In [2]:
```
import numpy as np
from numpy import random
import seaborn as sns
import matplotlib.pyplot as plt
import tensorflow as tf
import pandas as pd
from tensorflow.keras.datasets import mnist
from tensorflow.keras.layers import Input, LSTM, Dense, GlobalMaxPool1D, GlobalMa
from tensorflow.keras.models import Sequential
```

We start by importing the MNIST dataset and reshaping them.

In [3]:
```
(X, y), (X_test, y_test) = mnist.load_data()
print('X_train: ' + str(X.shape))
print('Y_train: ' + str(y.shape))
print('X_test:  '  + str(X_test.shape))
print('Y_test:  '  + str(y_test.shape))
#pyplot.imshow(X[i], cmap=pyplot.get_cmap('gray')) gives image
```

```
X_train: (60000, 28, 28)
Y_train: (60000,)
X_test:  (10000, 28, 28)
Y_test:  (10000,)
```

In [4]:
```
X_train = pd.DataFrame(X.reshape(-1, 784))
X_test = pd.DataFrame(X_test.reshape(-1, 784))
y_train = pd.DataFrame(y)[0]
y_test = pd.DataFrame(y_test)[0]
print('X_train: ' + str(X_train.shape))
print('Y_train: ' + str(y_train.shape))
print('X_test:  '  + str(X_test.shape))
print('Y_test:  '  + str(y_test.shape))
X_train,X_test = X_train / 255.0, X_test / 255.0
```

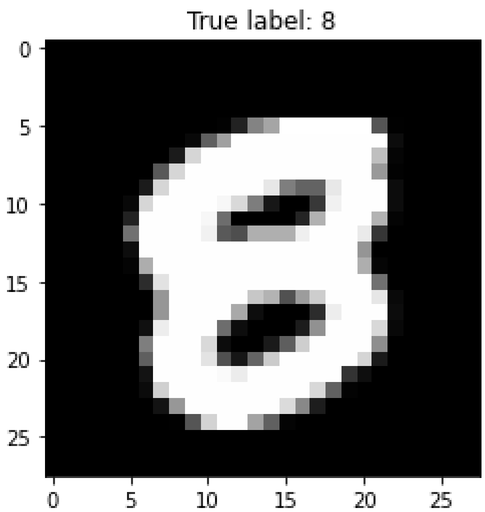
```
X_train: (60000, 784)
Y_train: (60000,)
X_test:  (10000, 784)
Y_test:  (10000,)
```

We write the functions for creation of **ANN** and other useful ones

In [4]:
```
def create_ann(op=10):
    model = tf.keras.models.Sequential([
        tf.keras.layers.Input(shape=(features,)),
        tf.keras.layers.Dense(128, activation='relu'),
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.Dense(128, activation='relu'),
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.Dense(128, activation='relu'),
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.Dense(op, activation='softmax')
    ])
    model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
    return model


def confidence(model, ip, label=None):
    v= ip.values
    v=v.reshape(-1,1)
    if not label:
      a=list(model.predict(v.T)[0])
      return a.index(max(a)),max(a)
    return model.predict(v.T)[0][label]

def confidence_distribution(model, ip,ind = 0,op=10):
    try:
        model = model.model
    except:
        pass
    ip=ip.iloc[ind,:]
    v= ip.values
    v=v.reshape(-1,1)
    l=model.predict(v.T)[0]
    plt.bar([i for i in range(op)],l)
    plt.show()


def show_mistake(model,df,i=None,y_test = y_test):
    try:
        model = model.model
    except:
        pass
    p_test = model.predict(df).argmax(axis=1)
    wrong_idx = np.where(p_test != y_test)[0]
    if i is None:
        i = np.random.choice(wrong_idx)
    display(df, y_test, i)
    print("Predicted: ",p_test[i])
    return i


def display(df, ydf, index):
    dd = df.iloc[index,:].to_numpy() *255
    try:
        if not ydf:
```

```
            plt.imshow(dd.reshape(28,28), cmap='gray')
    except:
        plt.title("True label: %s" % (ydf[index]))
        plt.imshow(dd.reshape(28,28), cmap='gray')

def threshold(df,t_val):
    out = df.copy()
    for i in range(df.shape[0]):
        out.iloc[i,:] = df.iloc[i,:].apply(lambda x: 0 if x<t_val else 1)
    return out

def model_stats(model):
    a_float = model.history['val_accuracy'][-1]*100
    plt.plot(model.history['accuracy'], label='train_acc')
    plt.plot(model.history['val_accuracy'], label='val_acc')
    plt.title("{:.2f}".format(a_float)+"% accuracy")
    plt.legend()

def load(m):
    try:
        return tf.keras.models.load_model(m)
    except OSError:
        print(str(m)+" not found")



def noise_analysis(model, conf_th = 0.75, noise_n = 100):
    noise = pd.DataFrame(np.random.rand(noise_n, 784))
    nums=[]
    cnum=[]
    try:
        model = model.model
    except:
        pass
    for i in range(noise.shape[0]):
        num,conf = confidence(model, noise.iloc[i,:])
        nums.append(num)
        if conf>conf_th:
            cnum.append(num)
    plt.hist(nums)
    plt.xticks(range(11))
    plt.title("Distribution of "+str(len(nums))+" noise data sets and their predi
    plt.show()
    plt.hist(cnum)
    plt.xticks(range(11))
    plt.title("Distribution of "+str(len(cnum))+"/"+str(len(nums))+" noise data s
    plt.show()


def shuff_together(df1,df2):
    joined = pd.concat([df1,df2], axis=1)
    joined = joined.iloc[np.random.permutation(len(joined))].reset_index(drop=Tru
    return joined.iloc[:,:-1],joined.iloc[:,-1]

def model_predictions(model,df,y_test=y_test):
    try:
        model = model.model
```

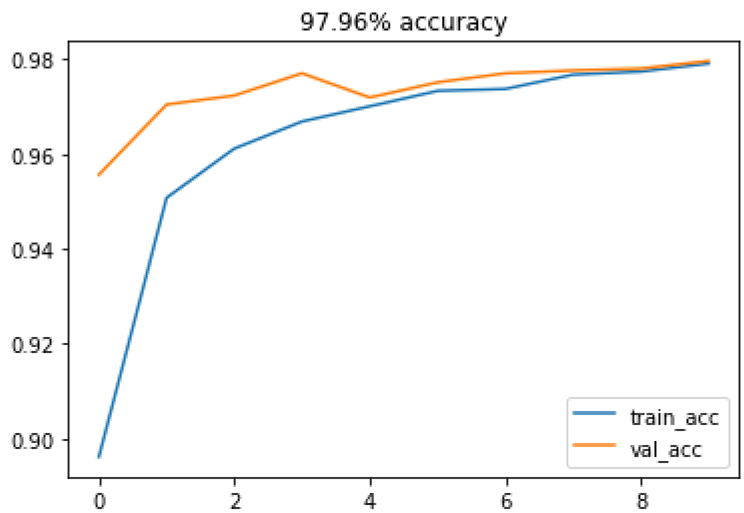
```
    except:
        pass
    preds = model.predict(df)
    l=[list(preds[i]).index(max(preds[i])) for i in range(preds.shape[0])]
    plt.hist(y_test, label=['Actual values'])
    plt.hist(l, label=['Predicted values'])
    plt.legend(loc='upper right')
    plt.title("Distribution of model predicted values vs actual labels")
    plt.show()
    return l

display(X_test, y_test, 8097)
```



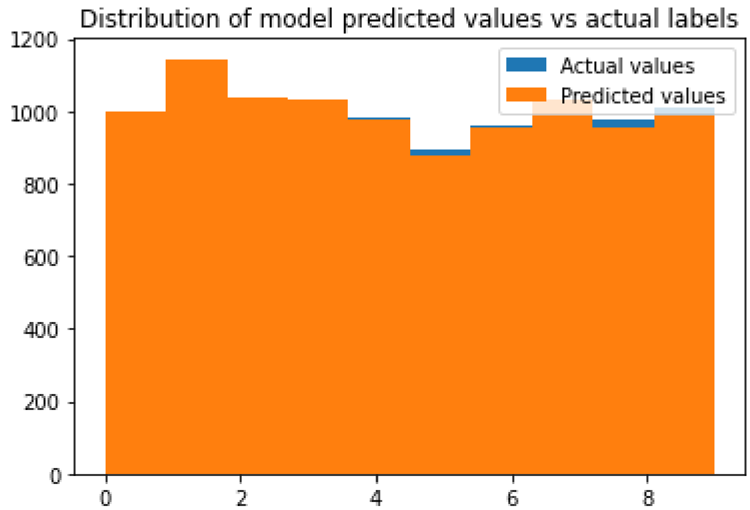
Standard MNIST **training** using ANN

In [5]:
```
features = X_train.shape[1]

model =  create_ann()
ann = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=10,ver
ann.model.save("ann")
model_stats(ann)
#load("ann")
```

```
INFO:tensorflow:Assets written to: ann/assets
```



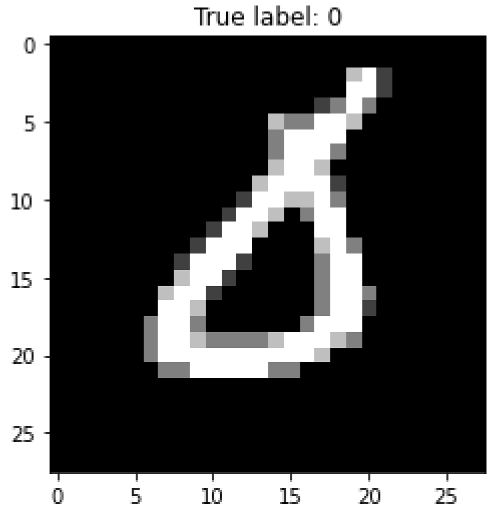
In [6]:
```
_ = model_predictions(ann,X_test)
```



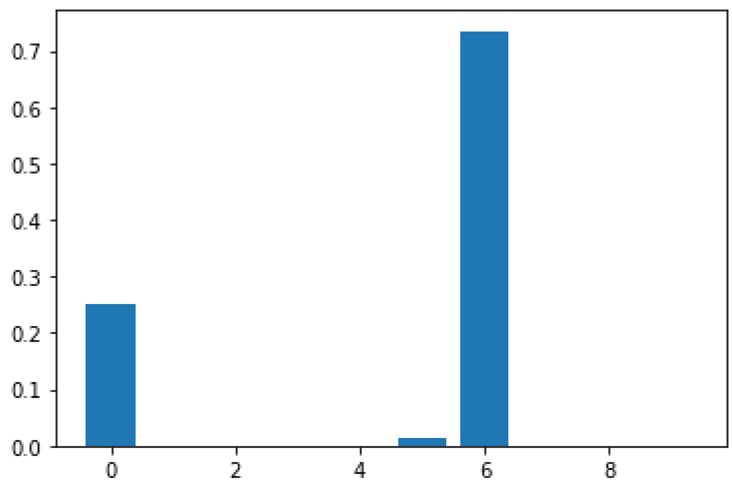
We look at one of the wrongly labelled test cases as well as its probability distribution prediction by the model.

In [ ]:
```
#Shows random mistake each time this cell is executed
i=show_mistake(ann,X_test)
```

```
Predicted:  6
```



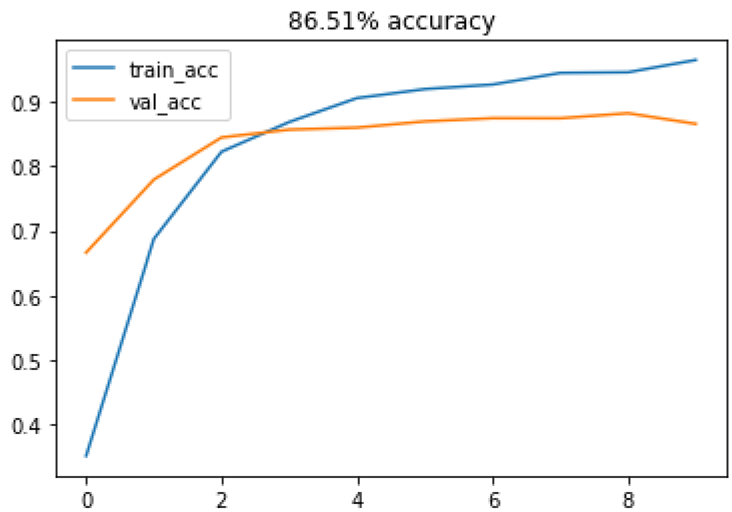
In [ ]:
```
confidence_distribution(ann, X_test,i)
```



Intelligence of a model is how well it learns to do its job correctly given a dataset. It is inversely proportional to the size of the training set.

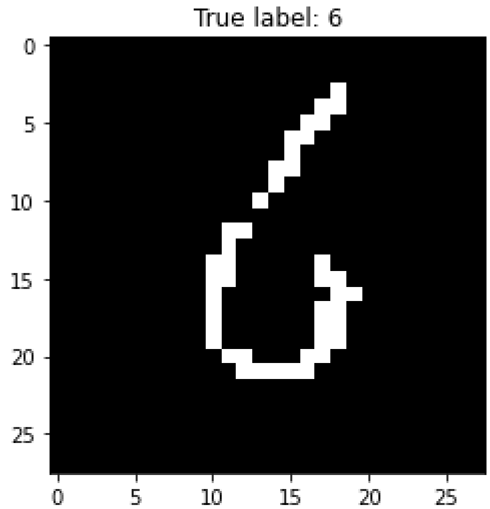
Here we will limit the training set to $maxrows$

In [ ]:
```
#INTELLIGENCE

model = create_ann()
maxrows = 1000
r = model.fit(X_train.iloc[:maxrows,:], y_train.iloc[:maxrows,], validation_data=
model_stats(r)
```



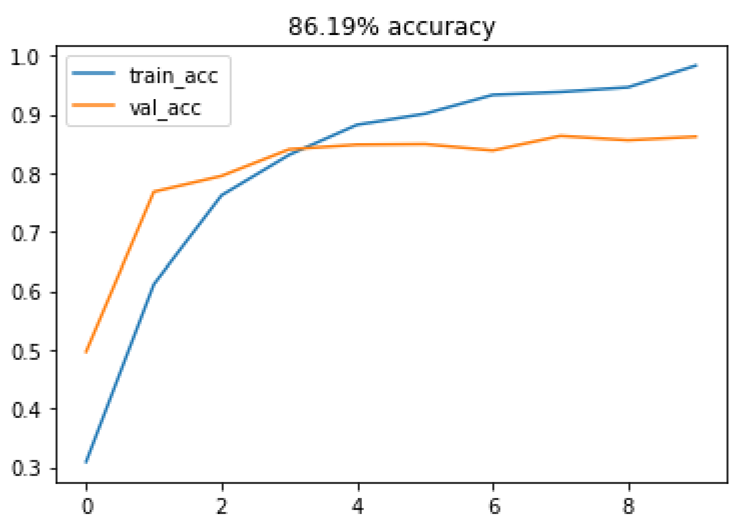
Trying pre processing of data using a threshold value. Below, everything above 90% of the pixel value is changed to 100% while other pixels are at 0%

In [ ]:
```
X_train_50 = threshold(X_train,0.9)
X_test_50 = threshold(X_test,0.9)
display(X_test_50, y_test, 50)
```

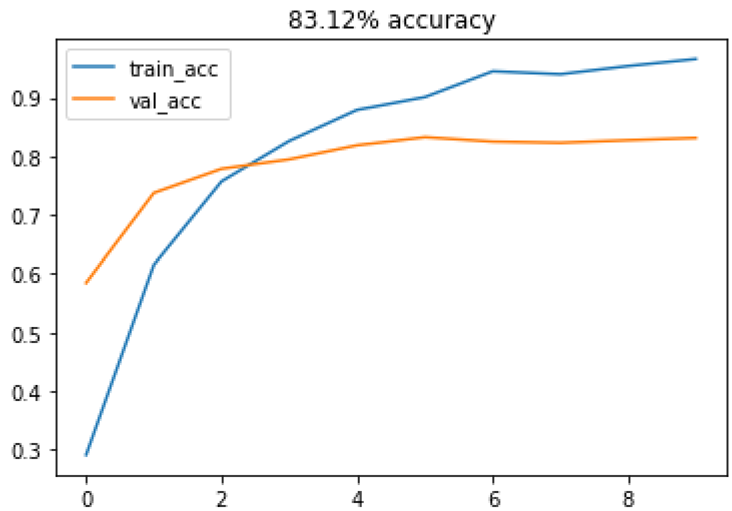


This does not seem to increase the intelligence when we test on normal test as well as pre processed test data

In [ ]:
```
model = create_ann()
r = model.fit(X_train_50.iloc[:maxrows,:], y_train.iloc[:maxrows,], validation_da
model_stats(r)
```

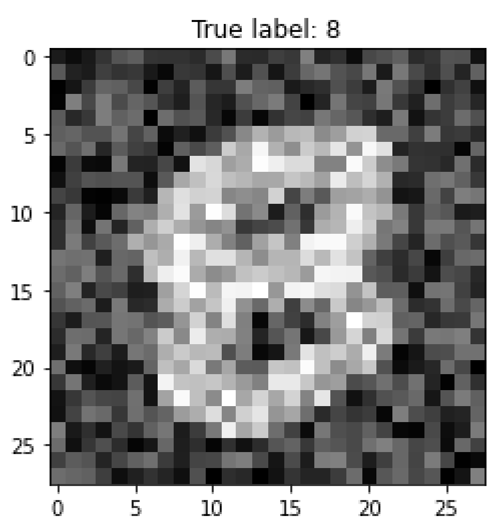


In [ ]:
```
model = create_ann()
r = model.fit(X_train_50.iloc[:maxrows,:], y_train.iloc[:maxrows,], validation_da
model_stats(r)
```



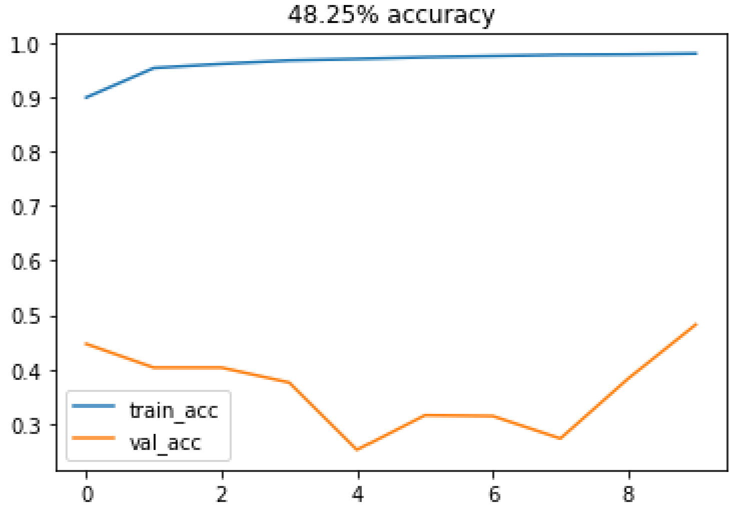
We will create noisy test data

In [ ]:
```
X_test_noisy = X_test.apply(lambda x: x-random.rand())
display(X_test_noisy, y_test, 8097)
```



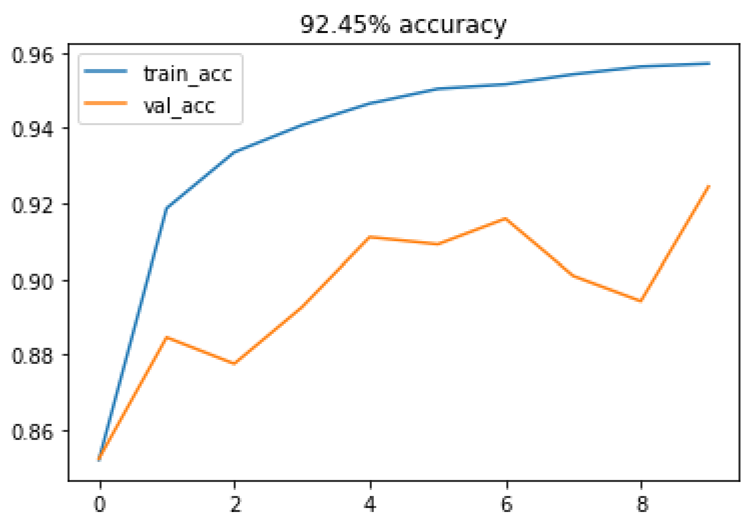
Trying to see if this model **ANN** works on this as a test of versatility and robustness

In [ ]:
```
model = create_ann()
ann = model.fit(X_train, y_train, validation_data=(X_test_noisy, y_test), epochs=
#ann.model.save("ann")
model_stats(ann)
```

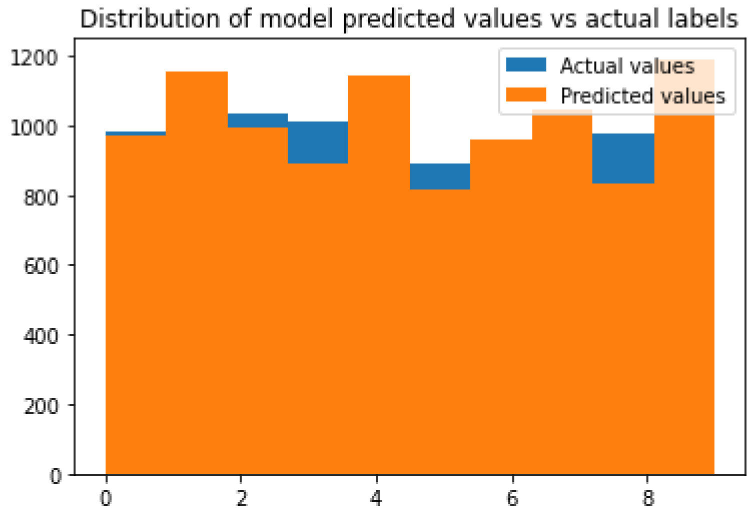


We will try to **train with noisy data** and see

In [ ]:
```
X_train_noisy = X_train.apply(lambda x: x-random.rand())
model = create_ann()
ann_noisy = model.fit(X_train_noisy, y_train, validation_data=(X_test_noisy, y_te
model_stats(ann_noisy)
```

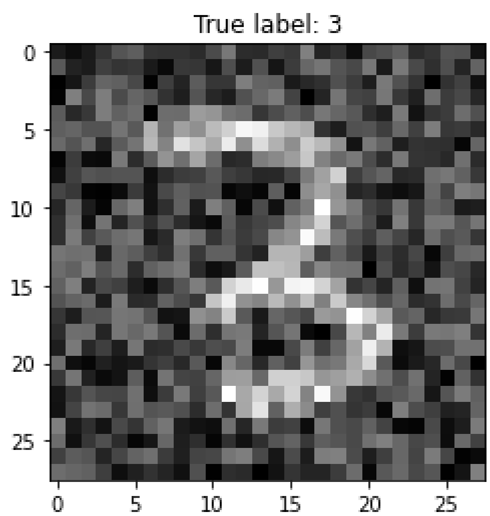


In [ ]:
```
_ = model_predictions(ann_noisy,X_test_noisy)
```

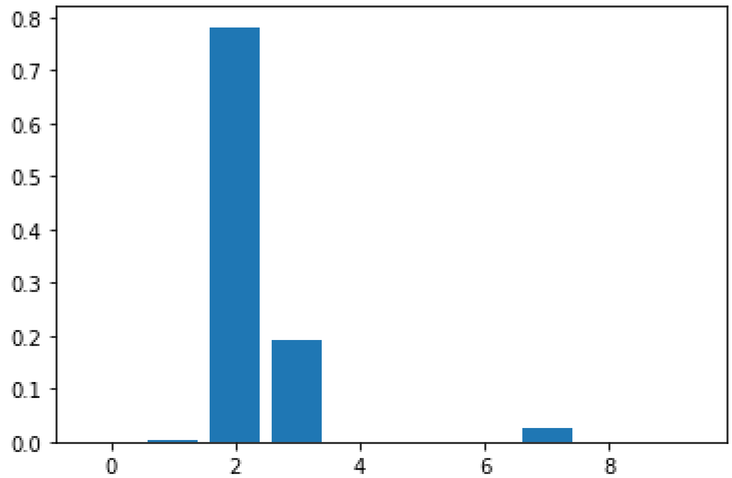


In [ ]:
```
i=show_mistake(ann_noisy,X_test_noisy)
```

Predicted: 2



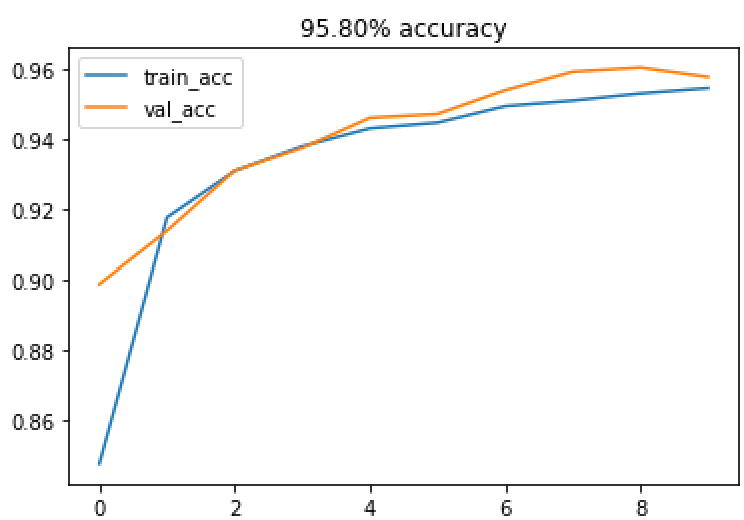
In [ ]:
```
confidence_distribution(ann_noisy, X_test_noisy,i)
```



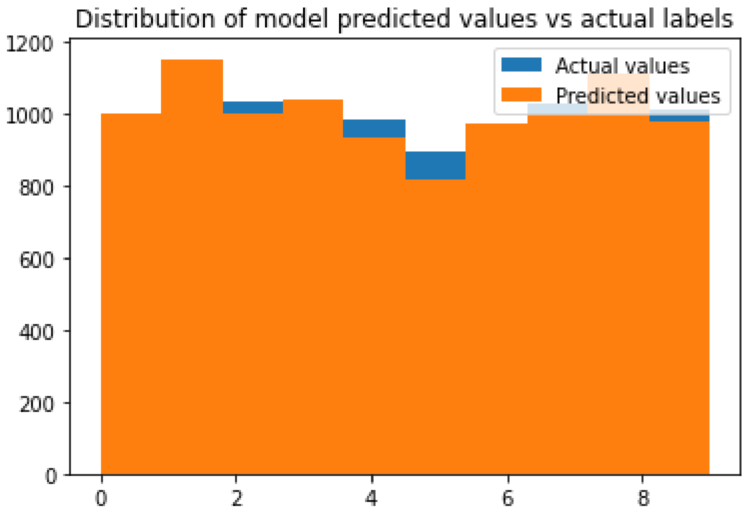
The model trained with noisy data (ann_noisy) seems to give much better accuracy for noisy test data and as good accuracy for the normal test data shown below making it more versatile

In [ ]:
```
model = create_ann()
ann_noisy = model.fit(X_train_noisy, y_train, validation_data=(X_test, y_test), e
model_stats(ann_noisy)
ann_noisy.model.save("ann_noisy")
```

```
INFO:tensorflow:Assets written to: ann_noisy\assets
```

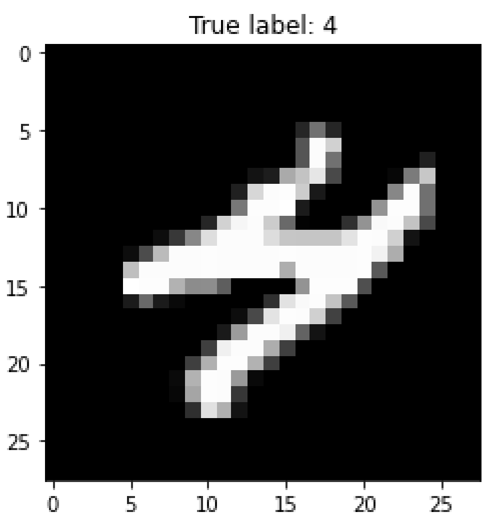


In [ ]:
```
_ = model_predictions(ann_noisy,X_test)
```

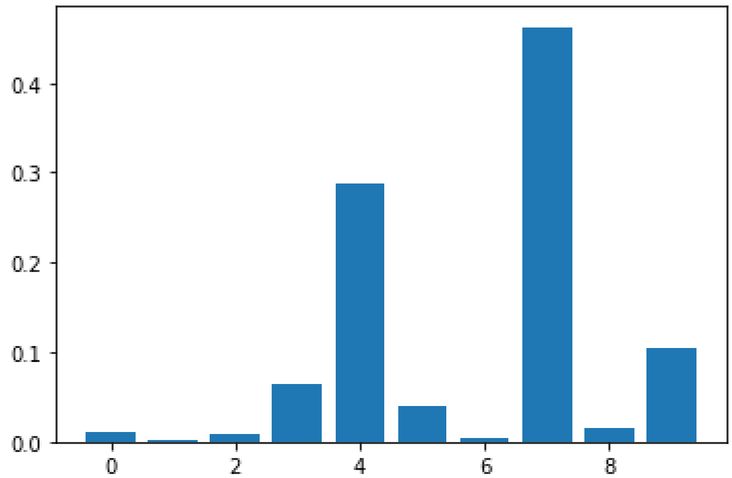


In [ ]:
```
i=show_mistake(ann_noisy,X_test)
```

```
Predicted:  7
```

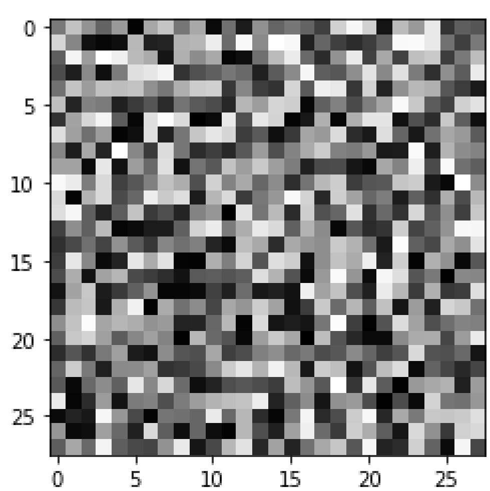


In [ ]:
```
confidence_distribution(ann_noisy, X_test,i)
```



Creating a **pure noise** dataset made of random pixels

In [ ]:
```
noise = pd.DataFrame(np.random.rand(100, 784))
display(noise,None, 55)
```



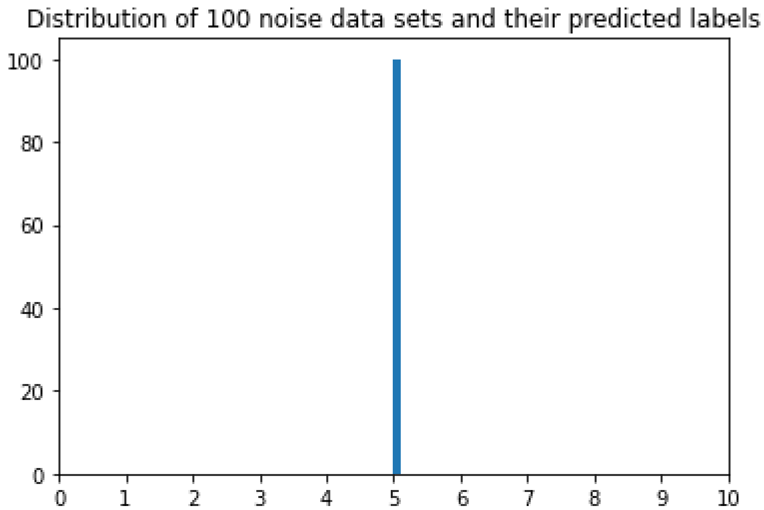
ann_noisy is more like to label a pure noise data with high level of certainty

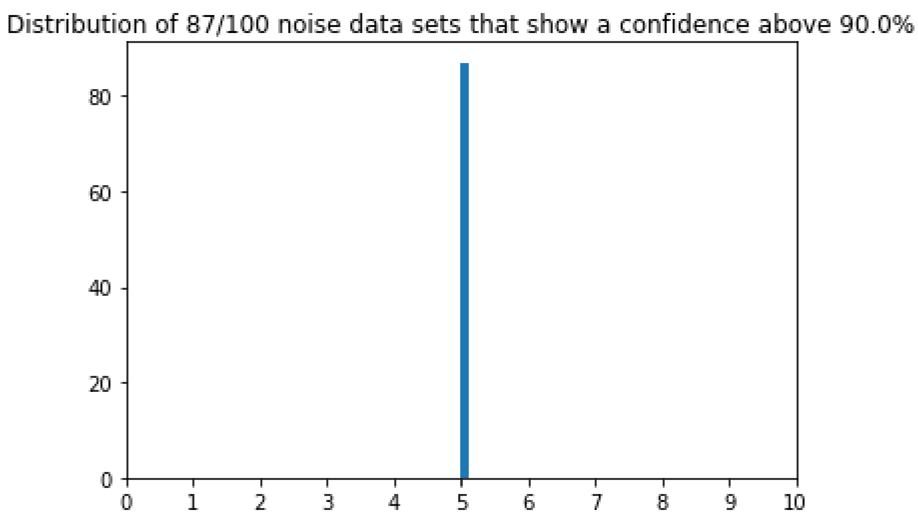
In [ ]:
```
ind = 32
print("ann_noisy model's label guess and confidence on a pure noise image is ",co
print("ann model's label guess and confidence on a pure noise image is ",confiden
```

```
ann_noisy model's label guess and confidence on a pure noise image is  (8, 0.94
46118)
ann model's label guess and confidence on a pure noise image is  (3, 0.9991881)
```

ann model is used to predict a set of noisy images. We find that a small number of them is labeled with very high confidence. It does not have high confidence in its predictions for noise data

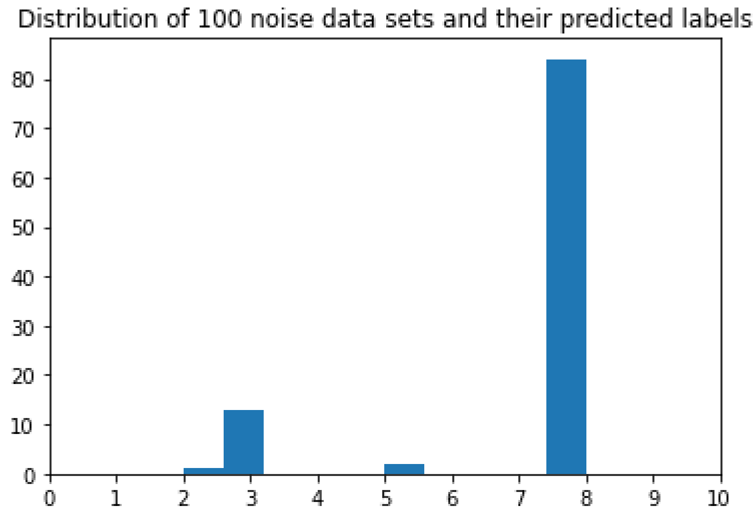
In [ ]:
```
noise_analysis(load('ann'),0.9)
```

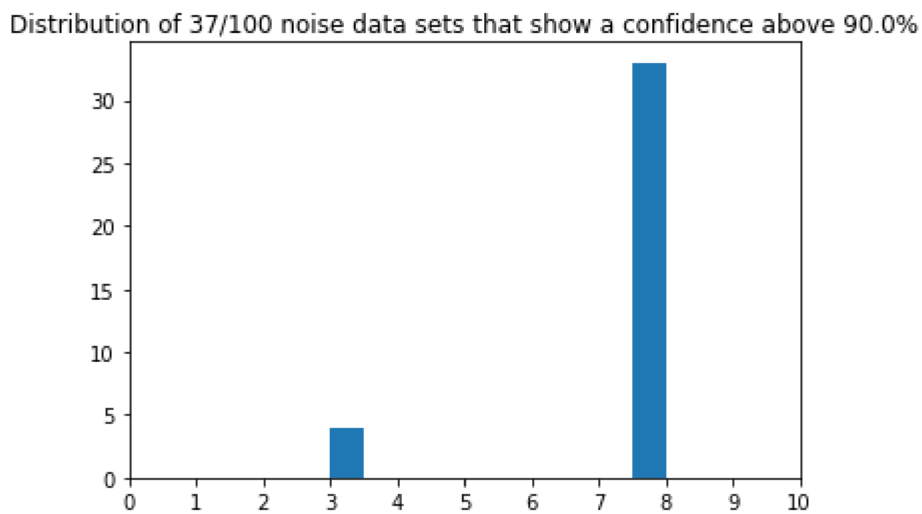




ann_noisy model is used to predict a set of noisy images. We find that fewer of them are labeled with very high confidence

In [ ]:
```
noise_analysis(ann_noisy,0.9)
```

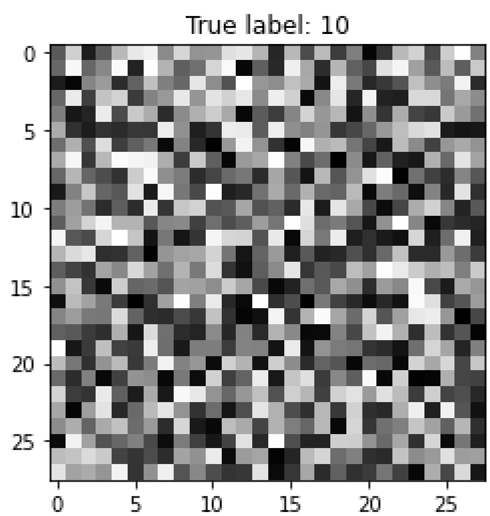




We append noise dataset to our original data and assign them to label:10

In [ ]:
```
noise = pd.DataFrame(np.random.rand(5000, 784))
X_train_plusnoisy = pd.concat([X_train, noise], axis=0)
y_min1 = pd.DataFrame(np.full((5000, ), 10))
y_train_plusnoisy = pd.concat([y_train, y_min1], axis=0)[0]
X_train_plusnoisy,y_train_plusnoisy = shuff_together(X_train_plusnoisy,y_train_pl
display(X_train_plusnoisy,y_train_plusnoisy,y_train_plusnoisy[y_train_plusnoisy =

noise = pd.DataFrame(np.random.rand(1000, 784))
X_test_plusnoisy = pd.concat([X_test, noise], axis=0)
y_min1 = pd.DataFrame(np.full((1000, ), 10))
y_test_plusnoisy = pd.concat([y_test, y_min1], axis=0)[0]
X_test_plusnoisy,y_test_plusnoisy = shuff_together(X_test_plusnoisy,y_test_plusnc
X_train_plusnoisy.shape,y_train_plusnoisy.shape
```

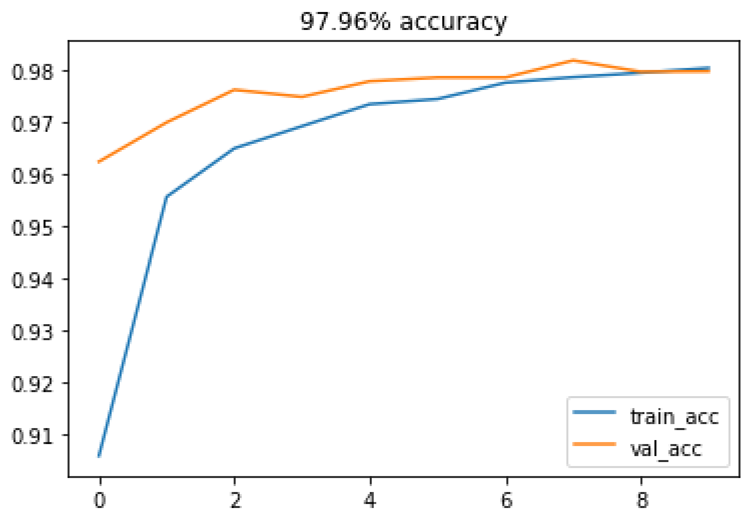
Out[28]: ((65000, 784), (65000,))



We now train an ANN with pure noise set as a seperate input

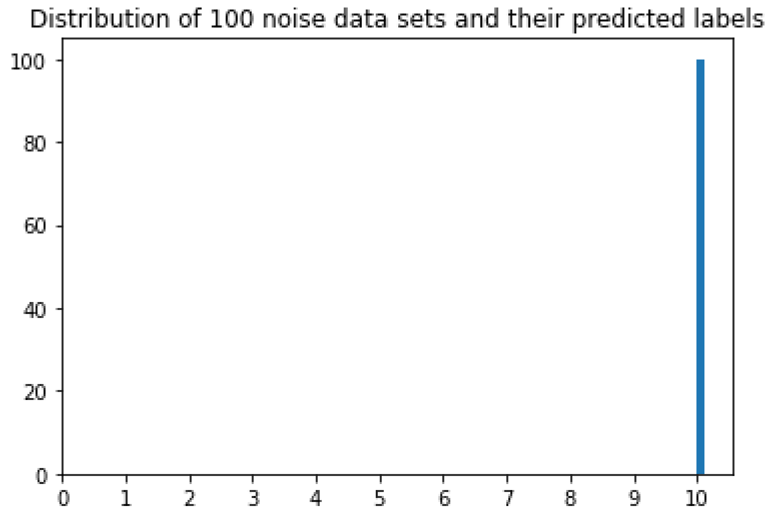
In [ ]:
```
features = X_train_plusnoisy.shape[1]

model = create_ann(11)
ann_plusnoisey = model.fit(X_train_plusnoisy, y_train_plusnoisy, validation_data=
ann_plusnoisey.model.save("ann_plusnoisey")
model_stats(ann_plusnoisey)
#load("ann")
```

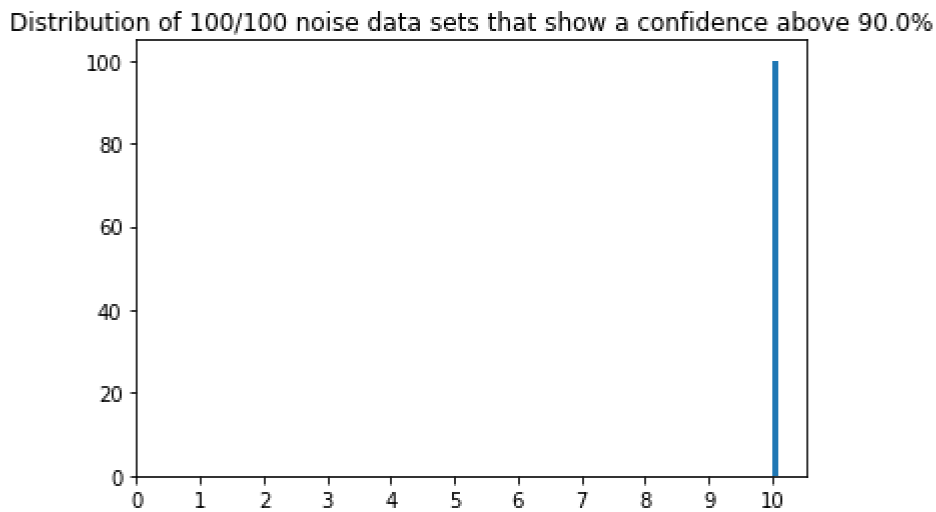
```
INFO:tensorflow:Assets written to: ann_plusnoisey\assets
```



This classifies noise correctly

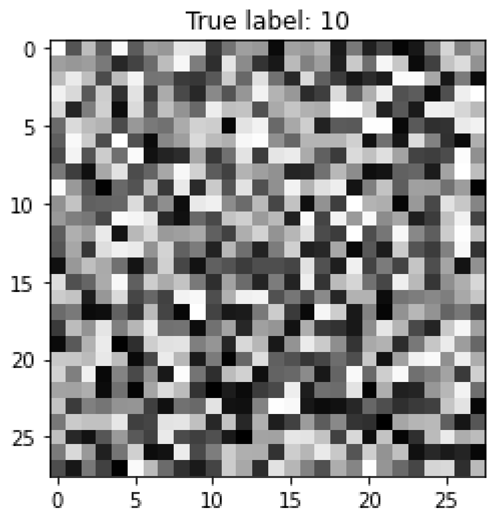
In [ ]:
```
noise_analysis(ann_plusnoisey,0.9)
```





We will create a training set that is noisy data plus noise

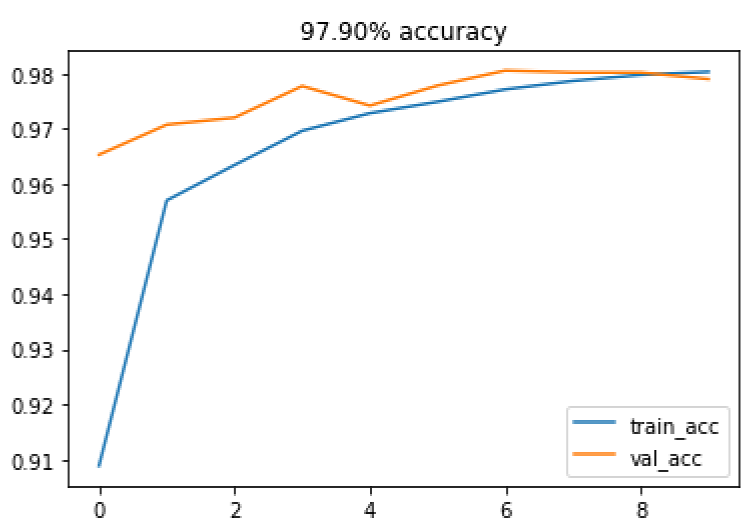
In [ ]:
```
noise = pd.DataFrame(np.random.rand(5000, 784))
X_trainnoisy_plusnoise = pd.concat([X_train_noisy, noise], axis=0)
y_min1 = pd.DataFrame(np.full((5000, ), 10))
y_trainnoisy_plusnoise = pd.concat([y_train, y_min1], axis=0)[0]
X_trainnoisy_plusnoise,y_trainnoisy_plusnoise = shuff_together(X_train_plusnoisy,
display(X_trainnoisy_plusnoise,y_trainnoisy_plusnoise,y_trainnoisy_plusnoise[y_tr
```



We can create an ANN that is trained on noisy data and noise and it does a good job of labelling original data and noise correctly

In [ ]:
```
features = X_trainnoisy_plusnoise.shape[1]

model = create_ann(11)
ann_noisy_plusnoise = model.fit(X_trainnoisy_plusnoise, y_trainnoisy_plusnoise, v
ann_noisy_plusnoise.model.save("ann_noisy_plusnoise")
model_stats(ann_noisy_plusnoise)
#Load("ann")
```

```
INFO:tensorflow:Assets written to: ann_noisy_plusnoise\assets
```



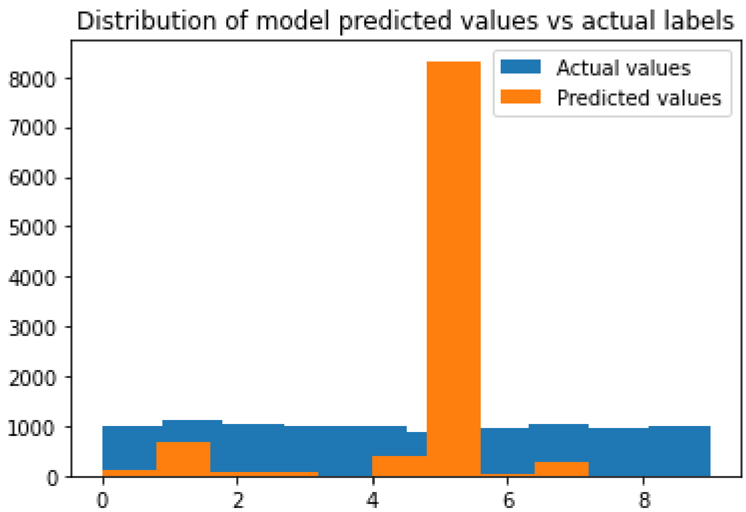
But it does a bad job of labelling noisy test data with most predictions being 5

In [ ]:
```
ann_noisy_plusnoise.model.evaluate(X_test_noisy,y_test)
```

```
313/313 [==============================] - 1s 1ms/step - loss: 7.8381 - accurac
y: 0.1930
```

Out[33]:
```
[7.838090419769287, 0.19300000369548798]
```

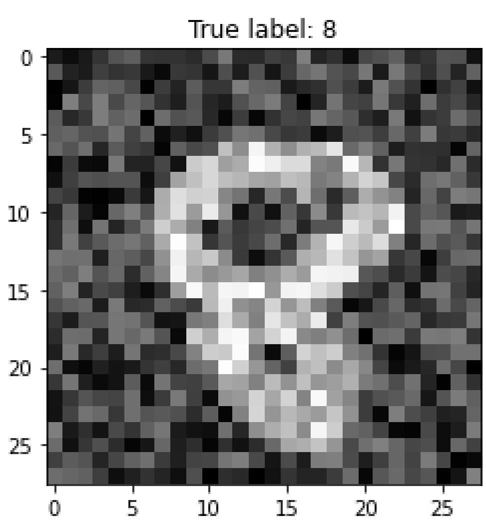
In [ ]:
```
_ = model_predictions(ann_noisy_plusnoise,X_test_noisy)
```



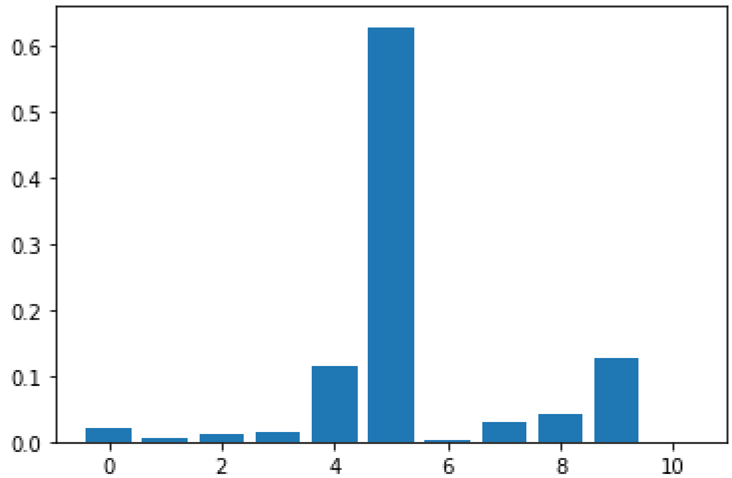
This also seem to show very high confidence in its incorrectly predicted labels.

In [ ]:
```
i=show_mistake(ann_noisy_plusnoise,X_test_noisy)
```

```
Predicted:  5
```

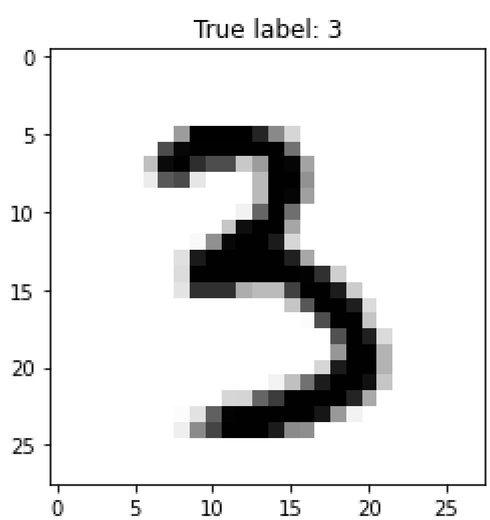


In [ ]:
```
confidence_distribution(ann_noisy_plusnoise, X_test_noisy,i,op=11)
```



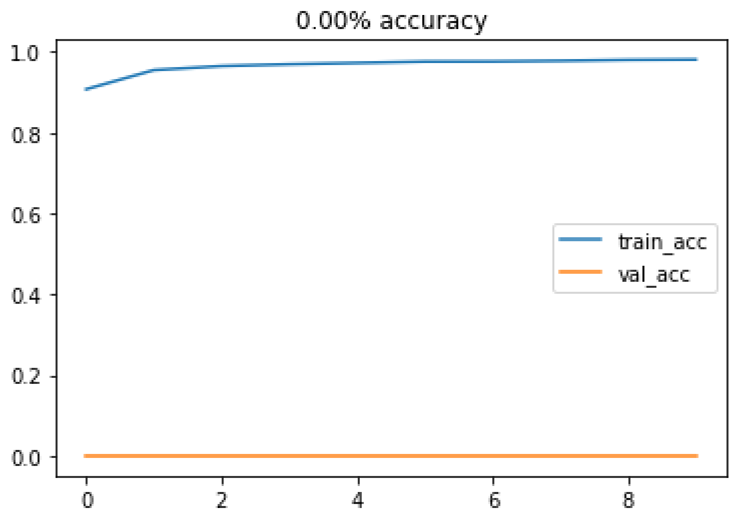
What will happen if the model is faced with inverted data?

In [ ]:
```
inverted = X_test.apply(lambda x: 1-x)
display(inverted,y_test,ind)
```

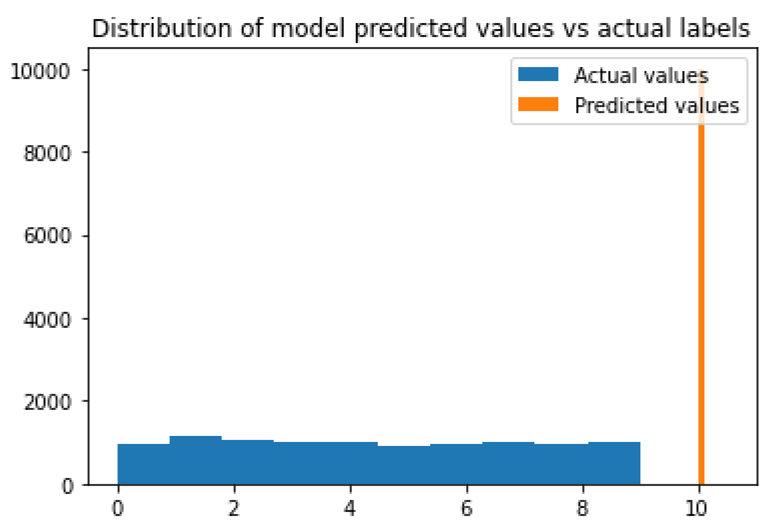


Every thing is labelled as noise with high certainty

In [ ]:
```
model = create_ann(11)
r = model.fit(X_train_plusnoisy, y_train_plusnoisy, validation_data=(inverted, y_
#ann.model.save("ann")
model_stats(r)
```

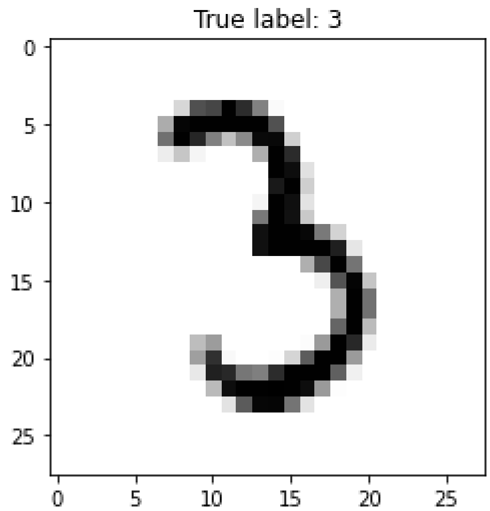


In [ ]:
```
_ = model_predictions(r,inverted)
```

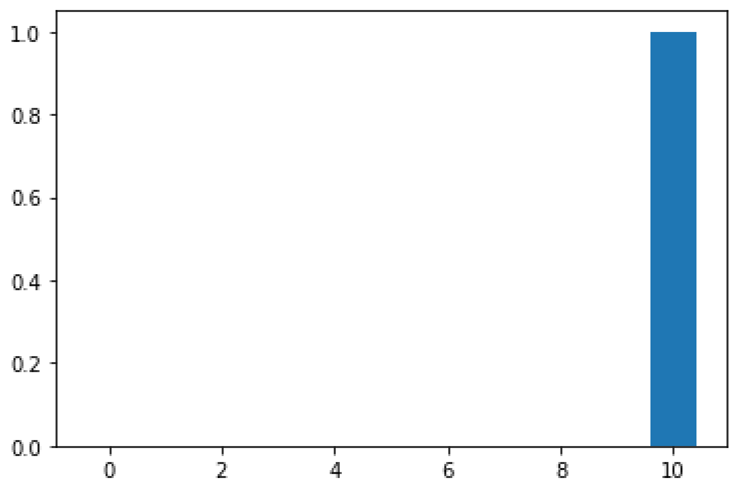


In [ ]:
```
i=show_mistake(r,inverted)
```

```
Predicted:  10
```

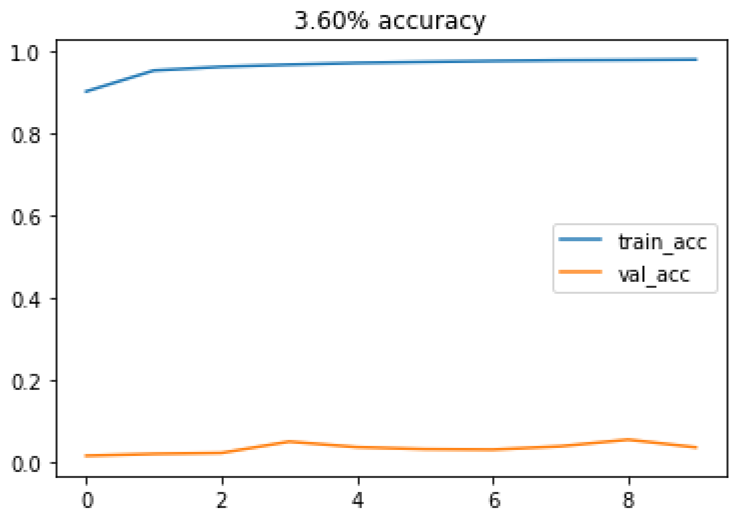


In [ ]:
```
confidence_distribution(r, inverted,i,11)
```

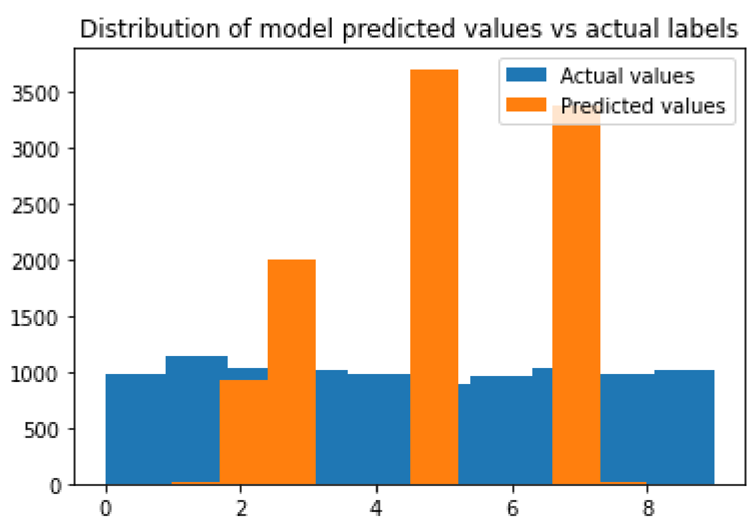


The original standard ANN without noise label predicted most inverted images as 5 with very high confidence

In [ ]:
```
model = create_ann()
r = model.fit(X_train, y_train, validation_data=(inverted, y_test), epochs=10,ver
#ann.model.save("ann")
model_stats(r)
```

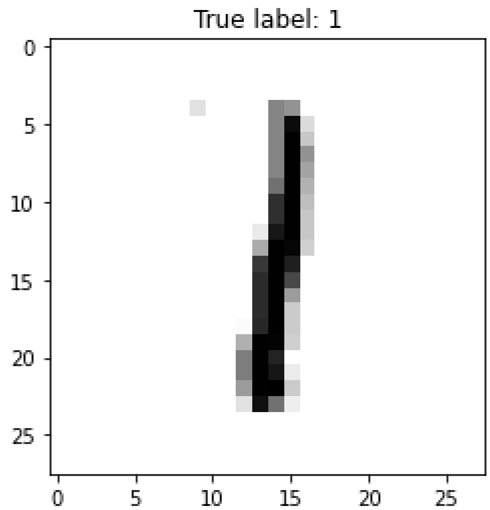


In [ ]:
```
_ = model_predictions(r,inverted)
```

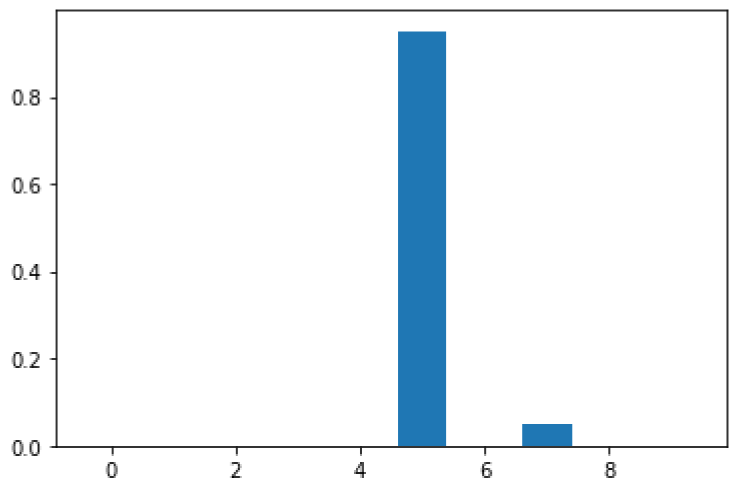


In [ ]:
```
i=show_mistake(r,inverted)
```

```
Predicted:  5
```



In [ ]:
```
confidence_distribution(r, inverted,i)
```



We will now create a model based on RNN

In [ ]:
```
(X, y), (X_t, y_t) = mnist.load_data()
X, X_t = X / 255.0, X_t / 255.0

def create_rnn():
    i = Input(shape=X[0].shape)
    x = LSTM(128, return_sequences=True,dropout=0.2)(i)
    x = GlobalMaxPool1D()(x)
    x = Dense(10, activation='softmax')(x)

    model = tf.keras.models.Model(i, x)

    model.compile(optimizer='adam',
                  loss='sparse_categorical_crossentropy',
                  metrics=['accuracy'])
    return model

def confidence(model, ip):
    try:
        model = model.model
    except:
        pass
    a=list(model.predict(np.expand_dims(ip, axis=0))[0])
    return a.index(max(a)),max(a)

def confidence_distribution(model, ip,ind = 0):
    try:
        model = model.model
    except:
        pass
    l=model.predict(ip.values.reshape(-1,1,28,28)[ind])[0]
    plt.bar([i for i in range(10)],l)
    plt.show()


def noise_analysis(model, conf_th = 0.75, noise_n = 100):
    noise = np.random.rand(noise_n, 28,28)
    nums=[]
    cnum=[]
    try:
        model = model.model
    except:
        pass
    for i in range(noise.shape[0]):
        num,conf = confidence(model, noise[i])
        nums.append(num)
        if conf>conf_th:
            cnum.append(num)
    plt.hist(nums)
    plt.xticks(range(11))
    plt.title("Distribution of "+str(len(nums))+" noise data sets and their predi
    plt.show()
    plt.hist(cnum)
    plt.xticks(range(11))
    plt.title("Distribution of "+str(len(cnum))+"/"+str(len(nums))+" noise data s
    plt.show()
```

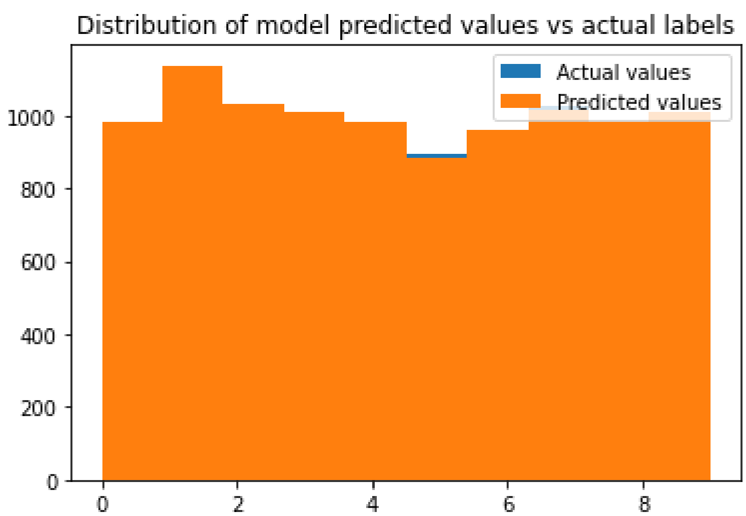
```
def show_mistake(model,df,i=None,y_test = y_test):
    try:
        model = model.model
    except:
        pass
    try:
        p_test = model.predict(df.values.reshape(-1,28,28)).argmax(axis=1)
    except:
        p_test = model.predict(df.argmax(axis=1))
    wrong_idx = np.where(p_test != y_test)[0]
    if i is None:
        i = np.random.choice(wrong_idx)
    display(df, y_test, i)
    print("Predicted: ",p_test[i])
    return i

def model_predictions(model,df,y_test=y_test):
    try:
        model = model.model
    except:
        pass
    try:
        preds = model.predict(df.values.reshape(-1,28,28)).argmax(axis=1)
    except:
        preds = model.predict(df.argmax(axis=1))
    plt.hist(y_test, label=['Actual values'])
    plt.hist(preds, label=['Predicted values'])
    plt.legend(loc='upper right')
    plt.title("Distribution of model predicted values vs actual labels")
    plt.show()
    return preds
```

We have high accuracy similar to ANN

In [ ]:
```
model = create_rnn()
rnn = model.fit(X, y, validation_data=(X_t, y_t), epochs=10, verbose=1)
model_stats(rnn)
```

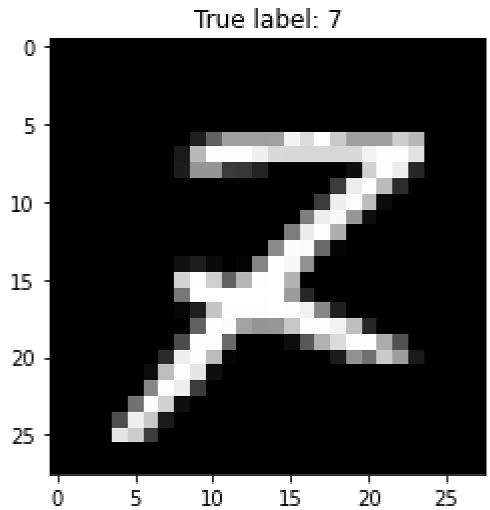
```
Epoch 1/10
1875/1875 [==============================] - 26s 13ms/step - loss: 0.7777 -
accuracy: 0.7581 - val_loss: 0.1553 - val_accuracy: 0.9539
Epoch 2/10
1875/1875 [==============================] - 24s 13ms/step - loss: 0.1461 -
accuracy: 0.9564 - val_loss: 0.0827 - val_accuracy: 0.9754
Epoch 3/10
1875/1875 [==============================] - 24s 13ms/step - loss: 0.0957 -
accuracy: 0.9714 - val_loss: 0.0633 - val_accuracy: 0.9823
Epoch 4/10
1875/1875 [==============================] - 24s 13ms/step - loss: 0.0762 -
accuracy: 0.9774 - val_loss: 0.0492 - val_accuracy: 0.9844
Epoch 5/10
1875/1875 [==============================] - 24s 13ms/step - loss: 0.0612 -
accuracy: 0.9812 - val_loss: 0.0549 - val_accuracy: 0.9830
Epoch 6/10
1875/1875 [==============================] - 24s 13ms/step - loss: 0.0489 -
accuracy: 0.9842 - val_loss: 0.0369 - val_accuracy: 0.9882
Epoch 7/10
```

In [ ]:
```
_ = model_predictions(rnn,X_test)
```

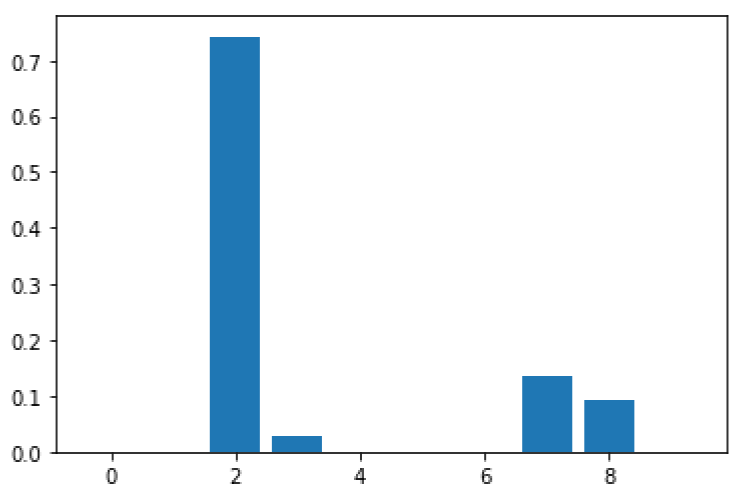


In [ ]:
```
i=show_mistake(rnn,X_test)
```

```
Predicted:  2
```



In [ ]:
```
confidence_distribution(rnn,X_test,i)
```



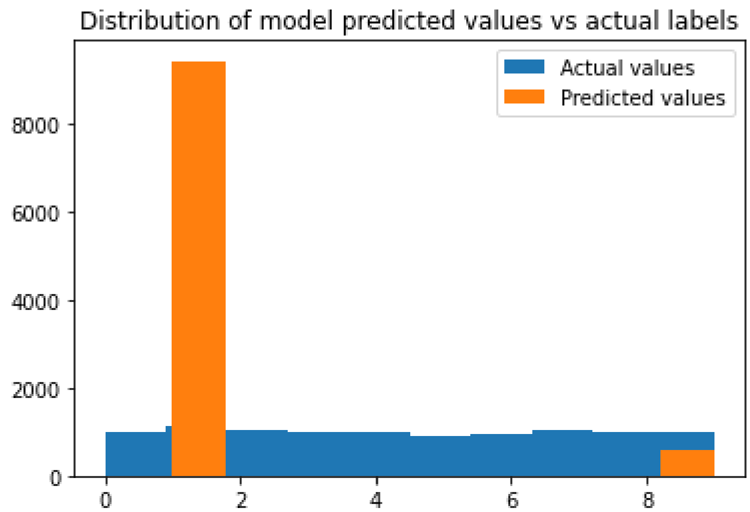
But its performance on noisy data is worse than ANN

In [ ]:
```
rnn.model.evaluate(X_test_noisy.values.reshape(-1,28,28), y_test)
```

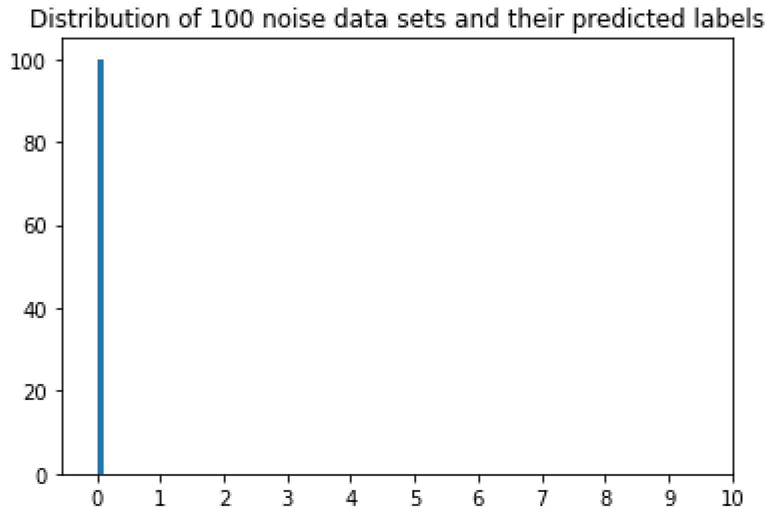
```
313/313 [==============================] - 2s 5ms/step - loss: 5.4675 - accurac
y: 0.1162
```

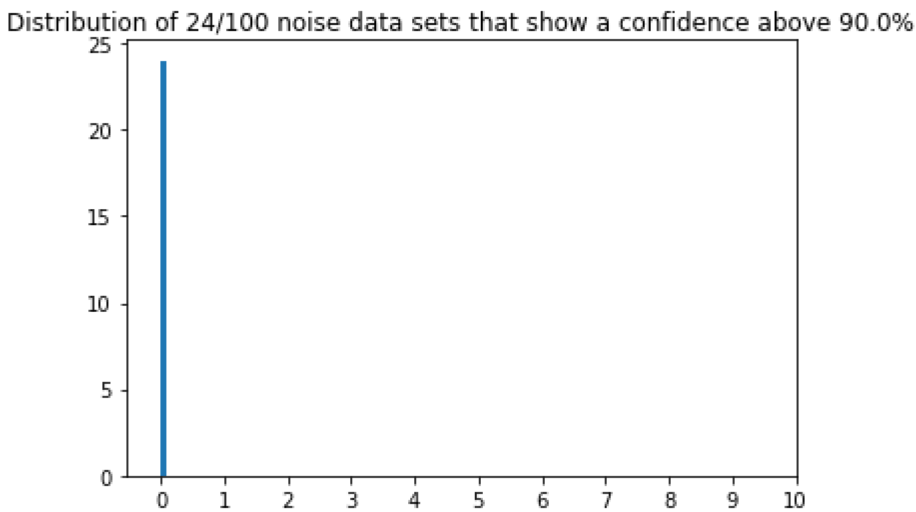
Out[51]:
```
[5.467532157897949, 0.11620000004768372]
```

In [ ]:
```
_ = model_predictions(rnn,X_test_noisy)
```



In [ ]:
```
noise_analysis(rnn,0.9)
```



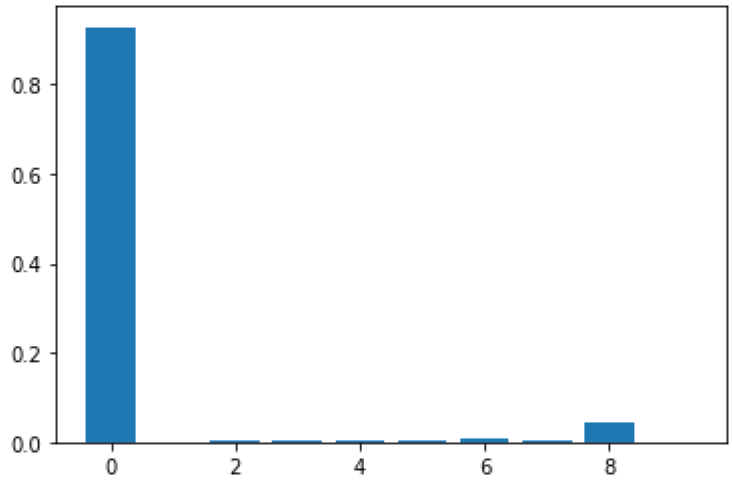


In [ ]:
```
noise_28by28 = noise.values.reshape(-1,28,28)
noise_28by28.shape
```

Out[54]:
```
(5000, 28, 28)
```

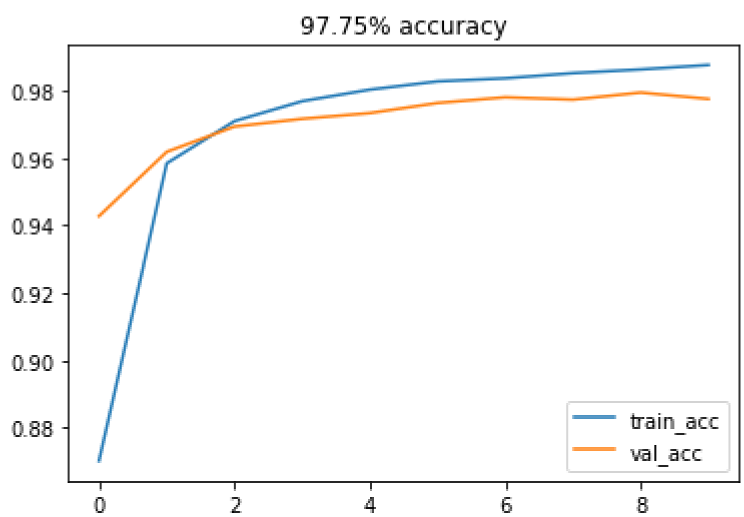
The rnn predicts each noise as almost entirely 0

In [ ]:
```
confidence_distribution(rnn,noise,np.random.randint(150))
```



Training and validation using noisy data

In [ ]:
```
model = create_rnn()
rnn_noisy = model.fit(X_train_noisy.values.reshape(-1,28,28), y_train, validatior
model_stats(rnn_noisy)
```



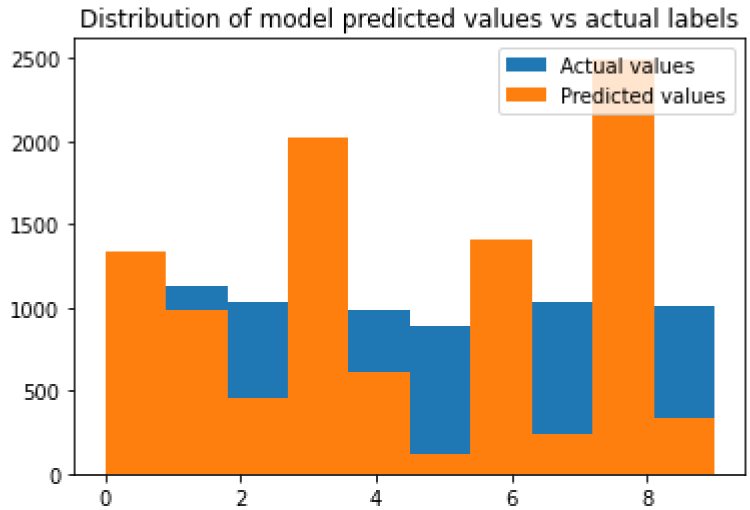
This model does not do well in predicting the standard test data, labelling most of them as certain 2 numbers

In [ ]:
```
rnn_noisy.model.evaluate(X_t, y_t)
```

```
313/313 [==============================] - 2s 5ms/step - loss: 1.5631 - accurac
y: 0.5597
```

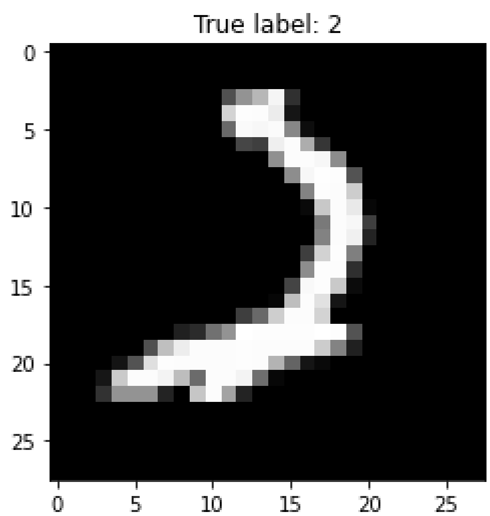
Out[57]:
```
[1.563126564025879, 0.5597000122070312]
```

In [ ]:
```
_ = model_predictions(rnn_noisy,X_test)
```

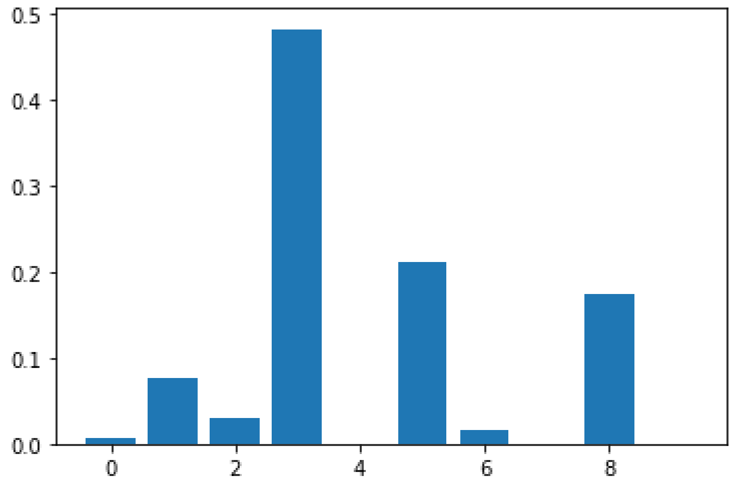


In [ ]:
```
i=show_mistake(rnn_noisy,X_test)
```

```
Predicted:  3
```

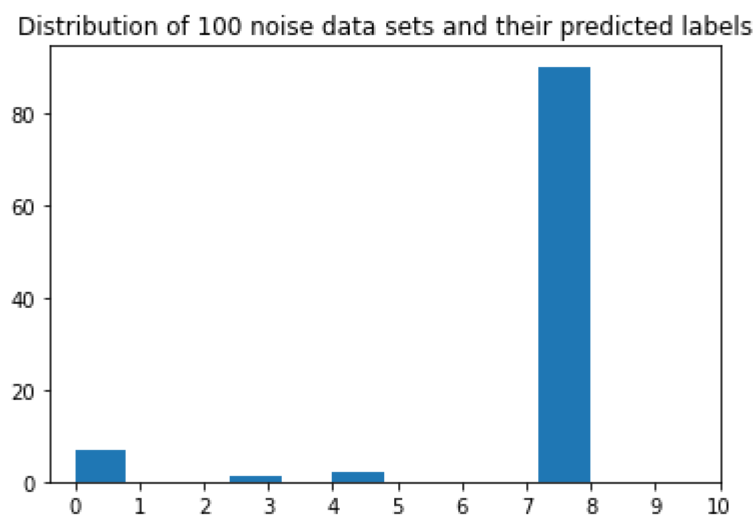


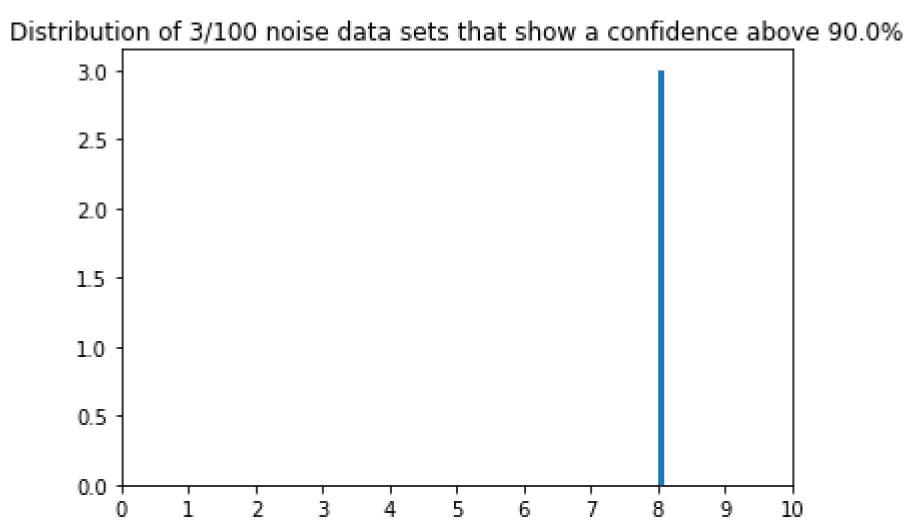
In [ ]:
```
confidence_distribution(rnn_noisy,X_test,i)
```



But it does seem to recognize pure noise well, not being confident about them

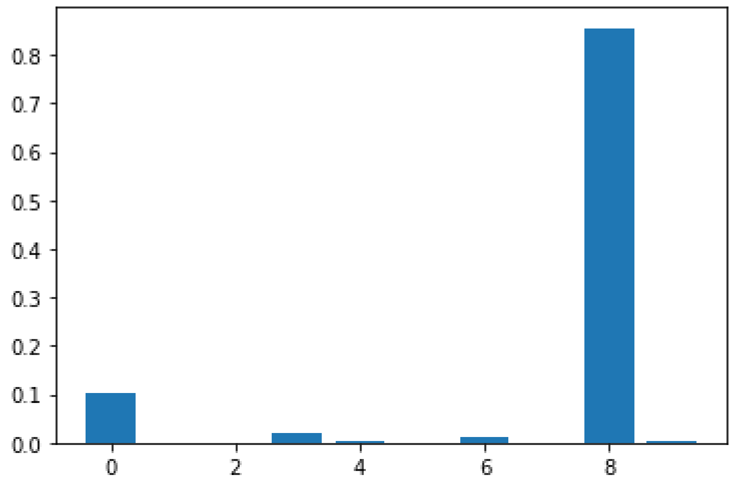
In [ ]:
```
noise_analysis(rnn_noisy,0.9)
```





confidence_distribution of random noise data

In [ ]:
```
confidence_distribution(rnn_noisy,noise,np.random.randint(150))
```



As expected, it does poorly with inverted data

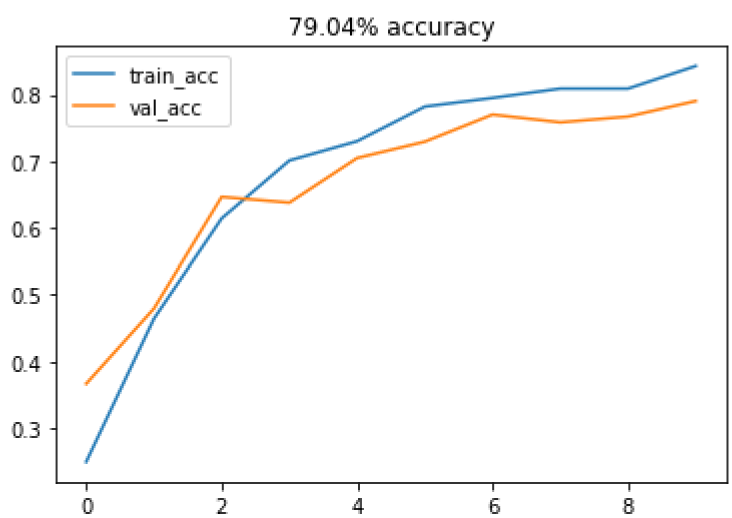
In [ ]:
```
rnn_noisy.model.evaluate(inverted.values.reshape(-1,28,28), y_t)
```

```
313/313 [==============================] - 2s 5ms/step - loss: 5.9361 - accurac
y: 0.0936
```

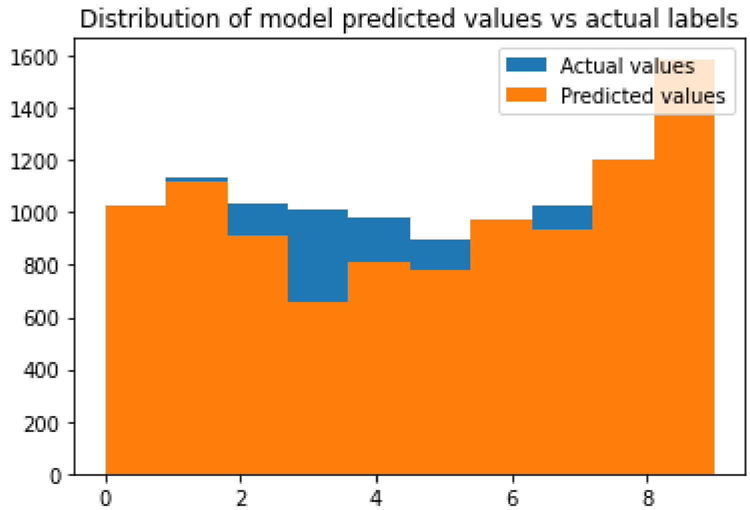
Out[63]: [5.9360527992248535, 0.09359999746084213]

The Intelligence seems to be comparable to the others

In [ ]:
```
model = create_rnn()
rnn = model.fit(X[:maxrows,:,:], y[:maxrows,], validation_data=(X_test.values.res
model_stats(rnn)
```

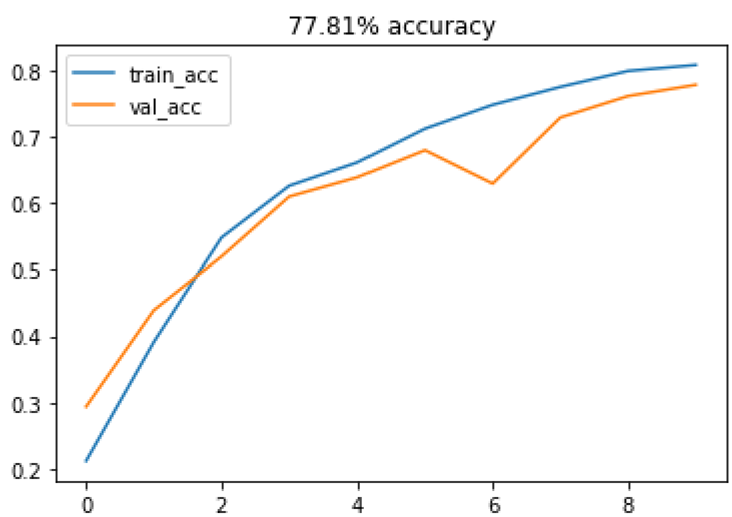


In [ ]:
```
_ = model_predictions(rnn,X_test)
```

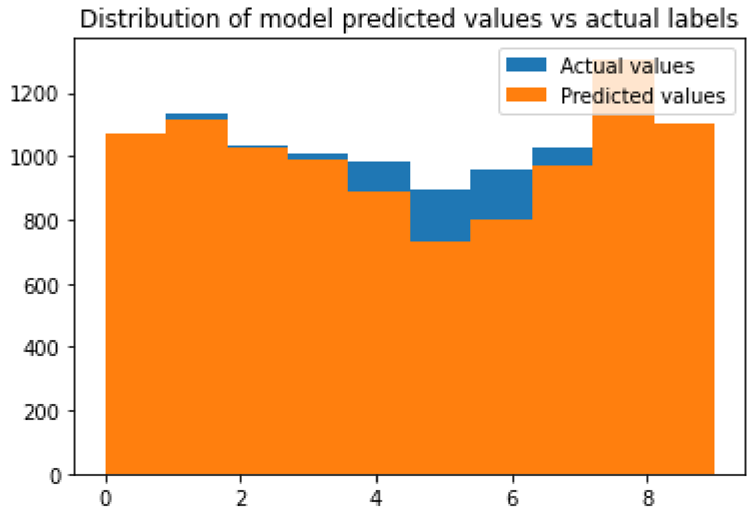


The Intelligence of threshold trained model set seems to be similar

In [ ]:
```
model = create_rnn()
rnn = model.fit(X_train_50[:maxrows].values.reshape(-1,28,28), y[:maxrows,], vali
model_stats(rnn)
```



In [ ]:
```
_ = model_predictions(rnn,X_test_50)
```



We will now create a model based on CNN

In [21]:
```
(X, y), (X_t, y_t) = mnist.load_data()

def create_cnn(op=10):
        model = tf.keras.models.Sequential([
        tf.keras.layers.Input(shape=(28, 28, 1)),
        tf.keras.layers.Conv2D(256, (3, 3), activation='relu'),
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.MaxPooling2D(pool_size=(2, 2)),
        #tf.keras.layers.Dropout(0.2),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(64),
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.Dense(op, activation='softmax')])
        model.compile(loss='sparse_categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
        return model

def model_stats(model):
    a_float = model.history.history['val_accuracy'][-1]*100
    plt.plot(model.history.history['accuracy'], label='train_acc')
    plt.plot(model.history.history['val_accuracy'], label='val_acc')
    plt.title("{:.2f}".format(a_float)+"% accuracy")
    plt.legend()

def model_predictions(model,df,y_test=y_test):
    try:
        model = model.model
    except:
        pass
    #preds = model.predict(df)
    try:
        l=model.predict(df).argmax(axis=1)
    except:
        l=model.predict(df.values.reshape(-1,28, 28,1)).argmax(axis=1)
    #l=[list(preds[i]).index(max(preds[i])) for i in range(preds.shape[0])]
    plt.hist(y_test, label=['Actual values'])
    plt.hist(l, label=['Predicted values'])
    plt.legend(loc='upper right')
    plt.title("Distribution of model predicted values vs actual labels")
    plt.show()
    return l

def show_mistake(model,df,i=None,y_test = y_test):
    try:
        model = model.model
    except:
        pass
    try:
        p_test=model.predict(df).argmax(axis=1)
    except:
        p_test=model.predict(df.values.reshape(-1,28, 28,1)).argmax(axis=1)
    #p_test = model.predict(df).argmax(axis=1)
    wrong_idx = np.where(p_test != y_test)[0]
    if i is None:
        i = np.random.choice(wrong_idx)
```

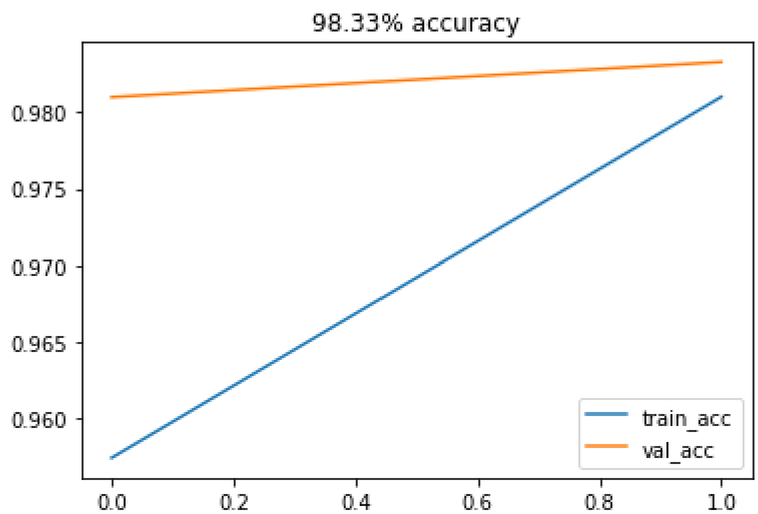
```
    display(df, y_test, i)
    print("Predicted: ",p_test[i])
    return i

def confidence_distribution(model, df,ind = 0,op=10):
    try:
        model = model.model
    except:
        pass
    try:
        l=model.predict(df[ind])[0]
    except:
        ip = df.values.reshape(-1,28, 28,1)
        l=model.predict(ip[ind].reshape(-1,28, 28,1))[0]
    plt.bar([i for i in range(op)],l)
    plt.show()


def confidence(model, ip, label=None):
    try:
        model = model.model
    except:
        pass
    #a=model.predict(ip)[0]
    try:
        a=model.predict(ip)[0]
    except:
        ip = ip.values.reshape(-1,28, 28,1)
        a=model.predict(ip.reshape(-1,28, 28,1))[0]
    #v= ip.values
    #v=v.reshape(-1,1)
    a=list(a)
    if not label:
      return a.index(max(a)),max(a)
    return a[label]


def noise_analysis(model, conf_th = 0.75, noise_n = 100):
    #noise = pd.DataFrame(np.random.rand(noise_n, 784))
    noise = np.random.rand(100, 1,28,28,1)
    nums=[]
    cnum=[]
    try:
        model = model.model
    except:
        pass
    for i in range(noise.shape[0]):
        num,conf = confidence(model, noise[i])
        nums.append(num)
        if conf>conf_th:
            cnum.append(num)
    plt.hist(nums)
    plt.xticks(range(11))
    plt.title("Distribution of "+str(len(nums))+" noise data sets and their predi
    plt.show()
    plt.hist(cnum)
    plt.xticks(range(11))
```

```
    plt.title("Distribution of "+str(len(cnum))+"/"+str(len(nums))+" noise data s
    plt.show()
```

Each data point accepted by the CNN must be 3 dimensional

In [ ]:

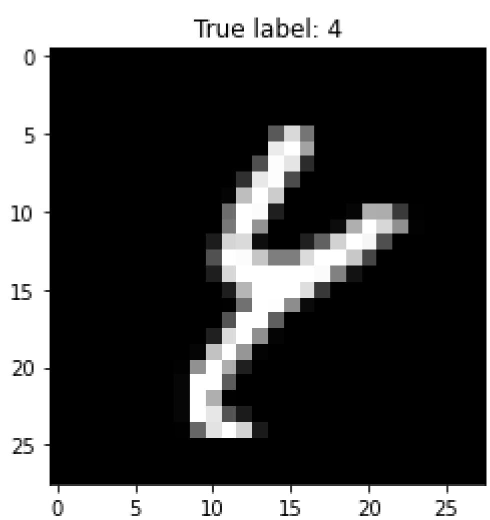
```
cnn = create_cnn()
#X = X.reshape(-1,28, 28,1)
#X_t = X_t.reshape(-1,28, 28,1)
cnn.fit(np.array(X_train).reshape(-1,28, 28,1), y, epochs=2, validation_data=(np.

model_stats(cnn)
```



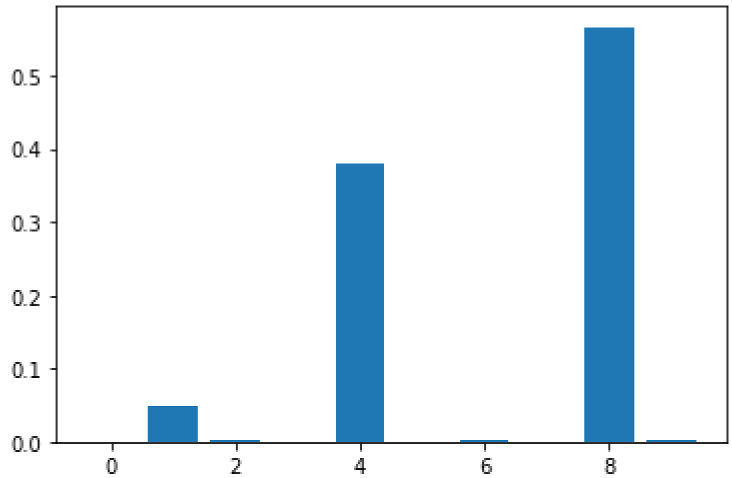
In [ ]:

```
i=show_mistake(cnn,X_test)
```

```
Predicted:  8
```

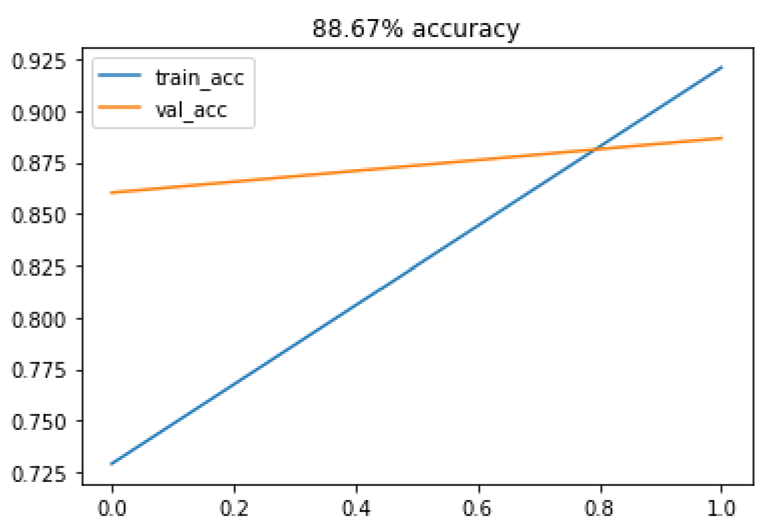


In [ ]:
```
confidence_distribution(cnn, X_test,i)
```



Intelligence

In [22]:
```
maxrows = 1000

cnn = create_cnn()
cnn.fit(np.array(X_train).reshape(-1,28, 28,1)[:maxrows,:,:], y[:maxrows], epochs
model_stats(cnn)
```



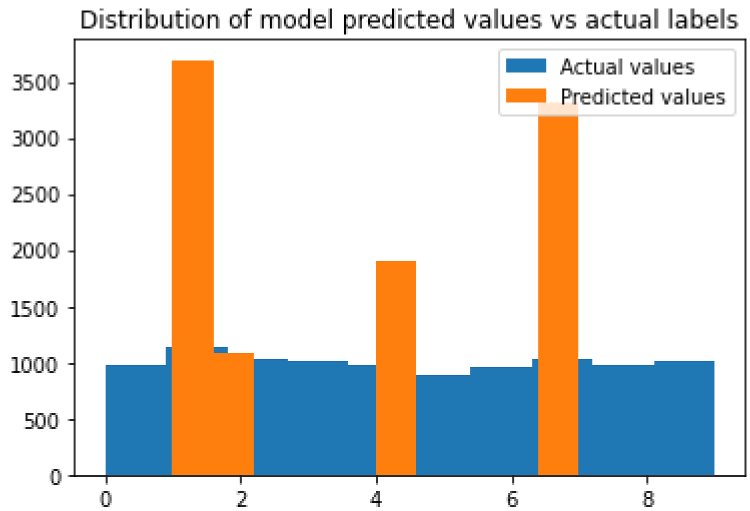
Trying to see if this CNN model works on noisy data, results appear worse than for ANN, with most predictions showing 1,7

In [ ]:
```
cnn.evaluate(np.array(X_test_noisy).reshape(-1,28, 28,1),y_t)
```

```
313/313 [==============================] - 4s 12ms/step - loss: 68.1384 - accur
acy: 0.2126
```

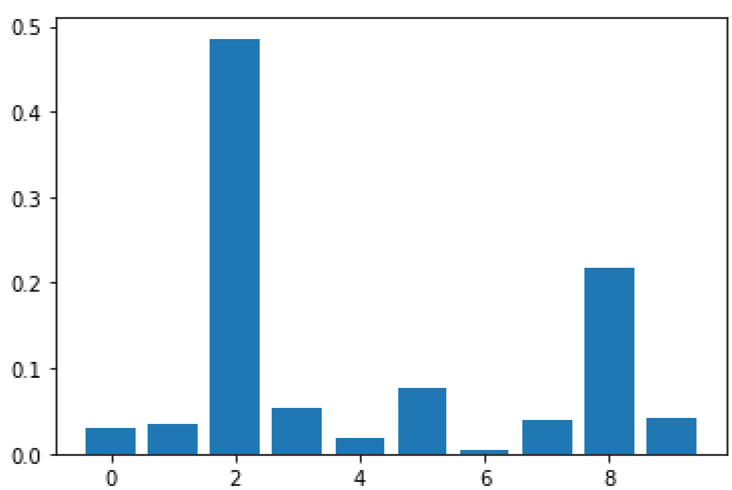
Out[72]:
```
[68.13839721679688, 0.2125999927520752]
```

In [ ]:
```
_ = model_predictions(cnn,X_test_noisy)
```



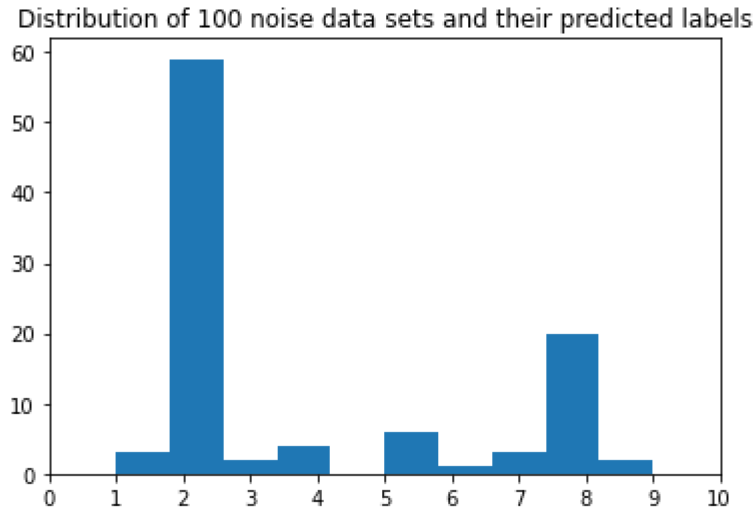
This is how it views pure noise data

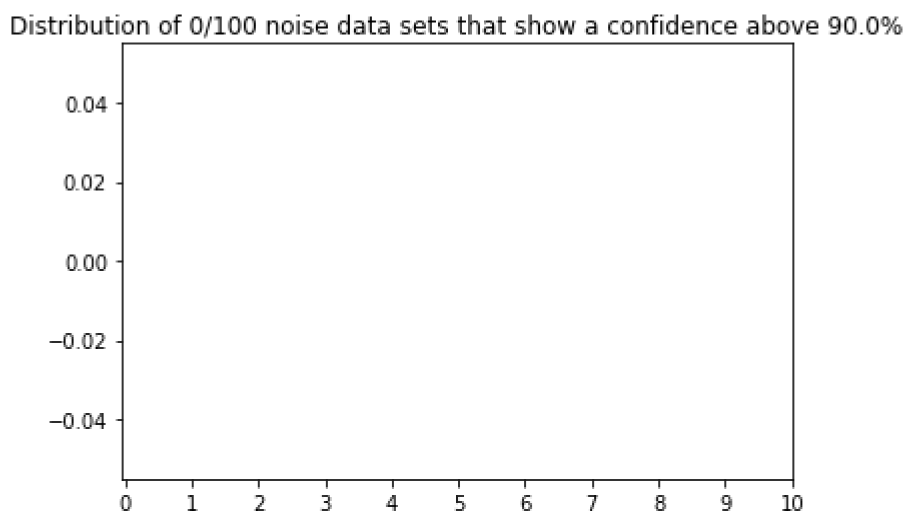
In [ ]:
```
noise = np.random.rand(100, 1,28,28,1)
confidence_distribution(cnn, noise,10)
```



It does seem to recognize pure noise well, not being confident about them

In [ ]:
```
noise_analysis(cnn,0.9)
```





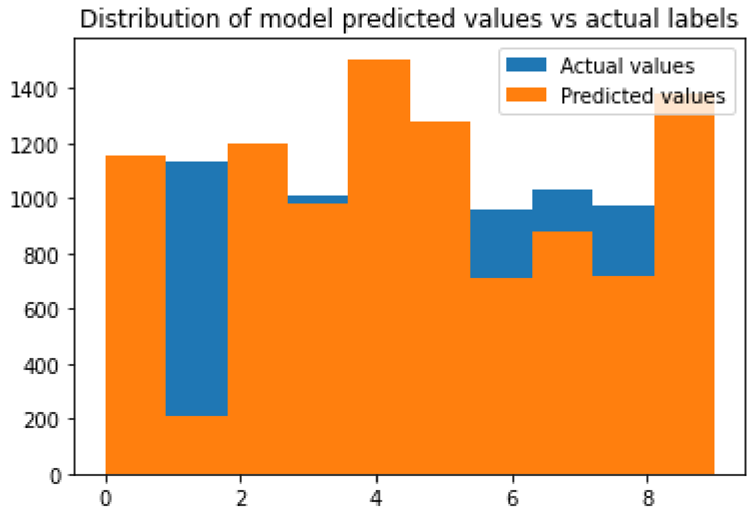
We see much better results when faced with inverted test data

In [ ]:
```
cnn.evaluate(np.array(inverted).reshape(-1,28, 28,1),y_t)
```

```
313/313 [==============================] - 4s 12ms/step - loss: 1.2094 - accura
cy: 0.6287
```

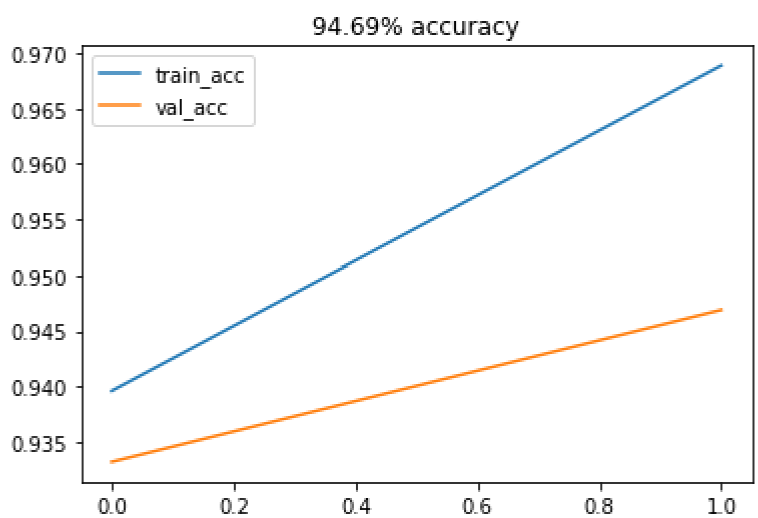
Out[76]:
```
[1.2093627452850342, 0.6287000179290771]
```

In [ ]:
```
_ = model_predictions(cnn,inverted)
```



Training CNN using noisy train data

In [ ]:
```
cnn = create_cnn()
cnn.fit(np.array(X_train_noisy).reshape(-1,28, 28,1), y, epochs=2, validation_dat
model_stats(cnn)
```



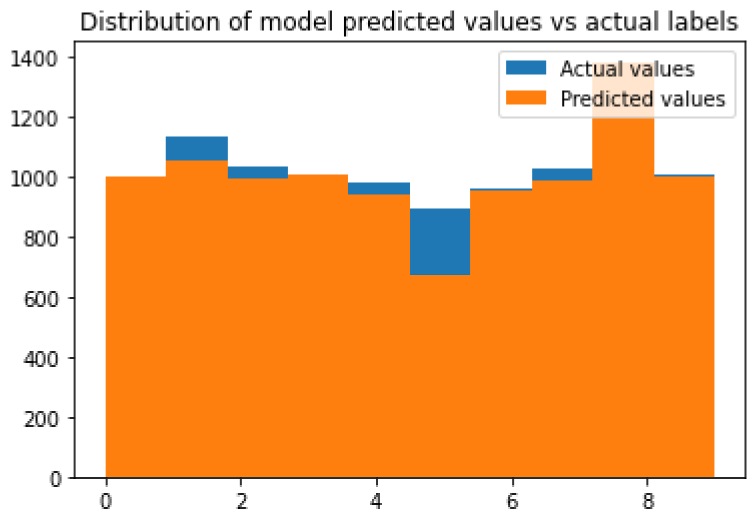
When trained on noisy data, CNN gives above 90% accuracy for both noisy and original test data

In [ ]:
```
cnn.evaluate(np.array(X_test).reshape(-1,28, 28,1),y_t)
```

```
313/313 [==============================] - 4s 12ms/step - loss: 0.2029 - accura
cy: 0.9351
```

Out[79]:
```
[0.20290842652320862, 0.9351000189781189]
```

In [ ]:
```
_ = model_predictions(cnn,X_test)
```



But gives worse perfomance on inverted test data

In [ ]:
```
cnn.evaluate(np.array(inverted).reshape(-1,28, 28,1),y_t)
```

```
313/313 [==============================] - 4s 12ms/step - loss: 5.8447 - accura
cy: 0.3773
```

Out[81]:
```
[5.844680309295654, 0.3772999942302704]
```

In [ ]:
```
_ = model_predictions(cnn,np.array(inverted).reshape(-1,28, 28,1))
```