HandWritten Alphabet Recognition

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df = pd.read_csv("A_Z Handwritten Data.csv")
df.head()
```

Out[2]:

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	...	0.639	0.640	0.641	0.642	0.643	0.644
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0

5 rows × 785 columns

In [3]:
```
df['0'].unique()
```

Out[3]:
```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
       17, 18, 19, 20, 21, 22, 23, 24, 25], dtype=int64)
```

Preprocessing

In [4]:
```
# dependent variable
y = df['0']
del df['0']
```

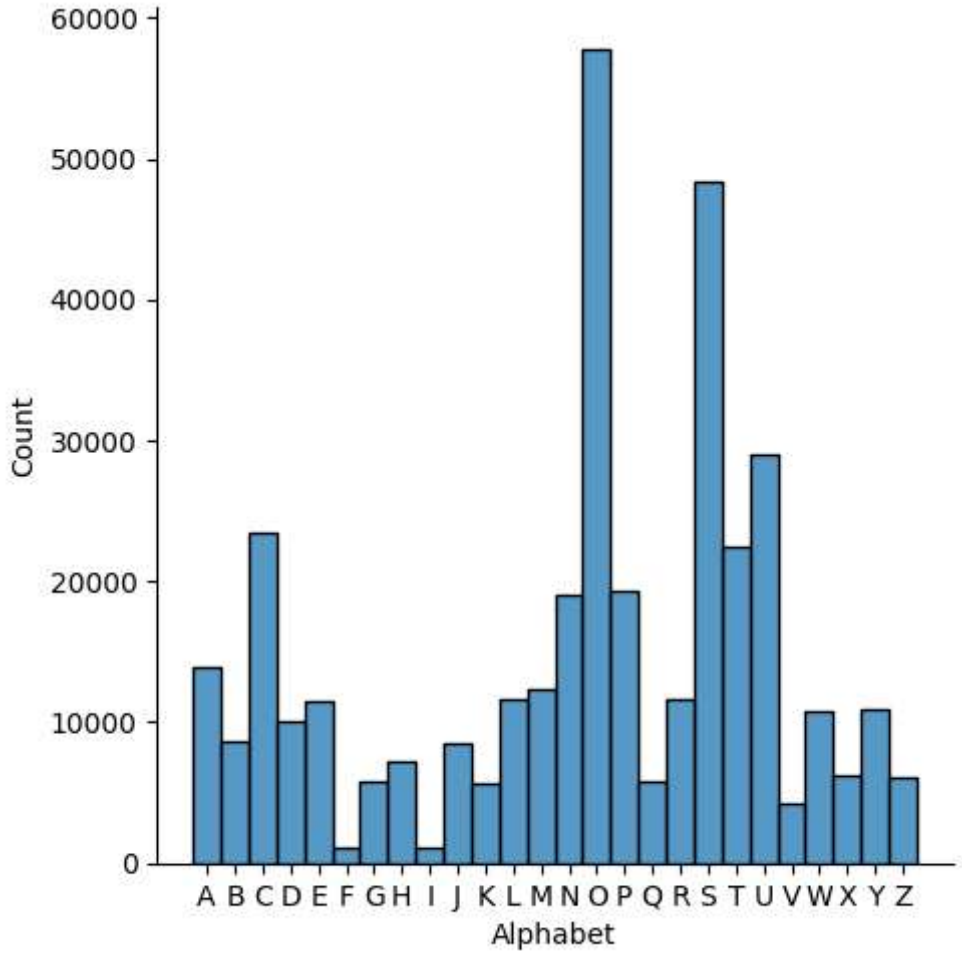
In [5]:
```
import string
x = y.replace([i for i in range(26)], list(string.ascii_uppercase))
x
```

Out[5]:
```
0         A
1         A
2         A
3         A
4         A
         ..
372445    Z
372446    Z
372447    Z
372448    Z
372449    Z
Name: 0, Length: 372450, dtype: object
```

In [6]:
```
plt.figure(figsize=(12, 10))
sns.displot(x)
```

```
plt.xlabel("Alphabet")
plt.show()
```

```
<Figure size 1200x1000 with 0 Axes>
```

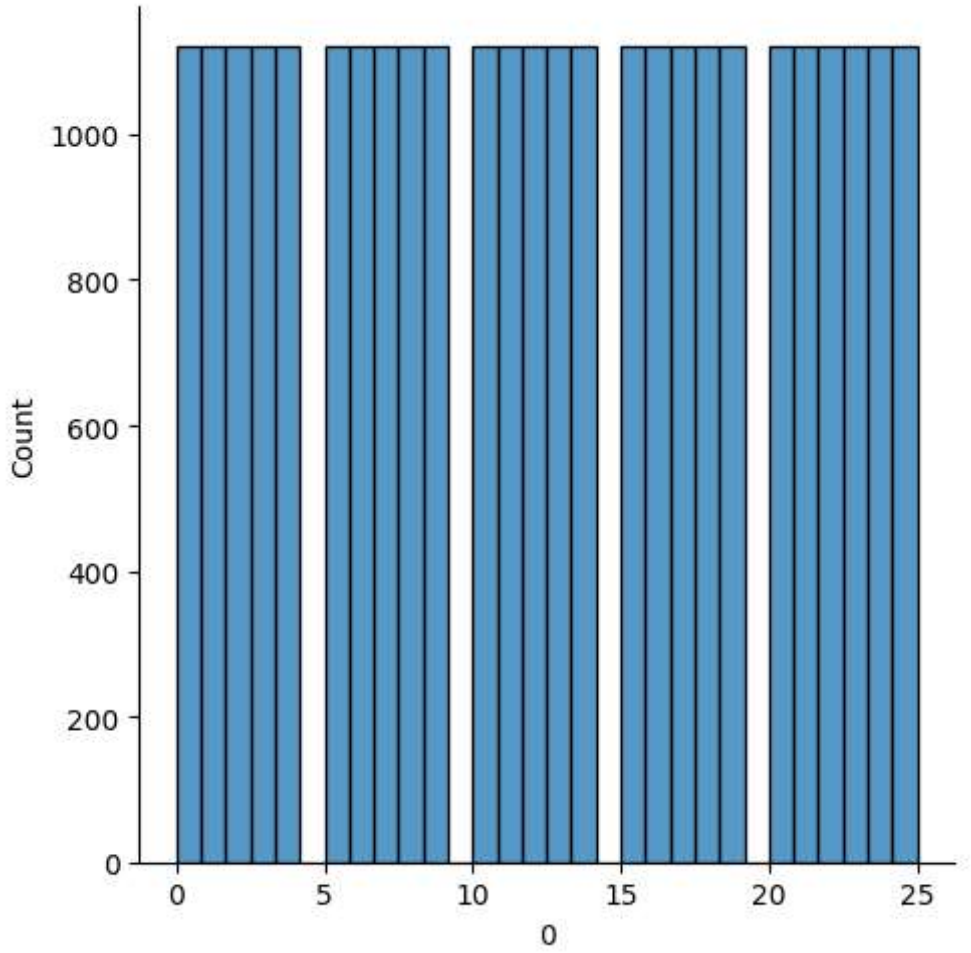


In [7]:
```
from imblearn.under_sampling  import NearMiss
```

In [8]:
```
nM = NearMiss()
X_data, y_data = nM.fit_resample(df, y)
```

In [9]:
```
plt.figure(figsize= (12, 10))
sns.displot(y_data)
plt.show()
```

```
<Figure size 1200x1000 with 0 Axes>
```



In [10]:
```
from keras.utils import np_utils
```

In [11]:
```
y = np_utils.to_categorical(y_data)

num_classes = y.shape[1]
num_classes
```

Out[11]:
```
26
```

In [12]:
```
y
```

Out[12]:
```
array([[1., 0., 0., ..., 0., 0., 0.],
       [1., 0., 0., ..., 0., 0., 0.],
       [1., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 1.],
       [0., 0., 0., ..., 0., 0., 1.],
       [0., 0., 0., ..., 0., 0., 1.]], dtype=float32)
```

In [13]:
```
y.shape, X_data.shape
```

Out[13]:
```
((29120, 26), (29120, 784))
```

Normalization

In [14]:
```
X_data = X_data/255
```

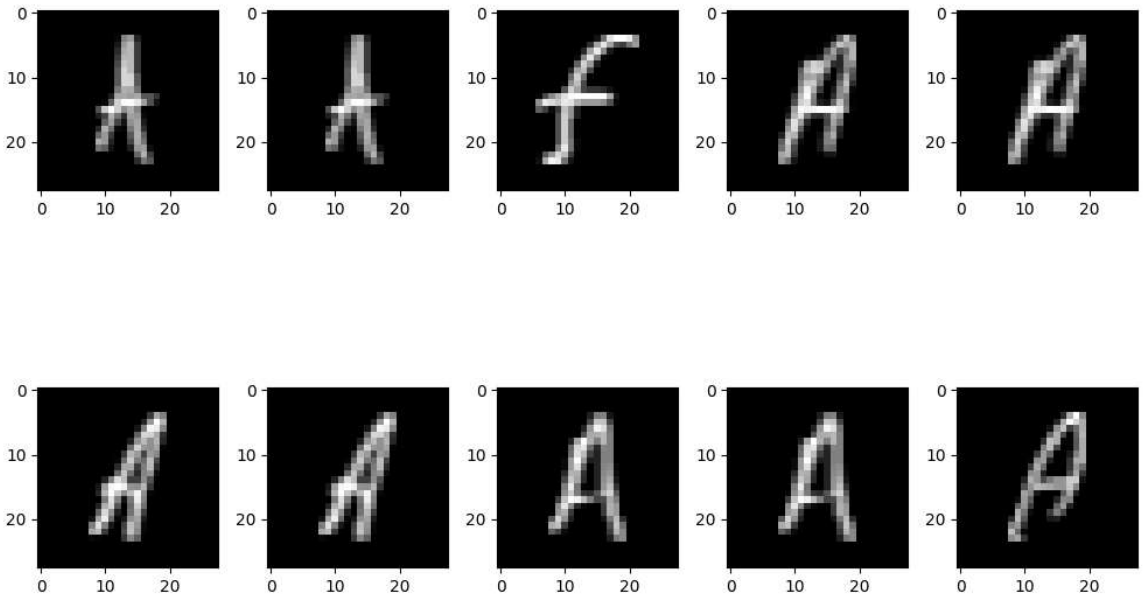
Visualization

In [15]:
```
X_data = np.array(X_data)
X_data = X_data.reshape(-1, 28, 28, 1)
```

In [16]:
```
X_data.shape
```

Out[16]:
```
(29120, 28, 28, 1)
```

In [17]:
```
f, ax = plt.subplots(2, 5)
f.set_size_inches(10, 10)

k = 0
for i in range(2):
    for j in range(5):
        ax[i, j].imshow(X_data[k], cmap='gray')
        k +=1
    plt.tight_layout()
```



Train Test Split

In [18]:
```
from sklearn.model_selection import train_test_split
```

In [19]:
```
X_train, X_test, y_train, y_test = train_test_split(X_data, y, test_size=0.2, ra
```

In [20]:
```
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(23296, 28, 28, 1) (5824, 28, 28, 1) (23296, 26) (5824, 26)
```

CNN Model

In [21]:
```
import keras
from keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from keras.layers import Conv2D, MaxPool2D, Flatten, Dense
```

In [22]:
```
model = Sequential()

model.add(Conv2D(64, (5, 5), input_shape= (28, 28, 1), activation='relu', paddir
model.add(MaxPool2D(pool_size=(2, 2),  padding= 'same'))

model.add(Conv2D(128, (5, 5), input_shape= (28, 28, 1), activation='relu',  padc
model.add(MaxPool2D(pool_size=(2, 2),  padding= 'same'))

model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accur

print(model.summary())
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 28, 28, 64)        1664

 max_pooling2d (MaxPooling2D  (None, 14, 14, 64)       0
 )

 conv2d_1 (Conv2D)           (None, 14, 14, 128)       204928

 max_pooling2d_1 (MaxPooling  (None, 7, 7, 128)        0
 2D)

 flatten (Flatten)           (None, 6272)              0

 dense (Dense)               (None, 128)               802944

 dense_1 (Dense)             (None, 26)                3354

=================================================================
Total params: 1,012,890
Trainable params: 1,012,890
Non-trainable params: 0
_________________________________________________________________
None
```

In [23]:
```
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=1
```

```
Epoch 1/10
91/91 [==============================] - 28s 293ms/step - loss: 0.8831 - accura
cy: 0.7502 - val_loss: 0.3281 - val_accuracy: 0.9059
Epoch 2/10
91/91 [==============================] - 28s 304ms/step - loss: 0.2257 - accura
cy: 0.9360 - val_loss: 0.1838 - val_accuracy: 0.9509
Epoch 3/10
91/91 [==============================] - 27s 294ms/step - loss: 0.1307 - accura
cy: 0.9632 - val_loss: 0.1194 - val_accuracy: 0.9658
Epoch 4/10
91/91 [==============================] - 28s 310ms/step - loss: 0.0872 - accura
cy: 0.9757 - val_loss: 0.1008 - val_accuracy: 0.9708
Epoch 5/10
91/91 [==============================] - 27s 296ms/step - loss: 0.0664 - accura
cy: 0.9812 - val_loss: 0.0996 - val_accuracy: 0.9722
Epoch 6/10
91/91 [==============================] - 27s 299ms/step - loss: 0.0492 - accura
cy: 0.9856 - val_loss: 0.0922 - val_accuracy: 0.9736
Epoch 7/10
91/91 [==============================] - 27s 301ms/step - loss: 0.0343 - accura
cy: 0.9908 - val_loss: 0.0751 - val_accuracy: 0.9801
Epoch 8/10
91/91 [==============================] - 27s 294ms/step - loss: 0.0311 - accura
cy: 0.9908 - val_loss: 0.0624 - val_accuracy: 0.9813
Epoch 9/10
91/91 [==============================] - 27s 297ms/step - loss: 0.0219 - accura
cy: 0.9939 - val_loss: 0.0748 - val_accuracy: 0.9804
Epoch 10/10
91/91 [==============================] - 29s 318ms/step - loss: 0.0177 - accura
cy: 0.9952 - val_loss: 0.0645 - val_accuracy: 0.9820
```

Model Analysis

In [24]:
```
scores_test = model.evaluate(X_test, y_test, verbose=0)
print(f"CNN Error on test data: {100 - (scores_test[1]*100):.2f}%")
```

```
CNN Error on test data: 1.80%
```

In [25]:
```
scores_train = model.evaluate(X_train, y_train, verbose=0)
print(f"CNN Error on train data: {100 - (scores_train[1]*100):.2f}%")
```

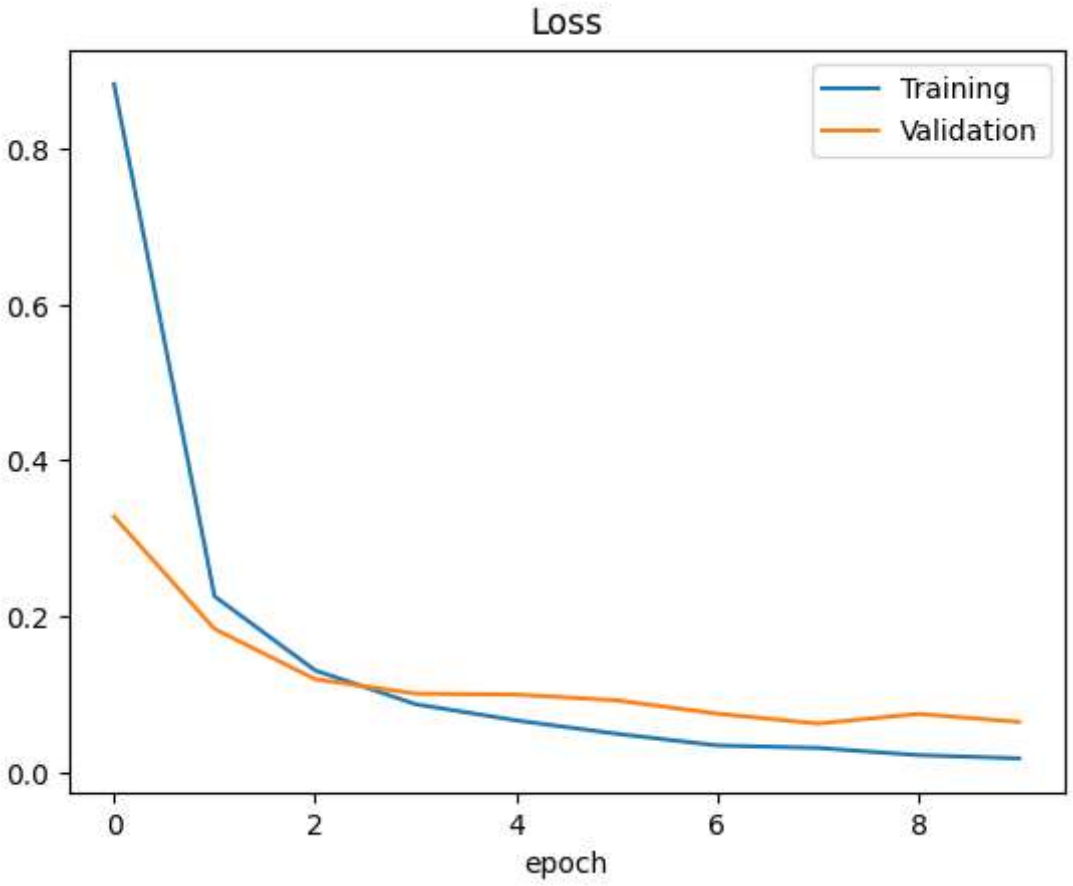
```
CNN Error on train data: 0.41%
```

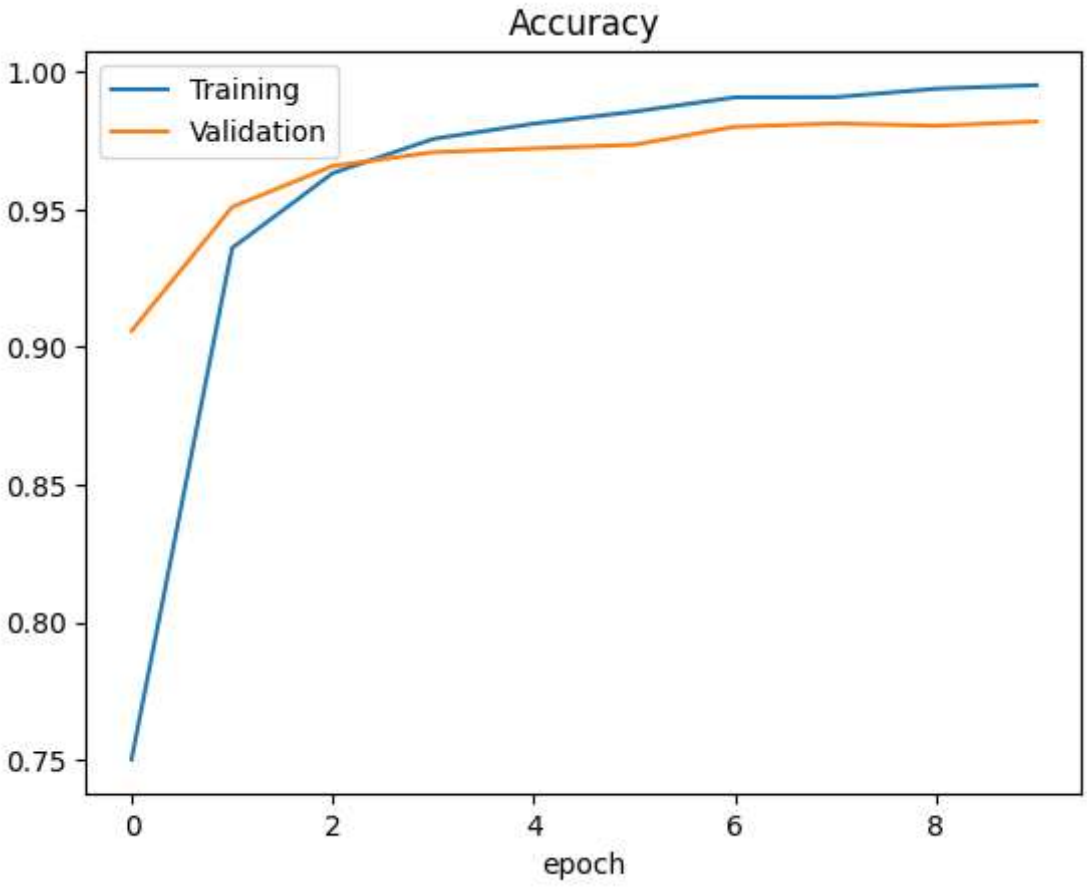
In [26]:
```
scores_all = model.evaluate(X_data, y, verbose=0)
print(f"CNN Error on overall data: {100 - (scores_all[1]*100):.2f}%")
```

```
CNN Error on overall data: 0.69%
```

In [27]:
```
plt.figure(1)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.legend(["Training", "Validation"])
plt.title("Loss")
plt.xlabel("epoch")

plt.figure(2)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.legend(["Training", "Validation"])
plt.title("Accuracy")
```

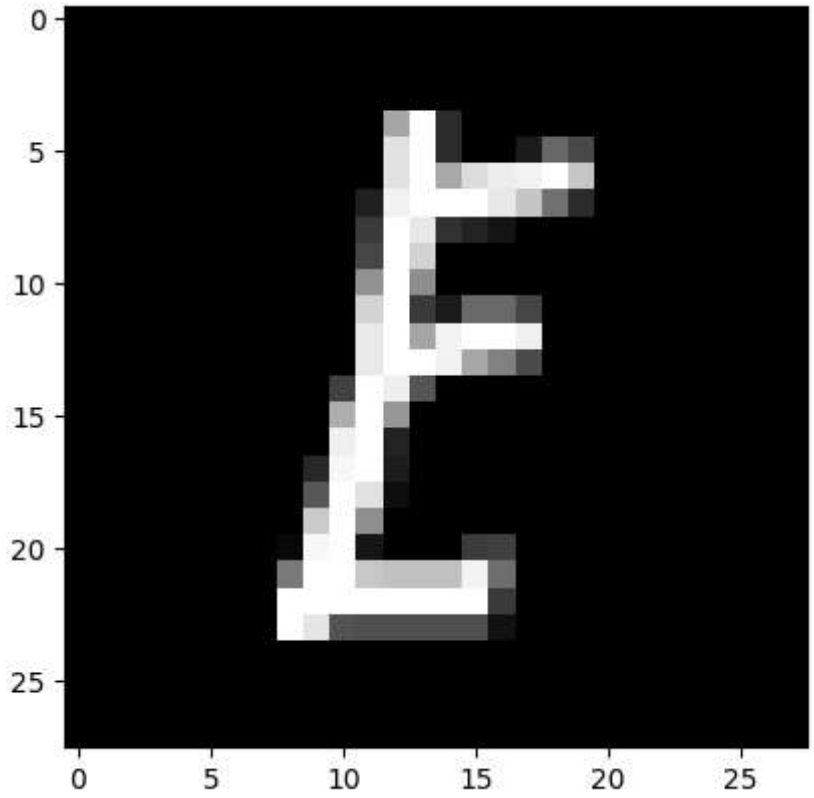
```
plt.xlabel("epoch")

plt.show()
```





In [28]:
```
plt.imshow(X_data[4552], cmap='gray')
X_data[4552].shape
```

Out[28]:
```
(28, 28, 1)
```



In [29]:
```
pred = model.predict(X_data[4552].reshape(1, 28, 28), verbose=0).argmax(axis=1)
output = list(string.ascii_uppercase)
output[pred[0]]
```

Out[29]:
```
'E'
```

In [ ]:
```

```