Introduction:

Predict (x,y) coordinate of bright pixel in 50×50 grayscale image using deep learning.

In [48]:
```
import tensorflow as tf
from tensorflow.keras import layers,models
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

1. Dataset Generation

Since real data was unavailable, a synthetic dataset was generated where each image contains one pixel with intensity 255 while others are zero. Random pixel selection ensures unbiased spatial distribution and sufficient samples help the model generalize well.

Generate a dataset where :

- Each image is 50 X 50 grayscale
- Excatly one pixel = 255
- Target label is (x,y) coordinate

In [16]:
```
def dataset(samples=15000,img_size=50):
  images=[]
  labels=[]
  for _ in range(samples):
    img=np.zeros((img_size,img_size),dtype=np.float32)
    x=np.random.randint(0,img_size)
    y=np.random.randint(0,img_size)
    img[x,y]=255
    images.append(img)
    labels.append([x,y])

  return np.array(images),np.array(labels)
```

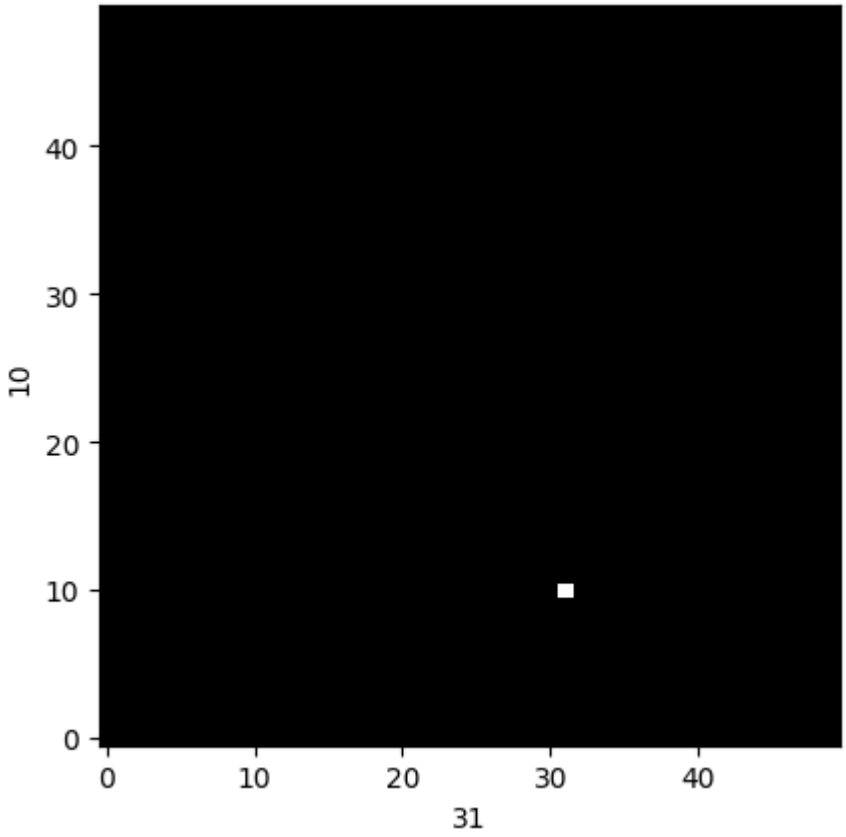
In [17]:
```
images,labels=dataset()
```

In [18]:
```
images.shape,labels.shape
```

Out[18]:
```
((15000, 50, 50), (15000, 2))
```

In [36]:
```
plt.imshow(images[0],cmap='gray',origin='lower')
plt.xlabel(labels[0][1])
plt.ylabel(labels[0][0])
```

Out[36]:
```
Text(0, 0.5, '10')
```



2. Preprocessing

In [37]:
```
# normalize images
images=images/255
```

In [20]:
```
images=np.expand_dims(images,axis=-1)
```

In [21]:
```
images.shape
```

Out[21]: (15000, 50, 50, 1)

In [38]:
```
# Train-validation-test split
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(images,labels,
                                               test_size=0.3,random_state=1234)
x_val,x_temp,y_val,y_temp=train_test_split(x_test,y_test,
                                          test_size=0.5,random_state=1234)
```

In [47]:
```
print('Train:',x_train.shape)
print('validation',x_val.shape)
print('Test',x_test.shape)
```

```
Train: (10500, 50, 50, 1)
validation (2250, 50, 50, 1)
Test (4500, 50, 50, 1)
```

3. Model Building (CNN)

In [49]:
```
model=models.Sequential()
```

```
model.add(layers.Conv2D(16,(3,3),activation='relu',input_shape=(50,50,1)))
model.add(layers.MaxPooling2D((2,2)))

model.add(layers.Conv2D(32,(3,3),activation='relu'))
model.add(layers.MaxPooling2D((2,2)))

model.add(layers.Flatten())

model.add(layers.Dense(64,activation='relu'))
model.add(layers.Dense(2))
```

```
/usr/local/lib/python3.12/dist-packages/keras/src/layers/convolutional/base_conv.
py:113: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a laye
r. When using Sequential models, prefer using an `Input(shape)` object as the fir
st layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

In [51]:
```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 48, 48, 16)	160
max_pooling2d (MaxPooling2D)	(None, 24, 24, 16)	0
conv2d_1 (Conv2D)	(None, 22, 22, 32)	4,640
max_pooling2d_1 (MaxPooling2D)	(None, 11, 11, 32)	0
flatten (Flatten)	(None, 3872)	0
dense (Dense)	(None, 64)	247,872
dense_1 (Dense)	(None, 2)	130

Total params: 252,802 (987.51 KB)

Trainable params: 252,802 (987.51 KB)

Non-trainable params: 0 (0.00 B)

In [52]:
```
model.compile(optimizer='adam',loss='mse',metrics=['mae'])
```

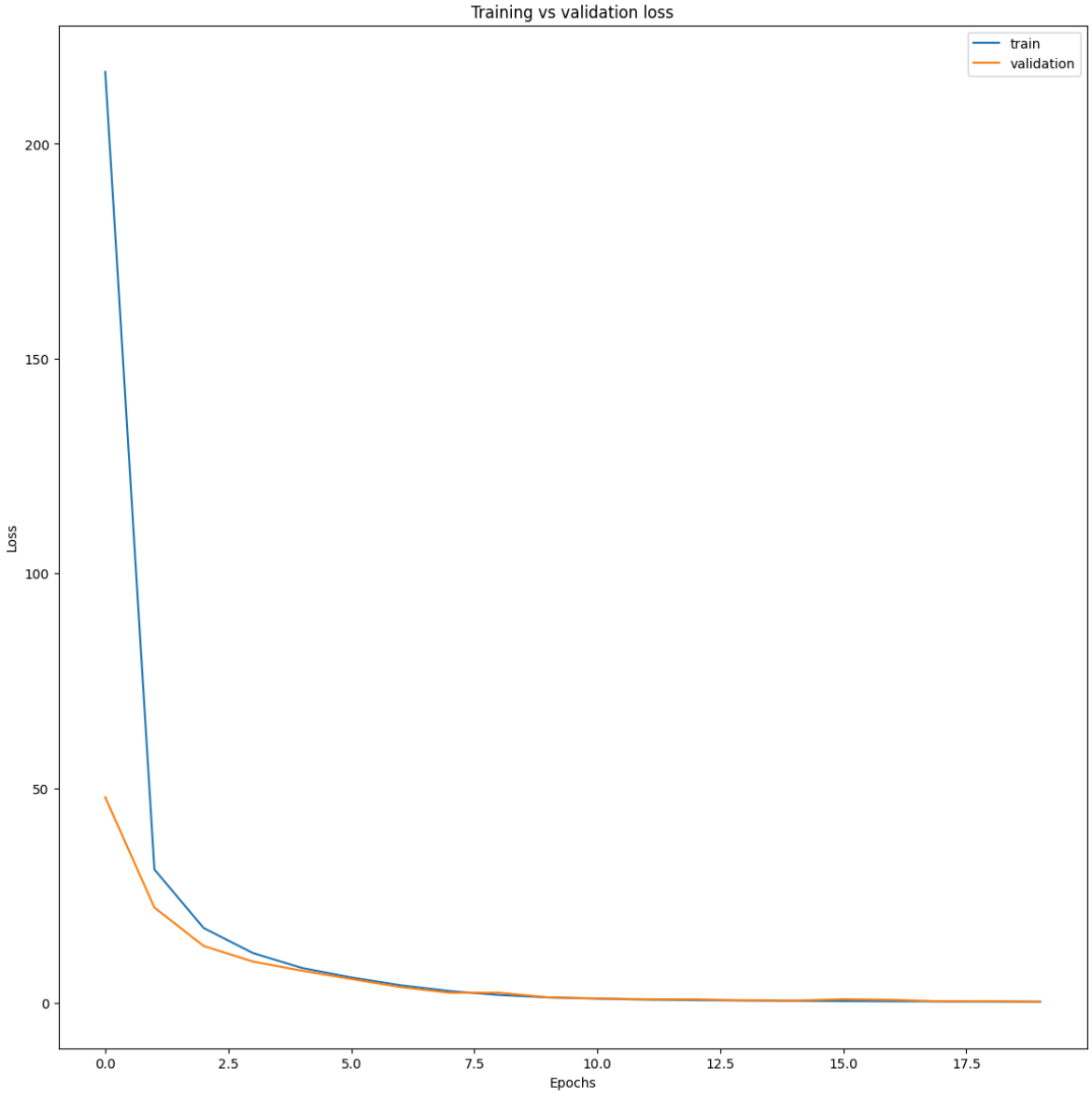
4. Training

In [53]:
```
histroy=model.fit(
    x_train,y_train,
    validation_data=(x_val,y_val),
    epochs=20,
    batch_size=64
)
```

```
Epoch 1/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 19s 106ms/step - loss: 393.8252 - mae: 15.8577 - val
_loss: 47.9017 - val_mae: 4.6140
Epoch 2/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 18s 108ms/step - loss: 38.4254 - mae: 3.9182 - val_l
oss: 22.2131 - val_mae: 3.0924
Epoch 3/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 16s 97ms/step - loss: 19.4842 - mae: 2.8974 - val_lo
ss: 13.2850 - val_mae: 2.4684
Epoch 4/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 21s 99ms/step - loss: 13.1998 - mae: 2.5324 - val_lo
ss: 9.6669 - val_mae: 2.1509
Epoch 5/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 21s 102ms/step - loss: 9.2207 - mae: 2.0918 - val_lo
ss: 7.5194 - val_mae: 1.9201
Epoch 6/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 16s 99ms/step - loss: 6.2911 - mae: 1.7439 - val_los
s: 5.5981 - val_mae: 1.6378
Epoch 7/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 17s 104ms/step - loss: 4.5894 - mae: 1.4517 - val_lo
ss: 3.7146 - val_mae: 1.2598
Epoch 8/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 16s 100ms/step - loss: 3.0290 - mae: 1.1178 - val_lo
ss: 2.3892 - val_mae: 0.9354
Epoch 9/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 21s 105ms/step - loss: 1.9573 - mae: 0.8906 - val_lo
ss: 2.4099 - val_mae: 1.0559
Epoch 10/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 21s 105ms/step - loss: 1.4320 - mae: 0.7812 - val_lo
ss: 1.3195 - val_mae: 0.6967
Epoch 11/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 17s 101ms/step - loss: 1.1161 - mae: 0.6842 - val_lo
ss: 1.0805 - val_mae: 0.6511
Epoch 12/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 17s 100ms/step - loss: 0.8354 - mae: 0.5969 - val_lo
ss: 0.8991 - val_mae: 0.5844
Epoch 13/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 16s 96ms/step - loss: 0.7020 - mae: 0.5625 - val_los
s: 0.8703 - val_mae: 0.6207
Epoch 14/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 20s 93ms/step - loss: 0.6270 - mae: 0.5424 - val_los
s: 0.6523 - val_mae: 0.5152
Epoch 15/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 22s 100ms/step - loss: 0.5246 - mae: 0.4907 - val_lo
ss: 0.5636 - val_mae: 0.4777
Epoch 16/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 16s 100ms/step - loss: 0.4355 - mae: 0.4568 - val_lo
ss: 0.8984 - val_mae: 0.7261
Epoch 17/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 16s 98ms/step - loss: 0.4072 - mae: 0.4569 - val_los
s: 0.7595 - val_mae: 0.6546
Epoch 18/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 17s 104ms/step - loss: 0.4173 - mae: 0.4588 - val_lo
ss: 0.3906 - val_mae: 0.4127
Epoch 19/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 16s 96ms/step - loss: 0.3516 - mae: 0.4284 - val_los
s: 0.4380 - val_mae: 0.4795
Epoch 20/20
165/165 ━━━━━━━━━━━━━━━━━━━━ 21s 98ms/step - loss: 0.3269 - mae: 0.3986 - val_los
s: 0.2995 - val_mae: 0.3729
```

5. Training Graphs

In [56]:
```
plt.figure(figsize=(14,14))
plt.plot(histroy.history['loss'])
plt.plot(histroy.history['val_loss'])
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training vs validation loss')
plt.legend(['train','validation'])
plt.show()
```



6. Evaluation

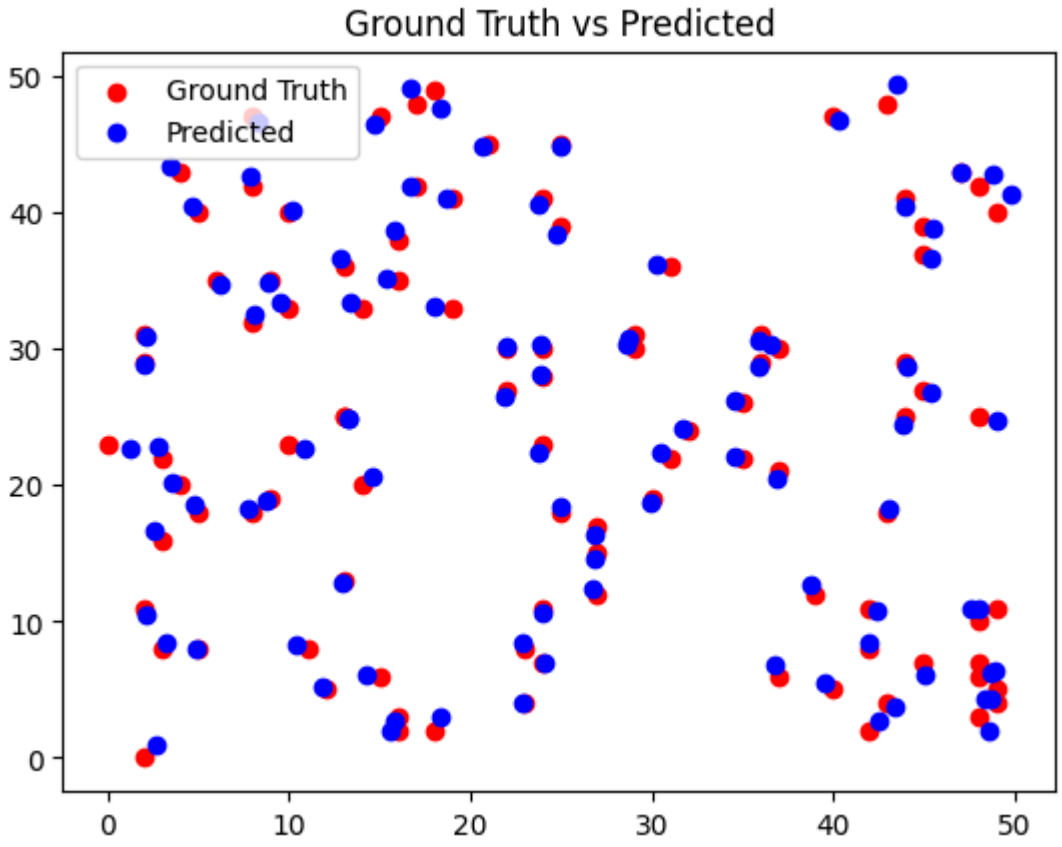
In [57]:
```
test_loss,test_mae=model.evaluate(x_temp,y_temp)
print('Test Loss',test_loss)
print('Test MAE',test_mae)
```

```
71/71 ━━━━━━━━━━━━━━━━━━━━ 2s 21ms/step - loss: 0.2491 - mae: 0.3711
Test Loss 0.26239150762557983
Test MAE 0.3676603138446808
```

7. Prediction Visualization

In [65]:
```
predictions=model.predict(x_temp[:100])
plt.scatter(y_temp[:100,0],y_temp[:100,1],color='red')
plt.scatter(predictions[:,0],predictions[:,1],color='blue')
plt.legend(['Ground Truth','Predicted'])
plt.title('Ground Truth vs Predicted')
plt.show()
```

```
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 61ms/step
```



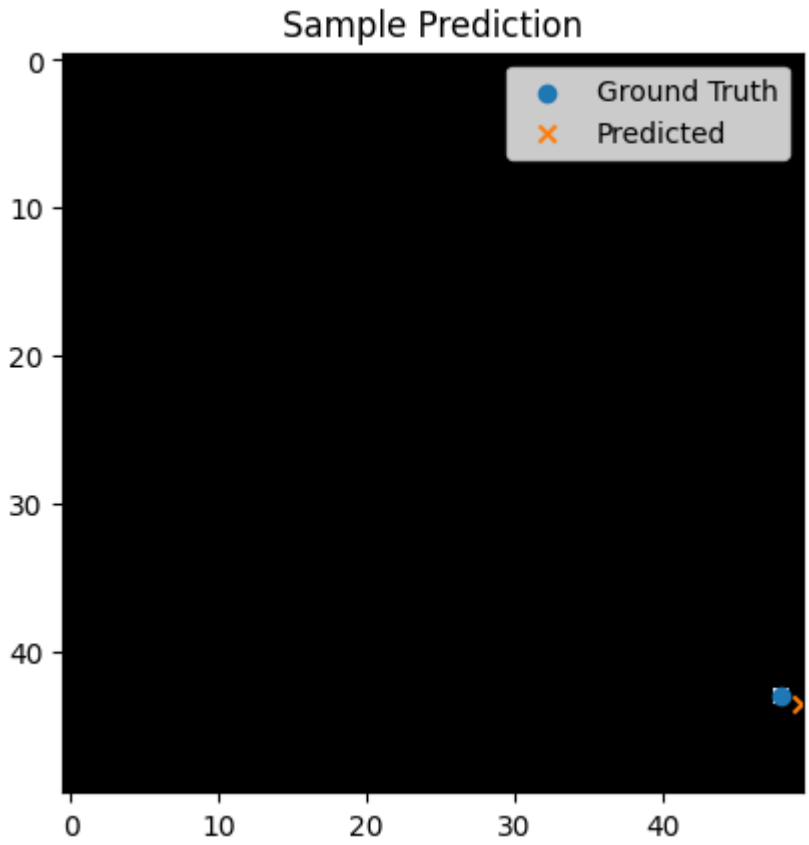
8. Sample Image Prediction

In [72]:
```
sample_img= x_temp[0]
true_cord=y_temp[0]
pred_cord=model.predict(np.expand_dims(sample_img,axis=0))[0]

plt.imshow(sample_img.squeeze(),cmap='gray')
plt.scatter(true_cord[1],true_cord[0],marker='o',label='Ground Truth')
plt.scatter(pred_cord[1],pred_cord[0],marker='x',label='Predicted')
plt.title('Sample Prediction')
plt.legend()
plt.show()

print('True coordinate',true_cord)
print('Predicted coordinate',pred_cord)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
```




```
True coordinate [43 48]
Predicted coordinate [43.55321 49.3492 ]
```

Dependencies:

- numpy
- tensorflow
- matplotlib
- scikit-learn