=====] - 1s 2ms/step - loss: 0.0026 -
accuracy: 0.9993 - val_loss: 0.1150 - val_accuracy: 0.9822
Epoch 33/100
469/469 [=====] - 1s 2ms/step - loss: 0.0022 -
accuracy: 0.9993 - val_loss: 0.1262 - val_accuracy: 0.9796
Epoch 34/100
469/469 [=====] - 1s 2ms/step - loss: 0.0095 -
accuracy: 0.9972 - val_loss: 0.1154 - val_accuracy: 0.9776
Epoch 35/100
469/469 [=====] - 1s 2ms/step - loss: 0.0058 -
accuracy: 0.9983 - val_loss: 0.1106 - val_accuracy: 0.9830
Epoch 36/100
469/469 [=====] - 1s 2ms/step - loss: 0.0050 -
accuracy: 0.9986 - val_loss: 0.0947 - val_accuracy: 0.9840

Epoch 37/100
469/469 [=====] - 1s 2ms/step - loss: 0.0013 -
accuracy: 0.9996 - val_loss: 0.1247 - val_accuracy: 0.9802
Epoch 38/100
469/469 [=====] - 1s 2ms/step - loss: 0.0075 -
accuracy: 0.9979 - val_loss: 0.1194 - val_accuracy: 0.9790
Epoch 39/100
469/469 [=====] - 1s 2ms/step - loss: 0.0046 -
accuracy: 0.9984 - val_loss: 0.1031 - val_accuracy: 0.9826
Epoch 40/100
469/469 [=====] - 1s 2ms/step - loss: 0.0012 -
accuracy: 0.9995 - val_loss: 0.0953 - val_accuracy: 0.9850
Epoch 41/100
469/469 [=====] - 1s 2ms/step - loss: 2.6404e-04 -
accuracy: 0.9999 - val_loss: 0.0837 - val_accuracy: 0.9860
Epoch 42/100
469/469 [=====] - 1s 2ms/step - loss: 0.0016 -
accuracy: 0.9995 - val_loss: 0.1018 - val_accuracy: 0.9834
Epoch 43/100
469/469 [=====] - 1s 2ms/step - loss: 0.0086 -
accuracy: 0.9976 - val_loss: 0.1125 - val_accuracy: 0.9820
Epoch 44/100
469/469 [=====] - 1s 2ms/step - loss: 0.0058 -
accuracy: 0.9981 - val_loss: 0.1201 - val_accuracy: 0.9820
Epoch 45/100
469/469 [=====] - 1s 2ms/step - loss: 0.0047 -
accuracy: 0.9986 - val_loss: 0.1172 - val_accuracy: 0.9806
Epoch 46/100
469/469 [=====] - 1s 2ms/step - loss: 0.0036 -
accuracy: 0.9988 - val_loss: 0.1235 - val_accuracy: 0.9810
Epoch 47/100
469/469 [=====] - 1s 2ms/step - loss: 0.0025 -
accuracy: 0.9991 - val_loss: 0.1197 - val_accuracy: 0.9808
Epoch 48/100
469/469 [=====] - 1s 2ms/step - loss: 0.0033 -
accuracy: 0.9989 - val_loss: 0.1126 - val_accuracy: 0.9828
Epoch 49/100
469/469 [=====] - 1s 2ms/step - loss: 0.0015 -
accuracy: 0.9996 - val_loss: 0.1064 - val_accuracy: 0.9836
Epoch 50/100
469/469 [=====] - 1s 2ms/step - loss: 0.0010 -
accuracy: 0.9997 - val_loss: 0.1045 - val_accuracy: 0.9852
Epoch 51/100
469/469 [=====] - 1s 2ms/step - loss: 0.0053 -
accuracy: 0.9984 - val_loss: 0.1499 - val_accuracy: 0.9780
Epoch 52/100
469/469 [=====] - 1s 2ms/step - loss: 0.0092 -
accuracy: 0.9974 - val_loss: 0.1352 - val_accuracy: 0.9792

Epoch 53/100
469/469 [=====] - 1s 2ms/step - loss: 0.0040 -
accuracy: 0.9988 - val_loss: 0.1120 - val_accuracy: 0.9826
Epoch 54/100
469/469 [=====] - 1s 2ms/step - loss: 0.0021 -
accuracy: 0.9993 - val_loss: 0.1175 - val_accuracy: 0.9812
Epoch 55/100
469/469 [=====] - 1s 2ms/step - loss: 2.9564e-04 -
accuracy: 0.9999 - val_loss: 0.0974 - val_accuracy: 0.9838
Epoch 56/100
469/469 [=====] - 1s 2ms/step - loss: 8.8317e-05 -
accuracy: 1.0000 - val_loss: 0.0919 - val_accuracy: 0.9850
Epoch 57/100
469/469 [=====] - 1s 2ms/step - loss: 1.6913e-05 -
accuracy: 1.0000 - val_loss: 0.0925 - val_accuracy: 0.9854
Epoch 58/100
469/469 [=====] - 1s 2ms/step - loss: 1.0944e-05 -
accuracy: 1.0000 - val_loss: 0.0925 - val_accuracy: 0.9850
Epoch 59/100
469/469 [=====] - 1s 2ms/step - loss: 8.7046e-06 -
accuracy: 1.0000 - val_loss: 0.0929 - val_accuracy: 0.9848
Epoch 60/100
469/469 [=====] - 1s 2ms/step - loss: 7.2106e-06 -
accuracy: 1.0000 - val_loss: 0.0934 - val_accuracy: 0.9854
Epoch 61/100
469/469 [=====] - 1s 2ms/step - loss: 5.9695e-06 -
accuracy: 1.0000 - val_loss: 0.0938 - val_accuracy: 0.9852
Epoch 62/100
469/469 [=====] - 1s 2ms/step - loss: 4.9962e-06 -
accuracy: 1.0000 - val_loss: 0.0943 - val_accuracy: 0.9852
Epoch 63/100
469/469 [=====] - 1s 2ms/step - loss: 4.1346e-06 -
accuracy: 1.0000 - val_loss: 0.0950 - val_accuracy: 0.9852
Epoch 64/100
469/469 [=====] - 1s 2ms/step - loss: 3.4688e-06 -
accuracy: 1.0000 - val_loss: 0.0953 - val_accuracy: 0.9852
Epoch 65/100
469/469 [=====] - 1s 2ms/step - loss: 2.8735e-06 -
accuracy: 1.0000 - val_loss: 0.0961 - val_accuracy: 0.9850
Epoch 66/100
469/469 [=====] - 1s 2ms/step - loss: 2.3961e-06 -
accuracy: 1.0000 - val_loss: 0.0966 - val_accuracy: 0.9850
Epoch 67/100
469/469 [=====] - 1s 2ms/step - loss: 1.9753e-06 -
accuracy: 1.0000 - val_loss: 0.0970 - val_accuracy: 0.9856
Epoch 68/100
469/469 [=====] - 1s 2ms/step - loss: 1.6392e-06 -
accuracy: 1.0000 - val_loss: 0.0979 - val_accuracy: 0.9852

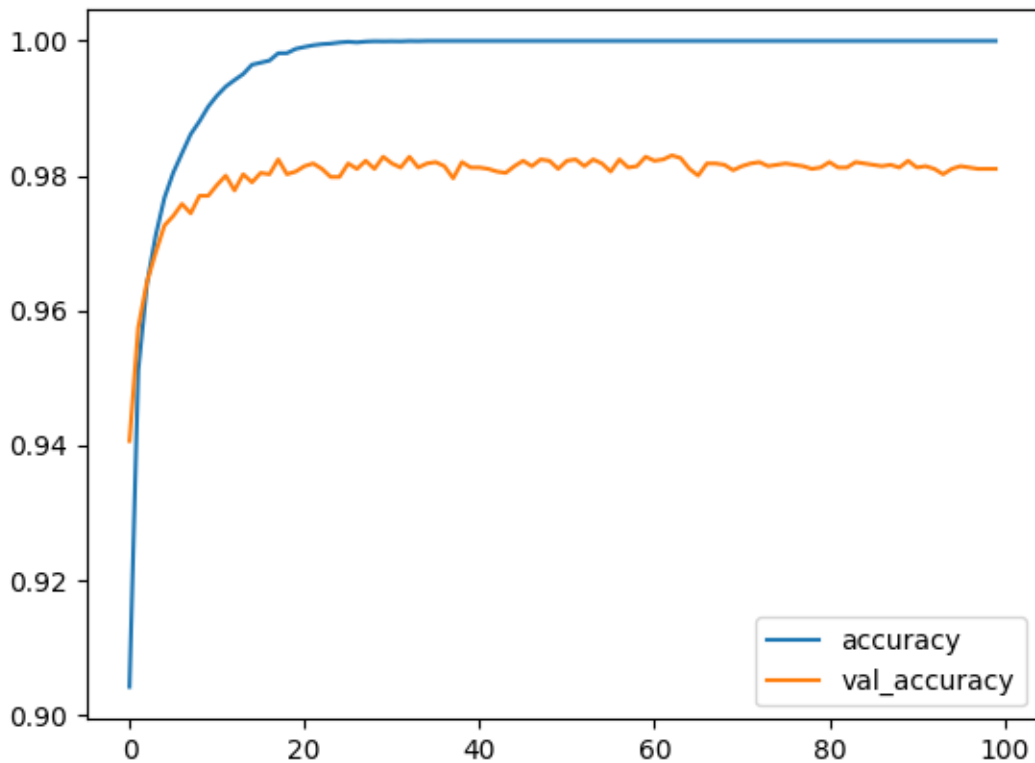
Epoch 69/100
469/469 [=====] - 1s 2ms/step - loss: 1.3451e-06 - accuracy: 1.0000 - val_loss: 0.0988 - val_accuracy: 0.9852
Epoch 70/100
469/469 [=====] - 1s 2ms/step - loss: 1.1000e-06 - accuracy: 1.0000 - val_loss: 0.0995 - val_accuracy: 0.9862
Epoch 71/100
469/469 [=====] - 1s 2ms/step - loss: 8.9507e-07 - accuracy: 1.0000 - val_loss: 0.1003 - val_accuracy: 0.9860
Epoch 72/100
469/469 [=====] - 1s 2ms/step - loss: 7.2458e-07 - accuracy: 1.0000 - val_loss: 0.1012 - val_accuracy: 0.9858
Epoch 73/100
469/469 [=====] - 1s 2ms/step - loss: 5.9134e-07 - accuracy: 1.0000 - val_loss: 0.1019 - val_accuracy: 0.9864
Epoch 74/100
469/469 [=====] - 1s 2ms/step - loss: 4.7992e-07 - accuracy: 1.0000 - val_loss: 0.1031 - val_accuracy: 0.9862
Epoch 75/100
469/469 [=====] - 1s 2ms/step - loss: 3.8427e-07 - accuracy: 1.0000 - val_loss: 0.1034 - val_accuracy: 0.9866
Epoch 76/100
469/469 [=====] - 1s 2ms/step - loss: 3.1060e-07 - accuracy: 1.0000 - val_loss: 0.1047 - val_accuracy: 0.9862
Epoch 77/100
469/469 [=====] - 1s 2ms/step - loss: 2.5012e-07 - accuracy: 1.0000 - val_loss: 0.1054 - val_accuracy: 0.9862
Epoch 78/100
469/469 [=====] - 1s 2ms/step - loss: 2.0019e-07 - accuracy: 1.0000 - val_loss: 0.1063 - val_accuracy: 0.9864
Epoch 79/100
469/469 [=====] - 1s 2ms/step - loss: 1.6169e-07 - accuracy: 1.0000 - val_loss: 0.1076 - val_accuracy: 0.9862
Epoch 80/100
469/469 [=====] - 1s 2ms/step - loss: 1.3246e-07 - accuracy: 1.0000 - val_loss: 0.1086 - val_accuracy: 0.9862
Epoch 81/100
469/469 [=====] - 1s 2ms/step - loss: 1.0631e-07 - accuracy: 1.0000 - val_loss: 0.1095 - val_accuracy: 0.9868
Epoch 82/100
469/469 [=====] - 1s 2ms/step - loss: 8.6252e-08 - accuracy: 1.0000 - val_loss: 0.1109 - val_accuracy: 0.9866
Epoch 83/100
469/469 [=====] - 1s 2ms/step - loss: 6.9020e-08 - accuracy: 1.0000 - val_loss: 0.1117 - val_accuracy: 0.9870
Epoch 84/100
469/469 [=====] - 1s 2ms/step - loss: 5.6138e-08 - accuracy: 1.0000 - val_loss: 0.1125 - val_accuracy: 0.9868

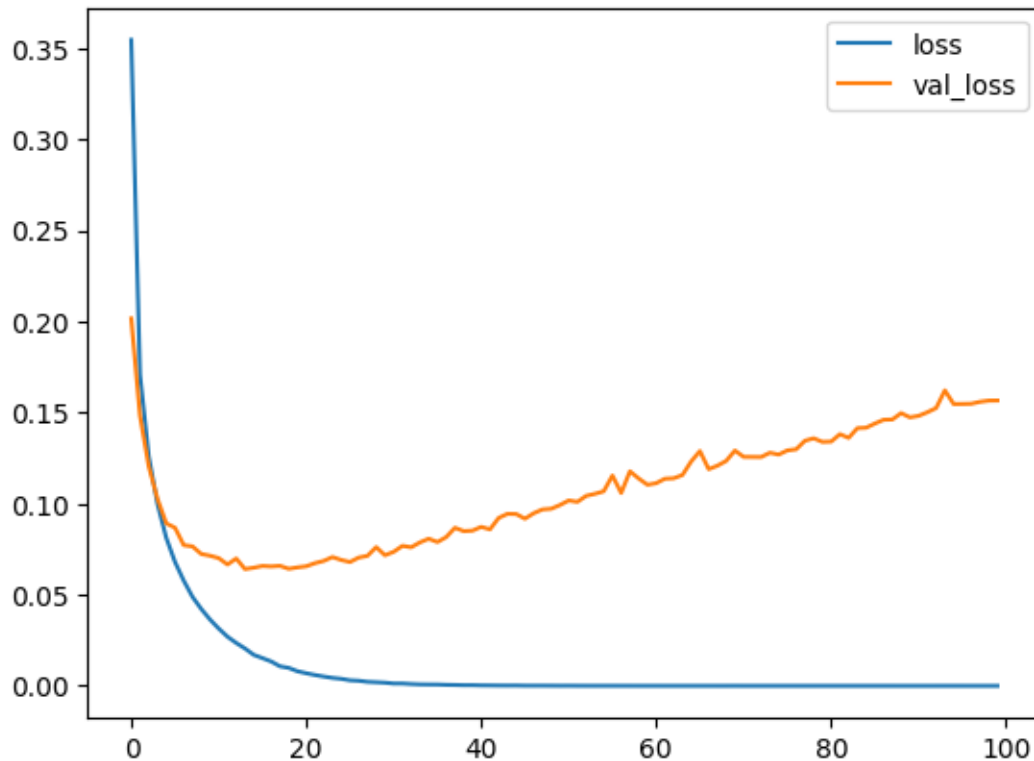
Epoch 85/100
469/469 [=====] - 1s 2ms/step - loss: 4.5379e-08 -
accuracy: 1.0000 - val_loss: 0.1140 - val_accuracy: 0.9868
Epoch 86/100
469/469 [=====] - 1s 2ms/step - loss: 3.7420e-08 -
accuracy: 1.0000 - val_loss: 0.1146 - val_accuracy: 0.9874
Epoch 87/100
469/469 [=====] - 1s 2ms/step - loss: 3.0255e-08 -
accuracy: 1.0000 - val_loss: 0.1157 - val_accuracy: 0.9874
Epoch 88/100
469/469 [=====] - 1s 2ms/step - loss: 2.5058e-08 -
accuracy: 1.0000 - val_loss: 0.1165 - val_accuracy: 0.9870
Epoch 89/100
469/469 [=====] - 1s 2ms/step - loss: 2.0595e-08 -
accuracy: 1.0000 - val_loss: 0.1177 - val_accuracy: 0.9870
Epoch 90/100
469/469 [=====] - 1s 2ms/step - loss: 1.6791e-08 -
accuracy: 1.0000 - val_loss: 0.1186 - val_accuracy: 0.9872
Epoch 91/100
469/469 [=====] - 1s 2ms/step - loss: 1.4108e-08 -
accuracy: 1.0000 - val_loss: 0.1193 - val_accuracy: 0.9870
Epoch 92/100
469/469 [=====] - 1s 2ms/step - loss: 1.1820e-08 -
accuracy: 1.0000 - val_loss: 0.1205 - val_accuracy: 0.9870
Epoch 93/100
469/469 [=====] - 1s 2ms/step - loss: 9.9142e-09 -
accuracy: 1.0000 - val_loss: 0.1212 - val_accuracy: 0.9872
Epoch 94/100
469/469 [=====] - 1s 2ms/step - loss: 8.4380e-09 -
accuracy: 1.0000 - val_loss: 0.1216 - val_accuracy: 0.9870
Epoch 95/100
469/469 [=====] - 1s 2ms/step - loss: 7.0969e-09 -
accuracy: 1.0000 - val_loss: 0.1224 - val_accuracy: 0.9868
Epoch 96/100
469/469 [=====] - 1s 2ms/step - loss: 6.1512e-09 -
accuracy: 1.0000 - val_loss: 0.1230 - val_accuracy: 0.9866
Epoch 97/100
469/469 [=====] - 1s 2ms/step - loss: 5.2651e-09 -
accuracy: 1.0000 - val_loss: 0.1240 - val_accuracy: 0.9864
Epoch 98/100
469/469 [=====] - 1s 2ms/step - loss: 4.6094e-09 -
accuracy: 1.0000 - val_loss: 0.1248 - val_accuracy: 0.9866
Epoch 99/100
469/469 [=====] - 1s 2ms/step - loss: 4.0193e-09 -
accuracy: 1.0000 - val_loss: 0.1252 - val_accuracy: 0.9864
Epoch 100/100
469/469 [=====] - 1s 2ms/step - loss: 3.5445e-09 -
accuracy: 1.0000 - val_loss: 0.1259 - val_accuracy: 0.9864

[21]: <keras.src.callbacks.History at 0x7fdd241ff2e0>

```
[ ]: # display key names from dictionary
model.history.history.keys()
# plot validation loss with training accuracy
plt.plot(model.history.history["accuracy"], label="accuracy")
plt.plot(model.history.history["val_accuracy"], label="val_accuracy")
plt.legend()
plt.show()
plt.close()

plt.plot(model.history.history["loss"], label="loss")
plt.plot(model.history.history["val_loss"], label="val_loss")
plt.legend()
plt.show()
plt.close()
```





```
[22]: from tensorflow.keras import models, layers, optimizers

# Define your model architecture
model = models.Sequential()
model.add(layers.Flatten(input_shape=(28, 28, 1)))
model.add(layers.Dense(units=255, activation="relu"))
model.add(layers.Dense(units=128, activation="relu"))
model.add(layers.Dense(units=10, activation="softmax"))
model.summary()

# Set a custom learning rate for the Adam optimizer
custom_learning_rate = 0.001 # Example learning rate, adjust as needed
adam_optimizer = optimizers.Adam(learning_rate=custom_learning_rate)

# Compile the model with the customized optimizer
model.compile(
    optimizer=adam_optimizer,
    loss="sparse_categorical_crossentropy",
    metrics=["accuracy"]
)

# Train the model
```

```

model.fit(
    dataset_train,
    epochs=50,
    validation_data=dataset_validate
)

```

Model: "sequential_6"

Layer (type)	Output Shape	Param #
flatten_6 (Flatten)	(None, 784)	0
dense_18 (Dense)	(None, 255)	200175
dense_19 (Dense)	(None, 128)	32768
dense_20 (Dense)	(None, 10)	1290

```

=====
Total params: 234233 (914.97 KB)
Trainable params: 234233 (914.97 KB)
Non-trainable params: 0 (0.00 Byte)

```

```

-----
Epoch 1/50
469/469 [=====] - 1s 2ms/step - loss: 0.2736 -
accuracy: 0.9214 - val_loss: 0.1196 - val_accuracy: 0.9652
Epoch 2/50
469/469 [=====] - 1s 2ms/step - loss: 0.1047 -
accuracy: 0.9690 - val_loss: 0.0937 - val_accuracy: 0.9700
Epoch 3/50
469/469 [=====] - 1s 2ms/step - loss: 0.0690 -
accuracy: 0.9790 - val_loss: 0.0758 - val_accuracy: 0.9736
Epoch 4/50
469/469 [=====] - 1s 2ms/step - loss: 0.0497 -
accuracy: 0.9842 - val_loss: 0.0704 - val_accuracy: 0.9768
Epoch 5/50
469/469 [=====] - 1s 2ms/step - loss: 0.0377 -
accuracy: 0.9879 - val_loss: 0.0692 - val_accuracy: 0.9780
Epoch 6/50
469/469 [=====] - 1s 2ms/step - loss: 0.0287 -
accuracy: 0.9907 - val_loss: 0.0922 - val_accuracy: 0.9708
Epoch 7/50
469/469 [=====] - 1s 2ms/step - loss: 0.0219 -
accuracy: 0.9930 - val_loss: 0.0752 - val_accuracy: 0.9766
Epoch 8/50
469/469 [=====] - 1s 2ms/step - loss: 0.0166 -
accuracy: 0.9947 - val_loss: 0.0741 - val_accuracy: 0.9778
Epoch 9/50

```

469/469 [=====] - 1s 2ms/step - loss: 0.0156 -
accuracy: 0.9947 - val_loss: 0.0844 - val_accuracy: 0.9772
Epoch 10/50
469/469 [=====] - 1s 2ms/step - loss: 0.0138 -
accuracy: 0.9956 - val_loss: 0.0929 - val_accuracy: 0.9746
Epoch 11/50
469/469 [=====] - 1s 2ms/step - loss: 0.0114 -
accuracy: 0.9962 - val_loss: 0.0830 - val_accuracy: 0.9788
Epoch 12/50
469/469 [=====] - 1s 2ms/step - loss: 0.0112 -
accuracy: 0.9962 - val_loss: 0.0805 - val_accuracy: 0.9790
Epoch 13/50
469/469 [=====] - 1s 2ms/step - loss: 0.0095 -
accuracy: 0.9970 - val_loss: 0.0834 - val_accuracy: 0.9790
Epoch 14/50
469/469 [=====] - 1s 2ms/step - loss: 0.0109 -
accuracy: 0.9962 - val_loss: 0.0827 - val_accuracy: 0.9814
Epoch 15/50
469/469 [=====] - 1s 2ms/step - loss: 0.0067 -
accuracy: 0.9977 - val_loss: 0.0923 - val_accuracy: 0.9796
Epoch 16/50
469/469 [=====] - 1s 2ms/step - loss: 0.0072 -
accuracy: 0.9977 - val_loss: 0.1027 - val_accuracy: 0.9786
Epoch 17/50
469/469 [=====] - 1s 2ms/step - loss: 0.0101 -
accuracy: 0.9968 - val_loss: 0.0865 - val_accuracy: 0.9822
Epoch 18/50
469/469 [=====] - 1s 2ms/step - loss: 0.0052 -
accuracy: 0.9985 - val_loss: 0.1159 - val_accuracy: 0.9744
Epoch 19/50
469/469 [=====] - 1s 2ms/step - loss: 0.0110 -
accuracy: 0.9962 - val_loss: 0.0899 - val_accuracy: 0.9786
Epoch 20/50
469/469 [=====] - 1s 2ms/step - loss: 0.0034 -
accuracy: 0.9988 - val_loss: 0.0934 - val_accuracy: 0.9810
Epoch 21/50
469/469 [=====] - 1s 2ms/step - loss: 0.0070 -
accuracy: 0.9978 - val_loss: 0.1051 - val_accuracy: 0.9776
Epoch 22/50
469/469 [=====] - 1s 2ms/step - loss: 0.0038 -
accuracy: 0.9988 - val_loss: 0.1103 - val_accuracy: 0.9788
Epoch 23/50
469/469 [=====] - 1s 2ms/step - loss: 0.0097 -
accuracy: 0.9970 - val_loss: 0.1053 - val_accuracy: 0.9800
Epoch 24/50
469/469 [=====] - 1s 2ms/step - loss: 0.0070 -
accuracy: 0.9973 - val_loss: 0.1108 - val_accuracy: 0.9776
Epoch 25/50

469/469 [=====] - 1s 2ms/step - loss: 0.0033 -
accuracy: 0.9990 - val_loss: 0.1321 - val_accuracy: 0.9778
Epoch 26/50
469/469 [=====] - 1s 2ms/step - loss: 0.0062 -
accuracy: 0.9979 - val_loss: 0.1383 - val_accuracy: 0.9778
Epoch 27/50
469/469 [=====] - 1s 2ms/step - loss: 0.0086 -
accuracy: 0.9974 - val_loss: 0.1040 - val_accuracy: 0.9812
Epoch 28/50
469/469 [=====] - 1s 2ms/step - loss: 0.0030 -
accuracy: 0.9993 - val_loss: 0.0997 - val_accuracy: 0.9820
Epoch 29/50
469/469 [=====] - 1s 2ms/step - loss: 4.3414e-04 -
accuracy: 1.0000 - val_loss: 0.0947 - val_accuracy: 0.9826
Epoch 30/50
469/469 [=====] - 1s 2ms/step - loss: 7.3158e-05 -
accuracy: 1.0000 - val_loss: 0.0947 - val_accuracy: 0.9822
Epoch 31/50
469/469 [=====] - 1s 2ms/step - loss: 3.9398e-05 -
accuracy: 1.0000 - val_loss: 0.0956 - val_accuracy: 0.9824
Epoch 32/50
469/469 [=====] - 1s 2ms/step - loss: 2.6842e-05 -
accuracy: 1.0000 - val_loss: 0.0979 - val_accuracy: 0.9828
Epoch 33/50
469/469 [=====] - 1s 2ms/step - loss: 1.9869e-05 -
accuracy: 1.0000 - val_loss: 0.1001 - val_accuracy: 0.9828
Epoch 34/50
469/469 [=====] - 1s 2ms/step - loss: 1.4590e-05 -
accuracy: 1.0000 - val_loss: 0.1028 - val_accuracy: 0.9824
Epoch 35/50
469/469 [=====] - 1s 2ms/step - loss: 1.1028e-05 -
accuracy: 1.0000 - val_loss: 0.1058 - val_accuracy: 0.9828
Epoch 36/50
469/469 [=====] - 1s 2ms/step - loss: 9.0002e-06 -
accuracy: 1.0000 - val_loss: 0.1070 - val_accuracy: 0.9832
Epoch 37/50
469/469 [=====] - 1s 2ms/step - loss: 7.1311e-06 -
accuracy: 1.0000 - val_loss: 0.1095 - val_accuracy: 0.9828
Epoch 38/50
469/469 [=====] - 1s 2ms/step - loss: 5.8362e-06 -
accuracy: 1.0000 - val_loss: 0.1112 - val_accuracy: 0.9826
Epoch 39/50
469/469 [=====] - 1s 2ms/step - loss: 5.0591e-06 -
accuracy: 1.0000 - val_loss: 0.1128 - val_accuracy: 0.9826
Epoch 40/50
469/469 [=====] - 1s 2ms/step - loss: 4.1043e-06 -
accuracy: 1.0000 - val_loss: 0.1142 - val_accuracy: 0.9830
Epoch 41/50

```

469/469 [=====] - 1s 2ms/step - loss: 3.3349e-06 -
accuracy: 1.0000 - val_loss: 0.1162 - val_accuracy: 0.9828
Epoch 42/50
469/469 [=====] - 1s 2ms/step - loss: 2.6967e-06 -
accuracy: 1.0000 - val_loss: 0.1168 - val_accuracy: 0.9832
Epoch 43/50
469/469 [=====] - 1s 2ms/step - loss: 2.5082e-06 -
accuracy: 1.0000 - val_loss: 0.1170 - val_accuracy: 0.9838
Epoch 44/50
469/469 [=====] - 1s 2ms/step - loss: 0.0305 -
accuracy: 0.9918 - val_loss: 0.1052 - val_accuracy: 0.9798
Epoch 45/50
469/469 [=====] - 1s 2ms/step - loss: 0.0038 -
accuracy: 0.9989 - val_loss: 0.0998 - val_accuracy: 0.9820
Epoch 46/50
469/469 [=====] - 1s 2ms/step - loss: 0.0023 -
accuracy: 0.9993 - val_loss: 0.1077 - val_accuracy: 0.9804
Epoch 47/50
469/469 [=====] - 1s 2ms/step - loss: 0.0015 -
accuracy: 0.9995 - val_loss: 0.1029 - val_accuracy: 0.9830
Epoch 48/50
469/469 [=====] - 1s 2ms/step - loss: 1.0316e-04 -
accuracy: 1.0000 - val_loss: 0.1005 - val_accuracy: 0.9844
Epoch 49/50
469/469 [=====] - 1s 2ms/step - loss: 4.7017e-05 -
accuracy: 1.0000 - val_loss: 0.1011 - val_accuracy: 0.9844
Epoch 50/50
469/469 [=====] - 1s 2ms/step - loss: 3.0495e-05 -
accuracy: 1.0000 - val_loss: 0.1017 - val_accuracy: 0.9848

```

[22]: <keras.src.callbacks.History at 0x7fdd2412a0e0>

1 Plot Adam with Custom Learning Rate

```

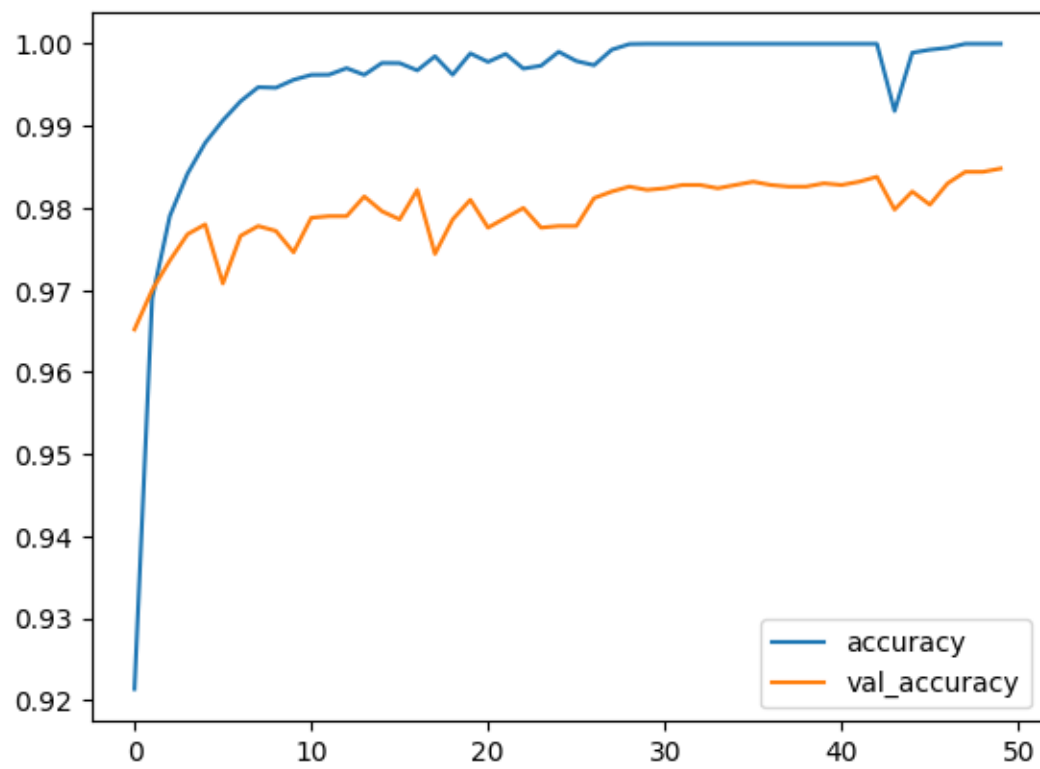
[23]: # display key names from dictionary
model.history.history.keys()
# plot validation loss with training accuracy
plt.plot(model.history.history["accuracy"], label="accuracy")
plt.plot(model.history.history["val_accuracy"], label="val_accuracy")
plt.legend()
plt.show()
plt.close()

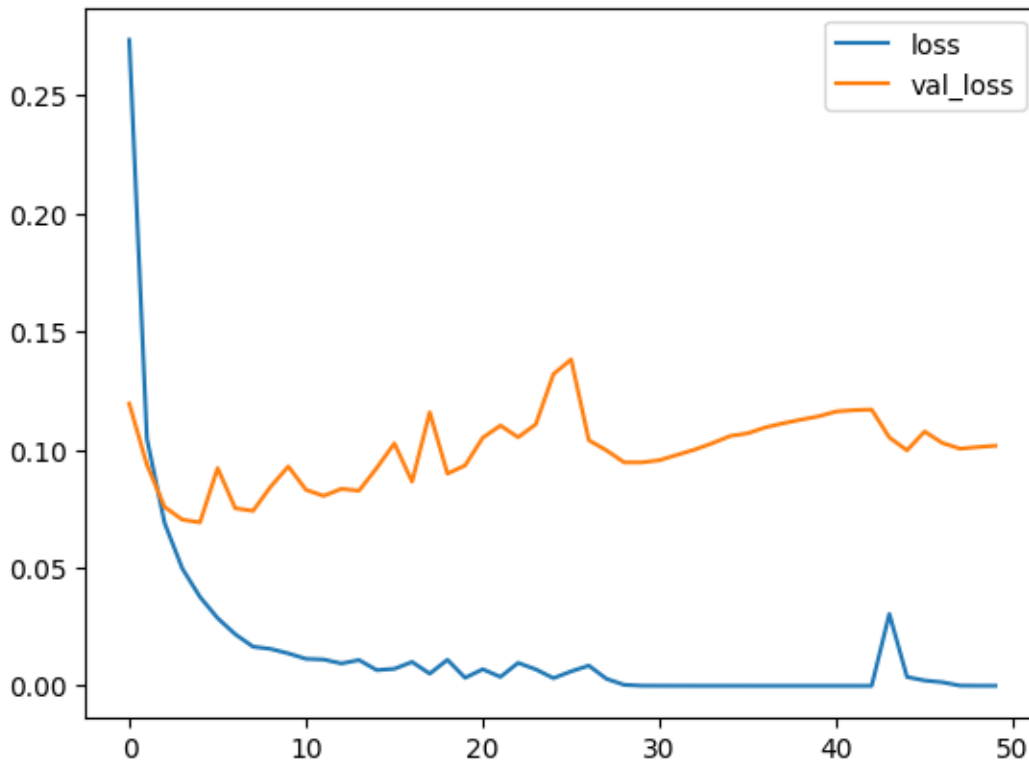
plt.plot(model.history.history["loss"], label="loss")
plt.plot(model.history.history["val_loss"], label="val_loss")
plt.legend()
plt.show()

```



```
plt.close()
```





```
[24]: from tensorflow.keras import models, layers, optimizers

# Define your model architecture
model = models.Sequential()
model.add(layers.Flatten(input_shape=(28, 28, 1)))
model.add(layers.Dense(units=255, activation="relu"))
model.add(layers.Dense(units=128, activation="relu"))
model.add(layers.Dense(units=10, activation="softmax"))
model.summary()

# Set a custom learning rate for the Adam optimizer
custom_learning_rate = 0.001 # Example learning rate, adjust as needed

# Set optimizer to Adam
#adam_optimizer = optimizers.Adam(learning_rate=custom_learning_rate)

# change adam optimizer to RMSprop
#rmsprop_optimizer = optimizers.RMSprop(learning_rate=custom_learning_rate)

# change optimizer to Adamax
adam_optimizer = optimizers.Adamax(learning_rate=custom_learning_rate)
```

```

# Compile the model with the customized optimizer
model.compile(
    #optimizer=adam_optimizer,
    optimizer=adam_optimizer,
    loss="sparse_categorical_crossentropy",
    metrics=["accuracy"]
)

# Train the model
model.fit(
    dataset_train,
    epochs=100,
    validation_data=dataset_validate
)

```

Model: "sequential_7"

Layer (type)	Output Shape	Param #
flatten_7 (Flatten)	(None, 784)	0
dense_21 (Dense)	(None, 255)	200175
dense_22 (Dense)	(None, 128)	32768
dense_23 (Dense)	(None, 10)	1290

```

=====
Total params: 234233 (914.97 KB)
Trainable params: 234233 (914.97 KB)
Non-trainable params: 0 (0.00 Byte)

```

```

-----
Epoch 1/100
469/469 [=====] - 2s 2ms/step - loss: 0.3589 -
accuracy: 0.9020 - val_loss: 0.2012 - val_accuracy: 0.9418
Epoch 2/100
469/469 [=====] - 1s 2ms/step - loss: 0.1696 -
accuracy: 0.9517 - val_loss: 0.1474 - val_accuracy: 0.9572
Epoch 3/100
469/469 [=====] - 1s 2ms/step - loss: 0.1254 -
accuracy: 0.9640 - val_loss: 0.1273 - val_accuracy: 0.9614
Epoch 4/100
469/469 [=====] - 1s 2ms/step - loss: 0.0989 -
accuracy: 0.9713 - val_loss: 0.1074 - val_accuracy: 0.9646
Epoch 5/100
469/469 [=====] - 1s 2ms/step - loss: 0.0797 -
accuracy: 0.9769 - val_loss: 0.0893 - val_accuracy: 0.9726
Epoch 6/100

```

469/469 [=====] - 1s 2ms/step - loss: 0.0665 -
accuracy: 0.9808 - val_loss: 0.0864 - val_accuracy: 0.9736
Epoch 7/100
469/469 [=====] - 1s 2ms/step - loss: 0.0561 -
accuracy: 0.9846 - val_loss: 0.0771 - val_accuracy: 0.9748
Epoch 8/100
469/469 [=====] - 1s 2ms/step - loss: 0.0485 -
accuracy: 0.9864 - val_loss: 0.0769 - val_accuracy: 0.9758
Epoch 9/100
469/469 [=====] - 1s 2ms/step - loss: 0.0414 -
accuracy: 0.9884 - val_loss: 0.0723 - val_accuracy: 0.9764
Epoch 10/100
469/469 [=====] - 1s 2ms/step - loss: 0.0359 -
accuracy: 0.9901 - val_loss: 0.0697 - val_accuracy: 0.9764
Epoch 11/100
469/469 [=====] - 1s 2ms/step - loss: 0.0307 -
accuracy: 0.9919 - val_loss: 0.0704 - val_accuracy: 0.9776
Epoch 12/100
469/469 [=====] - 1s 2ms/step - loss: 0.0268 -
accuracy: 0.9931 - val_loss: 0.0653 - val_accuracy: 0.9788
Epoch 13/100
469/469 [=====] - 1s 2ms/step - loss: 0.0233 -
accuracy: 0.9944 - val_loss: 0.0668 - val_accuracy: 0.9780
Epoch 14/100
469/469 [=====] - 1s 2ms/step - loss: 0.0203 -
accuracy: 0.9953 - val_loss: 0.0669 - val_accuracy: 0.9792
Epoch 15/100
469/469 [=====] - 1s 2ms/step - loss: 0.0171 -
accuracy: 0.9963 - val_loss: 0.0647 - val_accuracy: 0.9814
Epoch 16/100
469/469 [=====] - 1s 2ms/step - loss: 0.0149 -
accuracy: 0.9970 - val_loss: 0.0682 - val_accuracy: 0.9780
Epoch 17/100
469/469 [=====] - 1s 2ms/step - loss: 0.0129 -
accuracy: 0.9977 - val_loss: 0.0642 - val_accuracy: 0.9804
Epoch 18/100
469/469 [=====] - 1s 2ms/step - loss: 0.0110 -
accuracy: 0.9981 - val_loss: 0.0646 - val_accuracy: 0.9792
Epoch 19/100
469/469 [=====] - 1s 2ms/step - loss: 0.0094 -
accuracy: 0.9987 - val_loss: 0.0676 - val_accuracy: 0.9796
Epoch 20/100
469/469 [=====] - 1s 2ms/step - loss: 0.0084 -
accuracy: 0.9987 - val_loss: 0.0693 - val_accuracy: 0.9780
Epoch 21/100
469/469 [=====] - 1s 2ms/step - loss: 0.0070 -
accuracy: 0.9991 - val_loss: 0.0641 - val_accuracy: 0.9816
Epoch 22/100

469/469 [=====] - 1s 2ms/step - loss: 0.0062 -
accuracy: 0.9992 - val_loss: 0.0682 - val_accuracy: 0.9784
Epoch 23/100
469/469 [=====] - 1s 2ms/step - loss: 0.0051 -
accuracy: 0.9995 - val_loss: 0.0684 - val_accuracy: 0.9798
Epoch 24/100
469/469 [=====] - 1s 2ms/step - loss: 0.0044 -
accuracy: 0.9995 - val_loss: 0.0690 - val_accuracy: 0.9812
Epoch 25/100
469/469 [=====] - 1s 2ms/step - loss: 0.0037 -
accuracy: 0.9998 - val_loss: 0.0679 - val_accuracy: 0.9796
Epoch 26/100
469/469 [=====] - 1s 2ms/step - loss: 0.0033 -
accuracy: 0.9997 - val_loss: 0.0786 - val_accuracy: 0.9776
Epoch 27/100
469/469 [=====] - 1s 2ms/step - loss: 0.0027 -
accuracy: 0.9998 - val_loss: 0.0716 - val_accuracy: 0.9810
Epoch 28/100
469/469 [=====] - 1s 2ms/step - loss: 0.0025 -
accuracy: 0.9999 - val_loss: 0.0704 - val_accuracy: 0.9812
Epoch 29/100
469/469 [=====] - 1s 2ms/step - loss: 0.0020 -
accuracy: 0.9999 - val_loss: 0.0720 - val_accuracy: 0.9810
Epoch 30/100
469/469 [=====] - 1s 2ms/step - loss: 0.0018 -
accuracy: 0.9999 - val_loss: 0.0753 - val_accuracy: 0.9794
Epoch 31/100
469/469 [=====] - 1s 2ms/step - loss: 0.0016 -
accuracy: 0.9999 - val_loss: 0.0753 - val_accuracy: 0.9808
Epoch 32/100
469/469 [=====] - 1s 2ms/step - loss: 0.0012 -
accuracy: 1.0000 - val_loss: 0.0773 - val_accuracy: 0.9800
Epoch 33/100
469/469 [=====] - 1s 2ms/step - loss: 0.0011 -
accuracy: 1.0000 - val_loss: 0.0794 - val_accuracy: 0.9804
Epoch 34/100
469/469 [=====] - 1s 2ms/step - loss: 0.0011 -
accuracy: 1.0000 - val_loss: 0.0788 - val_accuracy: 0.9802
Epoch 35/100
469/469 [=====] - 1s 2ms/step - loss: 8.8012e-04 -
accuracy: 1.0000 - val_loss: 0.0795 - val_accuracy: 0.9808
Epoch 36/100
469/469 [=====] - 1s 2ms/step - loss: 7.0440e-04 -
accuracy: 1.0000 - val_loss: 0.0801 - val_accuracy: 0.9806
Epoch 37/100
469/469 [=====] - 1s 2ms/step - loss: 6.3360e-04 -
accuracy: 1.0000 - val_loss: 0.0823 - val_accuracy: 0.9802
Epoch 38/100

469/469 [=====] - 1s 2ms/step - loss: 5.5068e-04 -
accuracy: 1.0000 - val_loss: 0.0835 - val_accuracy: 0.9806
Epoch 39/100
469/469 [=====] - 1s 2ms/step - loss: 4.5120e-04 -
accuracy: 1.0000 - val_loss: 0.0860 - val_accuracy: 0.9814
Epoch 40/100
469/469 [=====] - 1s 2ms/step - loss: 3.5406e-04 -
accuracy: 1.0000 - val_loss: 0.0858 - val_accuracy: 0.9810
Epoch 41/100
469/469 [=====] - 1s 2ms/step - loss: 3.3350e-04 -
accuracy: 1.0000 - val_loss: 0.0874 - val_accuracy: 0.9806
Epoch 42/100
469/469 [=====] - 1s 2ms/step - loss: 3.2801e-04 -
accuracy: 1.0000 - val_loss: 0.0874 - val_accuracy: 0.9812
Epoch 43/100
469/469 [=====] - 1s 2ms/step - loss: 2.5007e-04 -
accuracy: 1.0000 - val_loss: 0.0887 - val_accuracy: 0.9806
Epoch 44/100
469/469 [=====] - 1s 2ms/step - loss: 2.3620e-04 -
accuracy: 1.0000 - val_loss: 0.0919 - val_accuracy: 0.9814
Epoch 45/100
469/469 [=====] - 1s 2ms/step - loss: 1.8708e-04 -
accuracy: 1.0000 - val_loss: 0.0904 - val_accuracy: 0.9806
Epoch 46/100
469/469 [=====] - 1s 2ms/step - loss: 2.0080e-04 -
accuracy: 1.0000 - val_loss: 0.0947 - val_accuracy: 0.9796
Epoch 47/100
469/469 [=====] - 1s 2ms/step - loss: 1.3432e-04 -
accuracy: 1.0000 - val_loss: 0.0935 - val_accuracy: 0.9812
Epoch 48/100
469/469 [=====] - 1s 2ms/step - loss: 1.3579e-04 -
accuracy: 1.0000 - val_loss: 0.0925 - val_accuracy: 0.9816
Epoch 49/100
469/469 [=====] - 1s 2ms/step - loss: 9.6509e-05 -
accuracy: 1.0000 - val_loss: 0.0941 - val_accuracy: 0.9818
Epoch 50/100
469/469 [=====] - 1s 2ms/step - loss: 1.0294e-04 -
accuracy: 1.0000 - val_loss: 0.1027 - val_accuracy: 0.9806
Epoch 51/100
469/469 [=====] - 1s 2ms/step - loss: 7.5686e-05 -
accuracy: 1.0000 - val_loss: 0.0970 - val_accuracy: 0.9808
Epoch 52/100
469/469 [=====] - 1s 2ms/step - loss: 7.3400e-05 -
accuracy: 1.0000 - val_loss: 0.1034 - val_accuracy: 0.9802
Epoch 53/100
469/469 [=====] - 1s 2ms/step - loss: 8.3005e-05 -
accuracy: 1.0000 - val_loss: 0.1010 - val_accuracy: 0.9802
Epoch 54/100

469/469 [=====] - 1s 2ms/step - loss: 4.4414e-05 -
accuracy: 1.0000 - val_loss: 0.1003 - val_accuracy: 0.9806
Epoch 55/100
469/469 [=====] - 1s 2ms/step - loss: 4.9763e-05 -
accuracy: 1.0000 - val_loss: 0.1020 - val_accuracy: 0.9808
Epoch 56/100
469/469 [=====] - 1s 2ms/step - loss: 4.0966e-05 -
accuracy: 1.0000 - val_loss: 0.1043 - val_accuracy: 0.9814
Epoch 57/100
469/469 [=====] - 1s 2ms/step - loss: 3.4979e-05 -
accuracy: 1.0000 - val_loss: 0.1063 - val_accuracy: 0.9810
Epoch 58/100
469/469 [=====] - 1s 2ms/step - loss: 3.5663e-05 -
accuracy: 1.0000 - val_loss: 0.1078 - val_accuracy: 0.9808
Epoch 59/100
469/469 [=====] - 1s 2ms/step - loss: 3.5515e-05 -
accuracy: 1.0000 - val_loss: 0.1031 - val_accuracy: 0.9820
Epoch 60/100
469/469 [=====] - 1s 2ms/step - loss: 2.3601e-05 -
accuracy: 1.0000 - val_loss: 0.1113 - val_accuracy: 0.9814
Epoch 61/100
469/469 [=====] - 1s 2ms/step - loss: 1.6765e-05 -
accuracy: 1.0000 - val_loss: 0.1096 - val_accuracy: 0.9808
Epoch 62/100
469/469 [=====] - 1s 2ms/step - loss: 1.7777e-05 -
accuracy: 1.0000 - val_loss: 0.1147 - val_accuracy: 0.9810
Epoch 63/100
469/469 [=====] - 1s 2ms/step - loss: 2.8621e-05 -
accuracy: 1.0000 - val_loss: 0.1127 - val_accuracy: 0.9820
Epoch 64/100
469/469 [=====] - 1s 3ms/step - loss: 1.0834e-05 -
accuracy: 1.0000 - val_loss: 0.1157 - val_accuracy: 0.9816
Epoch 65/100
469/469 [=====] - 1s 3ms/step - loss: 1.1615e-05 -
accuracy: 1.0000 - val_loss: 0.1170 - val_accuracy: 0.9810
Epoch 66/100
469/469 [=====] - 1s 3ms/step - loss: 9.1228e-06 -
accuracy: 1.0000 - val_loss: 0.1181 - val_accuracy: 0.9802
Epoch 67/100
469/469 [=====] - 1s 3ms/step - loss: 7.2703e-06 -
accuracy: 1.0000 - val_loss: 0.1190 - val_accuracy: 0.9812
Epoch 68/100
469/469 [=====] - 1s 2ms/step - loss: 9.4867e-06 -
accuracy: 1.0000 - val_loss: 0.1180 - val_accuracy: 0.9816
Epoch 69/100
469/469 [=====] - 1s 2ms/step - loss: 6.4726e-06 -
accuracy: 1.0000 - val_loss: 0.1213 - val_accuracy: 0.9820
Epoch 70/100

469/469 [=====] - 1s 2ms/step - loss: 5.0099e-06 -
accuracy: 1.0000 - val_loss: 0.1219 - val_accuracy: 0.9816
Epoch 71/100
469/469 [=====] - 1s 2ms/step - loss: 7.1123e-06 -
accuracy: 1.0000 - val_loss: 0.1259 - val_accuracy: 0.9806
Epoch 72/100
469/469 [=====] - 1s 2ms/step - loss: 3.8757e-06 -
accuracy: 1.0000 - val_loss: 0.1260 - val_accuracy: 0.9812
Epoch 73/100
469/469 [=====] - 1s 2ms/step - loss: 3.0234e-06 -
accuracy: 1.0000 - val_loss: 0.1271 - val_accuracy: 0.9806
Epoch 74/100
469/469 [=====] - 1s 3ms/step - loss: 3.9551e-06 -
accuracy: 1.0000 - val_loss: 0.1283 - val_accuracy: 0.9820
Epoch 75/100
469/469 [=====] - 2s 3ms/step - loss: 2.4892e-06 -
accuracy: 1.0000 - val_loss: 0.1279 - val_accuracy: 0.9822
Epoch 76/100
469/469 [=====] - 1s 3ms/step - loss: 2.5612e-06 -
accuracy: 1.0000 - val_loss: 0.1299 - val_accuracy: 0.9814
Epoch 77/100
469/469 [=====] - 1s 3ms/step - loss: 2.3788e-06 -
accuracy: 1.0000 - val_loss: 0.1311 - val_accuracy: 0.9812
Epoch 78/100
469/469 [=====] - 2s 4ms/step - loss: 2.1102e-06 -
accuracy: 1.0000 - val_loss: 0.1311 - val_accuracy: 0.9814
Epoch 79/100
469/469 [=====] - 2s 4ms/step - loss: 1.3450e-06 -
accuracy: 1.0000 - val_loss: 0.1331 - val_accuracy: 0.9816
Epoch 80/100
469/469 [=====] - 1s 3ms/step - loss: 1.2839e-06 -
accuracy: 1.0000 - val_loss: 0.1394 - val_accuracy: 0.9810
Epoch 81/100
469/469 [=====] - 1s 3ms/step - loss: 3.8159e-05 -
accuracy: 1.0000 - val_loss: 0.1351 - val_accuracy: 0.9802
Epoch 82/100
469/469 [=====] - 1s 2ms/step - loss: 2.1137e-06 -
accuracy: 1.0000 - val_loss: 0.1359 - val_accuracy: 0.9798
Epoch 83/100
469/469 [=====] - 1s 2ms/step - loss: 1.4488e-06 -
accuracy: 1.0000 - val_loss: 0.1348 - val_accuracy: 0.9806
Epoch 84/100
469/469 [=====] - 1s 2ms/step - loss: 1.2090e-06 -
accuracy: 1.0000 - val_loss: 0.1341 - val_accuracy: 0.9808
Epoch 85/100
469/469 [=====] - 1s 2ms/step - loss: 1.0416e-06 -
accuracy: 1.0000 - val_loss: 0.1349 - val_accuracy: 0.9810
Epoch 86/100


```

469/469 [=====] - 1s 2ms/step - loss: 9.1364e-07 -
accuracy: 1.0000 - val_loss: 0.1348 - val_accuracy: 0.9808
Epoch 87/100
469/469 [=====] - 1s 2ms/step - loss: 7.9984e-07 -
accuracy: 1.0000 - val_loss: 0.1356 - val_accuracy: 0.9810
Epoch 88/100
469/469 [=====] - 1s 2ms/step - loss: 7.0192e-07 -
accuracy: 1.0000 - val_loss: 0.1374 - val_accuracy: 0.9808
Epoch 89/100
469/469 [=====] - 1s 2ms/step - loss: 6.1023e-07 -
accuracy: 1.0000 - val_loss: 0.1379 - val_accuracy: 0.9812
Epoch 90/100
469/469 [=====] - 1s 2ms/step - loss: 5.3416e-07 -
accuracy: 1.0000 - val_loss: 0.1389 - val_accuracy: 0.9820
Epoch 91/100
469/469 [=====] - 1s 2ms/step - loss: 4.7227e-07 -
accuracy: 1.0000 - val_loss: 0.1417 - val_accuracy: 0.9814
Epoch 92/100
469/469 [=====] - 1s 2ms/step - loss: 4.1541e-07 -
accuracy: 1.0000 - val_loss: 0.1431 - val_accuracy: 0.9810
Epoch 93/100
469/469 [=====] - 1s 2ms/step - loss: 3.5037e-07 -
accuracy: 1.0000 - val_loss: 0.1437 - val_accuracy: 0.9814
Epoch 94/100
469/469 [=====] - 1s 2ms/step - loss: 6.3309e-07 -
accuracy: 1.0000 - val_loss: 0.1478 - val_accuracy: 0.9798
Epoch 95/100
469/469 [=====] - 1s 2ms/step - loss: 3.3524e-06 -
accuracy: 1.0000 - val_loss: 0.1462 - val_accuracy: 0.9820
Epoch 96/100
469/469 [=====] - 1s 2ms/step - loss: 3.1764e-07 -
accuracy: 1.0000 - val_loss: 0.1471 - val_accuracy: 0.9820
Epoch 97/100
469/469 [=====] - 1s 2ms/step - loss: 2.7162e-07 -
accuracy: 1.0000 - val_loss: 0.1481 - val_accuracy: 0.9816
Epoch 98/100
469/469 [=====] - 1s 2ms/step - loss: 2.4361e-07 -
accuracy: 1.0000 - val_loss: 0.1485 - val_accuracy: 0.9816
Epoch 99/100
469/469 [=====] - 1s 2ms/step - loss: 2.2248e-07 -
accuracy: 1.0000 - val_loss: 0.1489 - val_accuracy: 0.9814
Epoch 100/100
469/469 [=====] - 1s 2ms/step - loss: 2.0180e-07 -
accuracy: 1.0000 - val_loss: 0.1490 - val_accuracy: 0.9816

```

[24]: <keras.src.callbacks.History at 0x7fdd24571030>

2 Plot Adamx

```
[25]: # display key names from dictionary
model.history.history.keys()
# plot validation loss with training accuracy
plt.plot(model.history.history["accuracy"], label="accuracy")
plt.plot(model.history.history["val_accuracy"], label="val_accuracy")
plt.legend()
plt.show()
plt.close()

plt.plot(model.history.history["loss"], label="loss")
plt.plot(model.history.history["val_loss"], label="val_loss")
plt.legend()
plt.show()
plt.close()
```

