Problem Formulation:

We are given an image dataset, on which gray scaling and downsizing are already done. We are supposed to recognize the object in the images. In order to do that, we need to create a classifier that decides
the correct category of a given image.

So, I first tried to implement a simple Logistic Regression model by converting the image data into a NumPy array. It gave very low accuracy, due to which I started searching for other techniques. While exploring, I came across image classification techniques like SVM, Decision Tree, KNN, & CNN. After watching videos of each technique, I found that CNN Model is best suited for the provided dataset since it is mostly used for image recognition and object classification. So, I started exploring CNN over the internet and ways to solve the problem. Due to the time constraints, I could learn from limited resources and tried my best to achieve better accuracy.

Preprocessing:

- **Reading the dataset:** The dataset is in the file of .PKL. So, in order to read that file, we need to import pickle.
- Then, I specified the fraction of items to return to the sample. I set it to 1, to return all the data. Also, checked for null values.
- I also tried to print the images, but it's giving some error at the last step. It did print images before, but in order to smooth the functioning of the code, I commented on that part.
- Now, to split the dataset into training and testing, I used train_test_split. Also, reshaped the data.

Assumptions:

- I didn't use the test data (unlabelled dataset) as it doesn't have a target column.
- Pandas version is >= 1.4.1
- All the CNN layers work sequentially, without interfering with each other.

Model Design:

As stated earlier, I'm using CNN to find the solution to this problem.

I'm implementing a sequential classifier in order to achieve the goal. In sequential classifiers, the layers are arranged in a line and have exactly one input and output file.

Attaching the snippet of code for better understanding.

```
Classifier used: Sequential

Convolution Layers: 2

Dense Layers: 3 (Input, Hidden, Output)
```

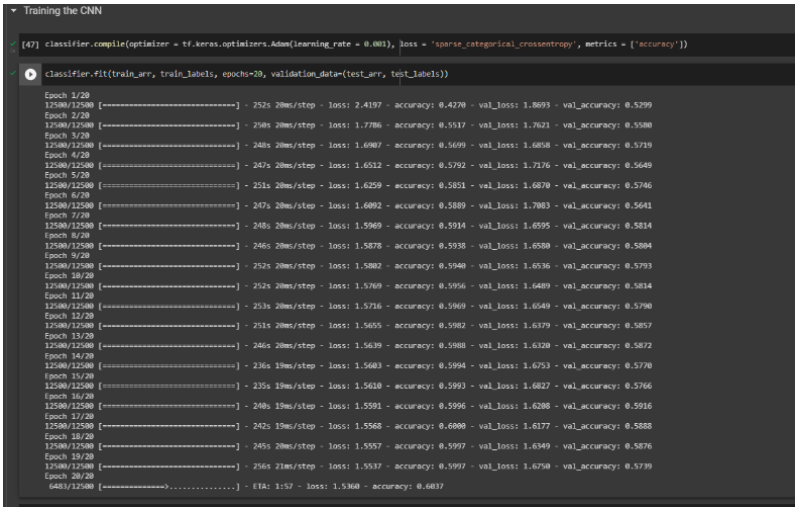
```
In [65]: from tensorflow.keras.utils import to_categorical
         from keras.models import Sequential
         from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense

In [66]: #Initialising the CNN. We are using sequential classifier as we don't have multiple inputs and outputs
         CNNModel = Sequential()

In [67]: #1st Convolution Layer
         CNNModel.add(Conv2D(32, (3, 3), activation = 'relu', padding='valid', input_shape = (28, 28, 1)))

         #Downsampling the dataset using Pooling
         CNNModel.add(MaxPooling2D(2, 2))

In [68]: #Second Convolution Layer
         CNNModel.add(Conv2D(64, (3, 3), activation="relu", padding='valid'))
         CNNModel.add(MaxPooling2D(2, 2))

In [69]: #Flattening
         CNNModel.add(Flatten())

In [70]: #Adding input layer
         CNNModel.add(Dense(units = 512, activation = 'relu', kernel_initializer='glorot_uniform'))

         #Adding Hidden Layers
         CNNModel.add(Dense(units = 256, activation = 'relu', kernel_initializer='glorot_uniform'))
         #CNNModel.add(Dense(units = 256, activation = 'relu', kernel_initializer='glorot_uniform'))

In [71]: #Adding Output Layer
         CNNModel.add(Dense(units = 100, activation = 'softmax'))
```

The model has 3 Dense Layers: 1 Input layer (with 512 neurons), 1 hidden layer (with 256 neurons), and 1 output layer (with 100 neurons).

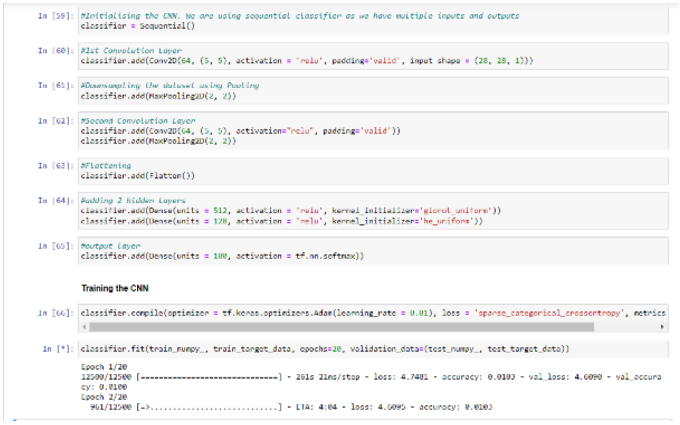
I tried various attributes for activation, kernel_initializer before finalizing with the one in the program. I'll explain the results for each attribute in the next point.

Results:

- First I implemented CNN without any hidden layers. The model contained only input and output layers, due to which the accuracy barely touched 60%. This model contained 16 steps and 128 units (Screenshot below)



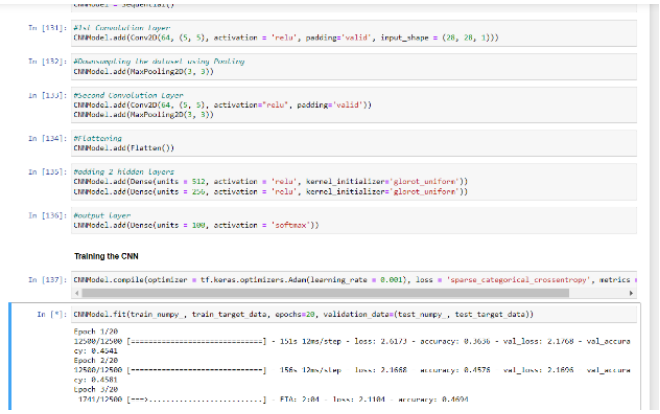
- Then, I added a hidden layer, set activation to "relu" and kernel_initializer to both "glorot_uniform" and "he_uniform" in order to achieve good accuracy. But the result was different. The accuracy worsened. It was found to be ~5%.



- The various resources over the internet suggested the implementation of the "he_uniform" kernel. So I used that. But turns out that the combination of "he_uniform" kernel and "relu" activation with specified height and width of image was not good either.

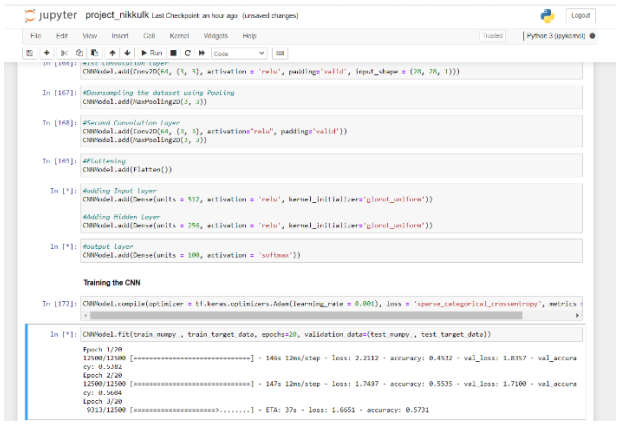
```
In [95]: #initialising the CNN. We are using sequential classifier as we have multiple inputs and outputs
         CNNModel = Sequential()

In [96]: #1st Convolution Layer
         CNNModel.add(Conv2D(64, (5, 5), activation = 'relu', padding='valid', input_shape = (28, 28, 1)))

In [97]: #Downsampling the dataset using Pooling
         CNNModel.add(MaxPooling2D(3, 3))

In [98]: #Second Convolution Layer
         CNNModel.add(Conv2D(64, (5, 5), activation="relu", padding='valid'))
         CNNModel.add(MaxPooling2D(3, 3))

In [99]: #Flattening
         CNNModel.add(Flatten())

In [100]: #adding 2 hidden layers
          CNNModel.add(Dense(units = 512, activation = 'relu', kernel_initializer='he_uniform'))
          CNNModel.add(Dense(units = 256, activation = 'relu', kernel_initializer='he_uniform'))

In [101]: #output layer
          CNNModel.add(Dense(units = 100, activation = 'softmax'))

          Training the CNN

In [102]: CNNModel.compile(optimizer = tf.keras.optimizers.Adam(learning_rate = 0.01), loss = 'sparse_categorical_crossentropy', metrics =

In [*]: CNNModel.fit(train_numpy_, train_target_data, epochs=20, validation_data=(test_numpy_, test_target_data))

        Epoch 1/20
        12500/12500 [==============================] - 147s 12ms/step - loss: 4.7020 - accuracy: 0.0100 - val_loss: 4.6098 - val_accura
        cy: 0.0056
        Epoch 2/20
         1038/12500 [=>............................] - ETA: 2:17 - loss: 4.6094 - accuracy: 0.0099
```

- So, I tried with the “glorot_uniform” kernel, which gave an accuracy of around 70%, best till now.



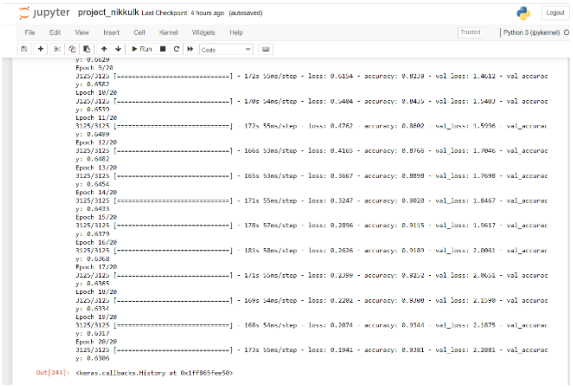
```
In [131]: #1st Convolution Layer
          CNNModel.add(Conv2D(64, (5, 5), activation = 'relu', padding='valid', input_shape = (28, 28, 1)))

In [132]: #Downsampling the dataset using Pooling
          CNNModel.add(MaxPooling2D(3, 3))

In [133]: #Second Convolution Layer
          CNNModel.add(Conv2D(64, (5, 5), activation="relu", padding='valid'))
          CNNModel.add(MaxPooling2D(3, 3))

In [134]: #Flattening
          CNNModel.add(Flatten())

In [135]: #adding 2 hidden layers
          CNNModel.add(Dense(units = 512, activation = 'relu', kernel_initializer='glorot_uniform'))
          CNNModel.add(Dense(units = 256, activation = 'relu', kernel_initializer='glorot_uniform'))

In [136]: #output layer
          CNNModel.add(Dense(units = 100, activation = 'softmax'))

          Training the CNN

In [137]: CNNModel.compile(optimizer = tf.keras.optimizers.Adam(learning_rate = 0.001), loss = 'sparse_categorical_crossentropy', metrics =

In [*]: CNNModel.fit(train_numpy_, train_target_data, epochs=20, validation_data=(test_numpy_, test_target_data))

        Epoch 1/20
        12500/12500 [==============================] - 151s 12ms/step - loss: 2.6173 - accuracy: 0.3636 - val_loss: 2.1768 - val_accura
        cy: 0.4041
        Epoch 2/20
        12500/12500 [==============================] - 156s 12ms/step - loss: 2.1668 - accuracy: 0.4478 - val_loss: 2.1696 - val_accura
        cy: 0.4581
        Epoch 3/20
         1741/12500 [===>..........................] - ETA: 2:04 - loss: 2.1104 - accuracy: 0.4694
```

- Again, to improve the accuracy, I decreased the image size from (5,5) to (3,3), which improved accuracy by around 7%, resulting to 77%

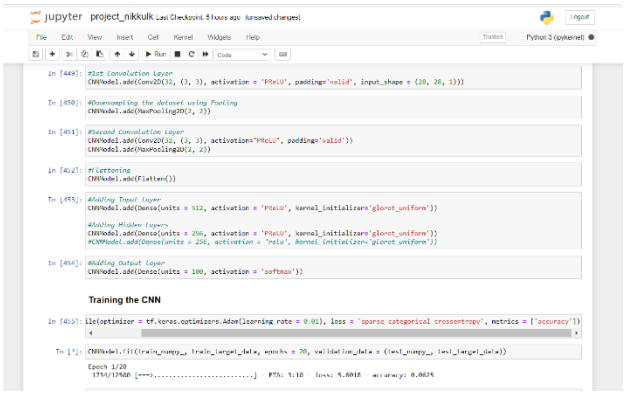


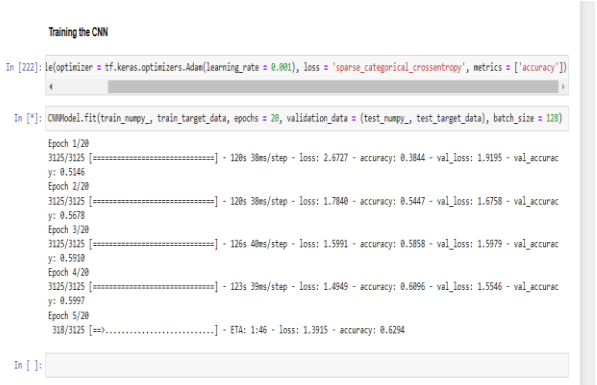
```
jupyter project_nikkulk Last Checkpoint: an hour ago (unsaved changes)
File Edit View Insert Cell Kernel Widgets Help
Logout
Trusted | Python 3 (ipykernel)

In [167]: #Downsampling the dataset using Pooling
          CNNModel.add(MaxPooling2D(3, 3))

In [168]: #Second Convolution Layer
          CNNModel.add(Conv2D(64, (3, 3), activation="relu", padding='valid'))
          CNNModel.add(MaxPooling2D(3, 3))

In [169]: #Flattening
          CNNModel.add(Flatten())

In [*]: #adding Input layer
        CNNModel.add(Dense(units = 512, activation = 'relu', kernel_initializer='glorot_uniform'))

        #Adding Hidden Layer
        CNNModel.add(Dense(units = 256, activation = 'relu', kernel_initializer='glorot_uniform'))

In [*]: #output layer
        CNNModel.add(Dense(units = 100, activation = 'softmax'))

        Training the CNN

In [172]: CNNModel.compile(optimizer = tf.keras.optimizers.Adam(learning_rate = 0.001), loss = 'sparse_categorical_crossentropy', metrics =

In [*]: CNNModel.fit(train_numpy_, train_target_data, epochs=20, validation_data=(test_numpy_, test_target_data))

        Epoch 1/20
        12500/12500 [==============================] - 146s 12ms/step - loss: 2.2112 - accuracy: 0.4532 - val_loss: 1.8357 - val_accura
        cy: 0.5282
        Epoch 2/20
        12500/12500 [==============================] - 147s 12ms/step - loss: 1.7497 - accuracy: 0.5535 - val_loss: 1.7100 - val_accura
        cy: 0.5604
        Epoch 3/20
         9313/12500 [=====================>........] - ETA: 37s - loss: 1.6651 - accuracy: 0.5731
```

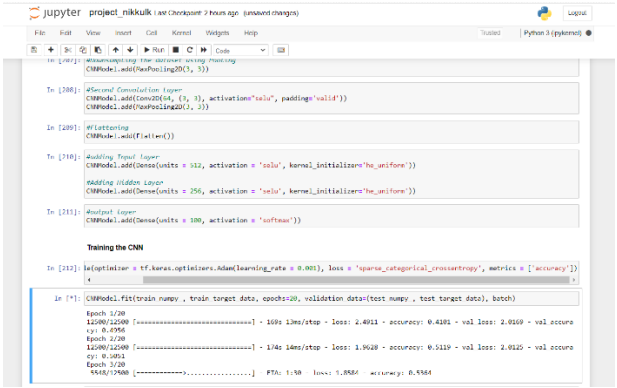
- I also received an accuracy of 94% at some point, when I set the value of neurons to 1024 for input layer. But I think the model was overfitting, so I didn’t submit that.

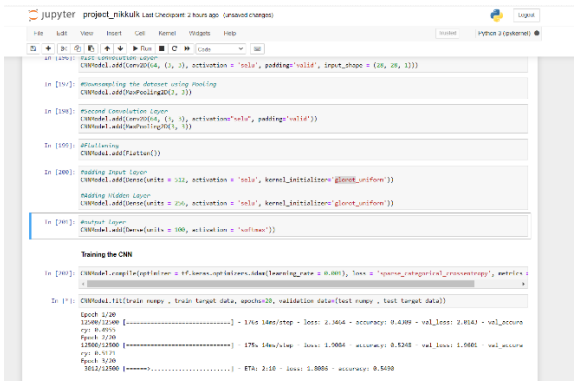


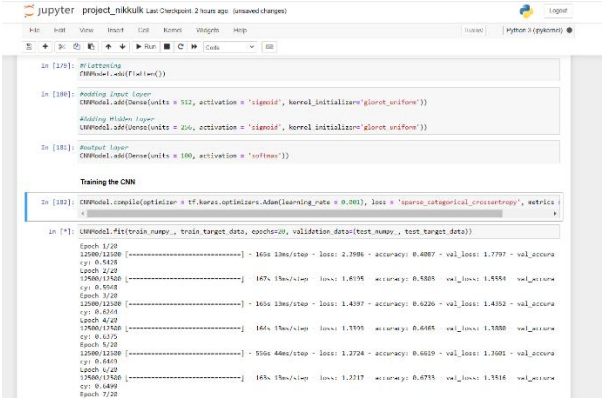
- After this accuracy, I was trying various permutations and combinations of kernel_initializers and activation (relu, selu, sigmoid, tanh, PReLU) in order to compare the accuracies. I found all these parameters over the internet when I was reading about the sequential classifier. The screenshots of the accuracies are attached below.



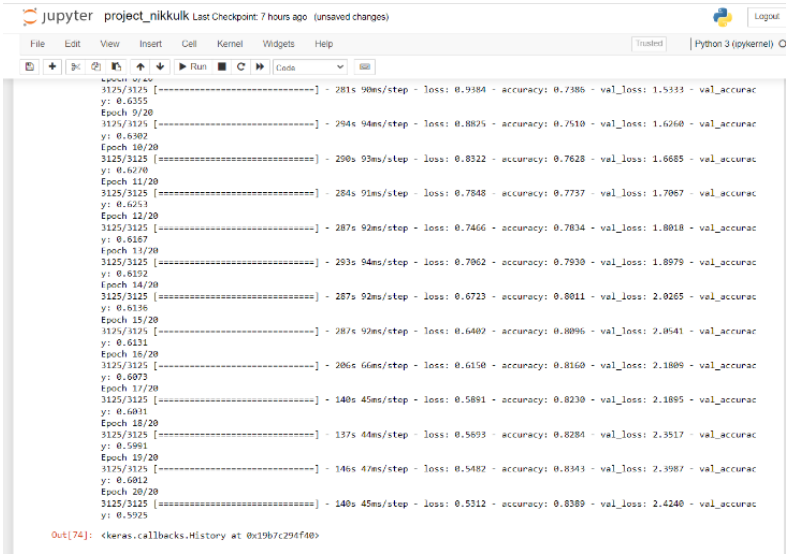








- I stopped at an accuracy of 83.89%.



Methods to improve the accuracy:

- If we don't have a time limit, we can add additional hidden layers which can improve the accuracy significantly.
- We can also increase the epochs. (Currently set to 20)
- We can increase the image size, which can add more details to the image, resulting in more data to train.
- We can lower the learning rate, resulting in more details while training. (Currently set to 0.01)