Assignment2(1828251)

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1 ACML Assignment 2

2 Ziyaad Ballim (1828251)

2.1 Importing Libraries

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix,accuracy_score
from prettytable import PrettyTable
import seaborn as sns
sns.set()
```

3 Reading in the data

This dataset has been collected from patients tested for diabetes. There are 8 features namely: -Pregnancies

-Glucose

-BloodPressure

-SkinThickness

-Insulin

-BMI

-DiabetesPedigreeFunction

-Age

and one output column "Ouput" which represents the presence of diabetes or not with 1 or 0 respectively.

[ ]:
```
data = pd.read_csv('diabetes-dataset.csv')
```

[ ]:
```
data.describe()
```

[ ]:
```
        Pregnancies      Glucose  BloodPressure  SkinThickness      Insulin  \
count  2000.000000  2000.000000    2000.000000    2000.000000  2000.000000
mean      3.703500   121.182500      69.145500      20.935000    80.254000
std       3.306063    32.068636      19.188315      16.103243   111.180534
min       0.000000     0.000000       0.000000       0.000000     0.000000
25%       1.000000    99.000000      63.500000       0.000000     0.000000
50%       3.000000   117.000000      72.000000      23.000000    40.000000
75%       6.000000   141.000000      80.000000      32.000000   130.000000
max      17.000000   199.000000     122.000000     110.000000   744.000000

               BMI  DiabetesPedigreeFunction          Age      Outcome
count  2000.000000               2000.000000  2000.000000  2000.000000
mean     32.193000                  0.470930    33.090500     0.342000
std       8.149901                  0.323553    11.786423     0.474498
min       0.000000                  0.078000    21.000000     0.000000
25%      27.375000                  0.244000    24.000000     0.000000
50%      32.300000                  0.376000    29.000000     0.000000
75%      36.800000                  0.624000    40.000000     1.000000
max      80.600000                  2.420000    81.000000     1.000000
```

[ ]:
```
data.head()
```

[ ]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            2      138             62             35        0  33.6
1            0       84             82             31      125  38.2
2            0      145              0              0        0  44.2
3            0      135             68             42      250  42.3
4            1      139             62             41      480  40.7

   DiabetesPedigreeFunction  Age  Outcome
0                     0.127   47        1
1                     0.233   23        0
2                     0.630   31        1
3                     0.365   24        1
4                     0.536   21        0
```

Checking for null values

[ ]:
```
data.isna().sum()
```

[ ]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
```

```
Age                         0
Outcome                     0
dtype: int64
```

3.1 Functions for splitting and standardizing the data

Splitting data into training, validation and testing subsets

```
[ ]: def SplitData(x,y,testSize):
             trainx,testx, trainy,testy =␣
      ↪train_test_split(x,y,test_size=testSize,random_state=40)
             return trainx,trainy,testx,testy
```

Standardizing the data

```
[ ]: def StandardizeData(data):
         rows,cols = np.shape(data)

         for i in range(cols):
             Feature = data[:,i]
             mean = np.mean(Feature)
             standard_deviation = np.std(Feature)
             Feature -= mean
             Feature /= standard_deviation
             data[:,i] = Feature

         return data
```

Scaling

```
[ ]: def ScaleData(data):
             scaledx  = StandardizeData(data)
             return scaledx
```

```
[ ]: def Split_Data(data,validation_and_test_size,scale):
             arrData = data.to_numpy()
             np.random.shuffle(arrData)

             rows,cols = np.shape(arrData)
             Features = arrData[:,:cols-1]
             Target = arrData[:, -1]
             Target = np.reshape(Target,(np.shape(Target)[0],1))
             if(scale):
                 Features = ScaleData(Features)
             test_size = np.round(validation_and_test_size*0.3,2)
             trainx,trainy,tempx,tempy␣
      ↪=SplitData(Features,Target,validation_and_test_size)
             validationx,validationy,testx,testy =SplitData(tempx,tempy,test_size)
```

```
        return trainx,validationx,testx, trainy,validationy,testy
```

3.2 Splitting and standardizing the data

[ ]:
```
trainx,validationx,testx,trainy,validationy,testy = Split_Data(data,0.3,True)
```

[ ]:
```
print(len(trainx))
print(len(validationx))
print(len(testx))
print(len(trainy))
print(len(validationy))
print(len(testy))
```

```
1400
546
54
1400
546
54
```

3.3 The functions below are used to construct, train and test the intended Neural Networks

Initialising the weights of the neural network between 0 and 1

[ ]:
```
def InitWeights(NumFeatures,NumHidLayers,NumNeurons,NumOutputNeurons):
        InLayerWeights = np.random.rand(NumNeurons[0],NumFeatures+1)
        Weights  = [InLayerWeights]
        for i in range(NumHidLayers):
            W = None
            if(NumHidLayers -1 == i):
                W = np.random.rand(NumOutputNeurons,NumNeurons[i]+1)

            else:
                W = np.random.rand(NumNeurons[i+1],NumNeurons[i]+1)

            Weights.append(W)

        return Weights
```

Converting the output probabilities to output classes

[ ]:
```
def ProbToClass(LatestActivation):
    Indices = np.where(LatestActivation<0.5)
    LatestActivation[Indices] = 0
    Indices2 = np.where(LatestActivation>=0.5)
    LatestActivation[Indices2] = 1
    return LatestActivation
```

Controling the use of the different activation functions

```
[ ]: def ActFunction(Z,Activation):
         a = None
         deriv_z = None
         if (Activation == "sigmoid"):
             a = (1/(1+np.exp(-Z)))
             deriv_z = a * (1-a)
         elif (Activation == "tanh"):
             a =  np.tanh(Z)
             deriv_z = 1 - (a**2)
         elif (Activation == "relu"):
             a =  np.maximum(0,Z)
             deriv_z = np.copy(a)
             deriv_z[deriv_z<=0]  = 0
             deriv_z[deriv_z>0]  = 1
         return a,deriv_z
```

Forward propogation in order to obtain predicted outputs

```
[ ]: def ForwardProp(features,weights,activations):
         A_Vals = [features]
         Derivs = [0]
         n = len(weights)
         for i in range(n):
             z  = None
             aprev = np.insert(A_Vals[i],0,1,axis=1)
             z = np.dot(weights[i],aprev.T)
             A_Vals[i]  = aprev
             a,derivative_of_z = ActFunction(z,activations[i])
             A_Vals.append(a.T)
             Derivs.append(derivative_of_z)

         return A_Vals,Derivs
```

Computing the errors

```
[ ]: def Errors(a,y,Weights,derivs):
         n = len(a)
         errors = [a[n-1]-y]
         loopLength = n -2
         for j in range(loopLength):
             e = (((Weights[loopLength - j].T)[1:,:])@(errors[j].T))*␣
      ↪derivs[loopLength - j]
             errors.append(e.T)

         return errors
```

Obtaining gradients

```
[ ]: def Grads(Errors,Activations):
         grads = []
         reversed_errors = list(reversed(Errors))
         n  = len(Activations)
         for i in range(n-1):
             g = (reversed_errors[i].T)@(Activations[i])
             grads.append(g)
         return grads
```

Performing back propogations

```
[ ]: def␣
      ↪BackProp(Features,Target,Weights,Activations,numDataPoints,regularization,gradients):
      ↪
         avalues,derivatives = ForwardProp(Features,Weights,Activations)

         errors = Errors(avalues,Target,Weights,derivatives)

         Updatedgradients = Grads(errors,avalues)
         for k in range(len(gradients)):
                 gradients[k]+=Updatedgradients[k]

         if(regularization != 0):
             n = len(gradients)
             for i in range(n):
                 gradients[i] = (1/numDataPoints)*gradients[i] +␣
      ↪regularization*Weights[i]
         else:
             n = len(gradients)
             for i in range(n):
                 gradients[i] = (1/numDataPoints)*gradients[i]

         return gradients
```

Checking for the convergence of the weights

```
[ ]: def WeightConv(NewWeights,OldWeights):
         n = len(NewWeights)
         Controls = []
         for k in range(n):
             if(np.linalg.norm(NewWeights[k]-OldWeights[k])<0.00005):
                 Controls.append(True)
             else:
                 Controls.append(False)

         numFalse = np.where(np.asarray(Controls)==False)
```

```
    length = len(numFalse[0])
    if(length>1):
        return False
    else:
        return True
```

Dealing with division errors

```
[ ]: def DivError(x):
         ETA = 0.0000000001
         return np.maximum(x, ETA)
```

Calculating the costs

```
[ ]: def Cost(Target,predicted,regularization,weights):
         n = len(Target)
         yhat_inv = np.subtract(1.0,predicted)
         y_inv = np.subtract(1.0,Target)
         yhat = DivError(predicted)
         yhat_inv = DivError(yhat_inv)
         weightsSummation=0;
         for w in weights:
             weightsSummation+= np.sum(w**2)
         loss = -1/n * (np.sum(np.multiply(np.log(yhat), Target) + np.
      ↪multiply((y_inv), np.log(yhat_inv))))+ (regularization/
      ↪(2*n))*weightsSummation
         return loss
```

Performing gradient descent

```
[ ]: def␣
      ↪GradDescent(Features,Target,weights,numDataPoints,learningRate,regularization,Epochs,Activa
      ↪
         gradients = [None]*len(weights)
         loss = []
         for i in range(len(gradients)):
             gradients[i] = np.zeros(np.shape(weights[i]))

         iterations=0
         control = True
         while iterations<Epochs and control:
             Old_Weights = weights.copy()
             D =␣
      ↪BackProp(Features,Target,weights,ActivationFunctions,numDataPoints,regularization,gradients


             for j in range(len(D)):
```

```
            weights[j] = weights[j]- learningRate*D[j]

        if(WeightConv(weights,Old_Weights)):
            control = False
        iterations+=1
        a,v = ForwardProp(Features,weights,ActivationFunctions)
        predictedValues = a[len(a)-1]
        lossValue = Cost(Target,predictedValues,regularization,weights)
        loss.append(lossValue)
    return weights,iterations,loss
```

Finding the output predictions

[ ]:
```
def Predict(testx,testy,weights,ActivationFunctions):
    act,der = ForwardProp(testx,weights,ActivationFunctions)
    act[len(act)-1] = ProbToClass(act[len(act)-1])
    predictedValues = act[len(act)-1]
    conf = confusion_matrix(testy,predictedValues)
    acc = accuracy_score(testy,predictedValues)
    print(f'The accuracy is: {acc*100}%')
    print("Confusion Matrix: ")
    sns.heatmap(conf,annot=True,fmt='g')
    plt.show()
    return acc
```

Plotting the error graph over time

[ ]:
```
def ErrorGraph(error):
    x = np.arange(1,(len(error)+1))
    sns.lineplot(x = x ,y = error)
    plt.title("Error vs Epochs")
    plt.xlabel("Epochs")
    plt.ylabel("Cost")
    plt.show()
```

Fitting the neural network using the above functions and getting the neccessary input

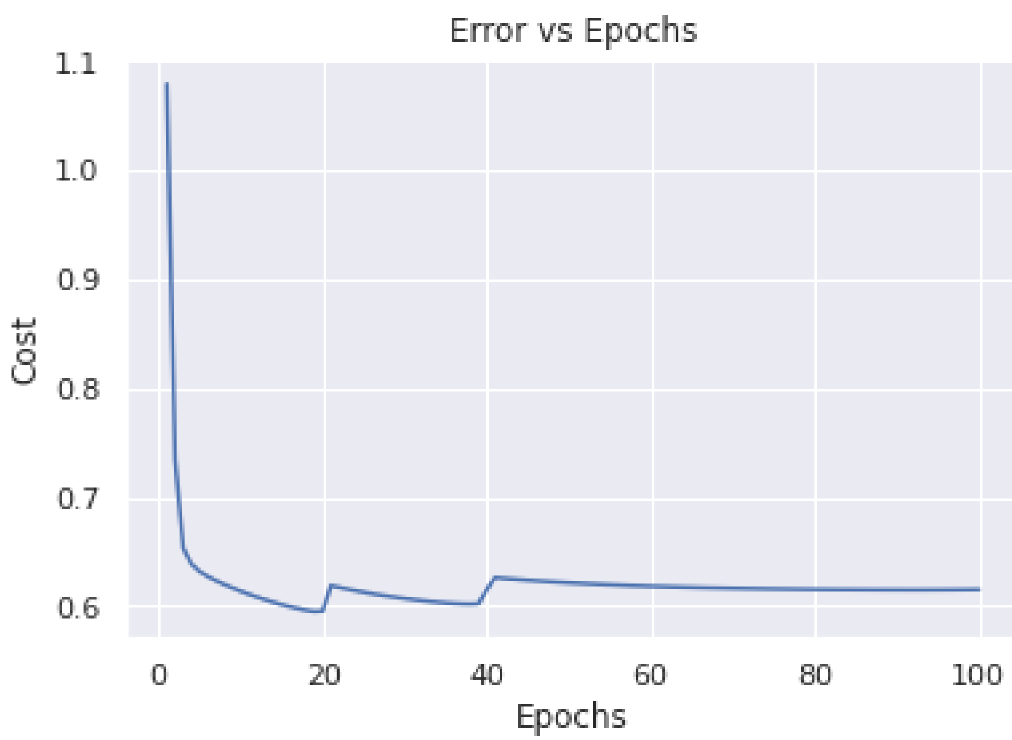
[ ]:
```
def␣
↪FitNN(TrainingX,TrainingY,NumberOfHiddenLayers,NumberOfNeuronsPerHiddenLayer,NumberOfNeuron
↪
    Number_of_datapoints, Number_of_features = np.shape(TrainingX)

    Weight_Parameters =␣
↪InitWeights(Number_of_features,NumberOfHiddenLayers,NumberOfNeuronsPerHiddenLayer,NumberOfN
    assert(len(ActivationFunctions) ==␣
↪NumberOfHiddenLayers+NumberOfNeuronsInOutputLayer), "Please ensure that the␣
↪number of activation functions specified is the same as the layers!"
```

```
    Weights,epochs_to_converge,error =␣
↪GradDescent(TrainingX,TrainingY,Weight_Parameters,Number_of_datapoints,learningRate,regular
    ErrorGraph(error)
    weights = Weights
    activationFunctions = ActivationFunctions
    return Weights,epochs_to_converge,error, activationFunctions
```

3.4 Implementation of Neural network and training the network using backpropogation

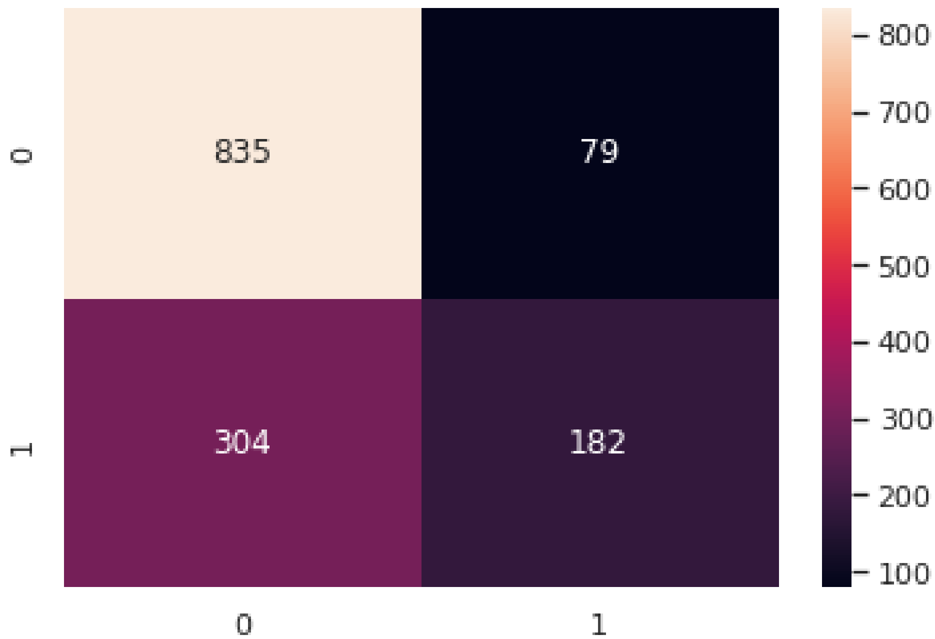
3.4.1 Relu Activation Function

[ ]:
```
ReluWeights, ReluEpochs, ReluError, ReluActivations =␣
↪FitNN(trainx,trainy,2,[2,2],1,["relu","relu","relu"],0.1,0,100)
print("Number of epochs until convergence:"+str(ReluEpochs)+"\n")
print("Training Accuracy")
Relu_Acc=Predict(trainx,trainy,ReluWeights,ReluActivations)
print("Validation Accuracy")
Relu_Acc_Val=Predict(validationx,validationy,ReluWeights,ReluActivations)
print("Test Accuracy")
Relu_Acc_Test=Predict(testx,testy,ReluWeights,ReluActivations)
```

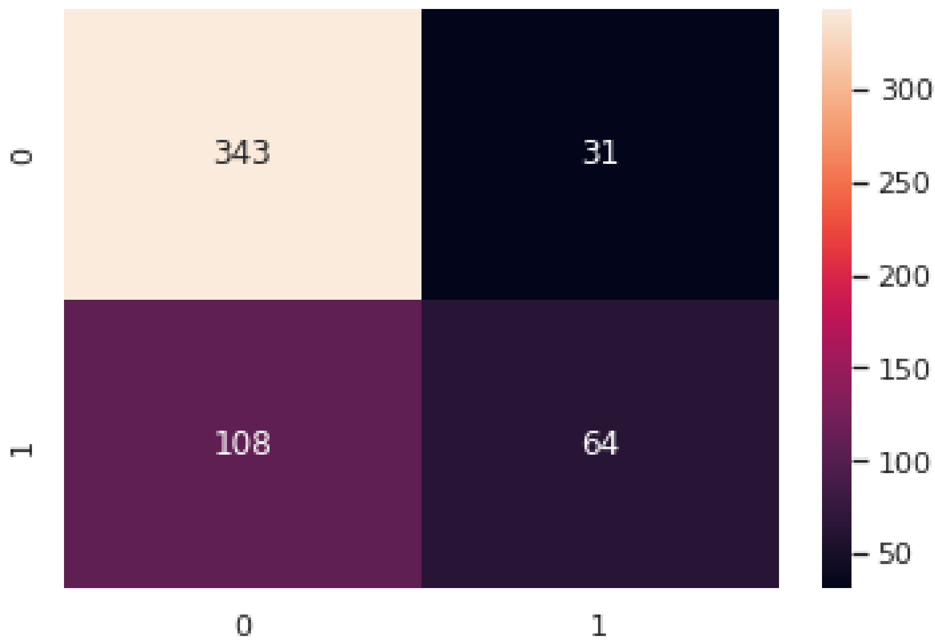



```
Number of epochs until convergence:100
```

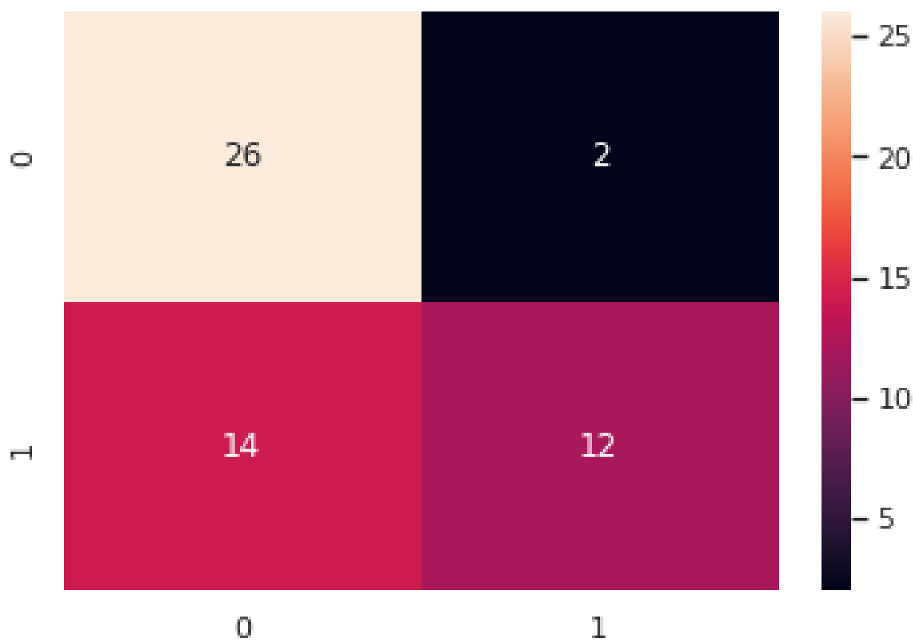
```
Training Accuracy
The accuracy is: 72.64285714285714%
Confusion Matrix:
```




```
Validation Accuracy
The accuracy is: 74.54212454212454%
Confusion Matrix:
```

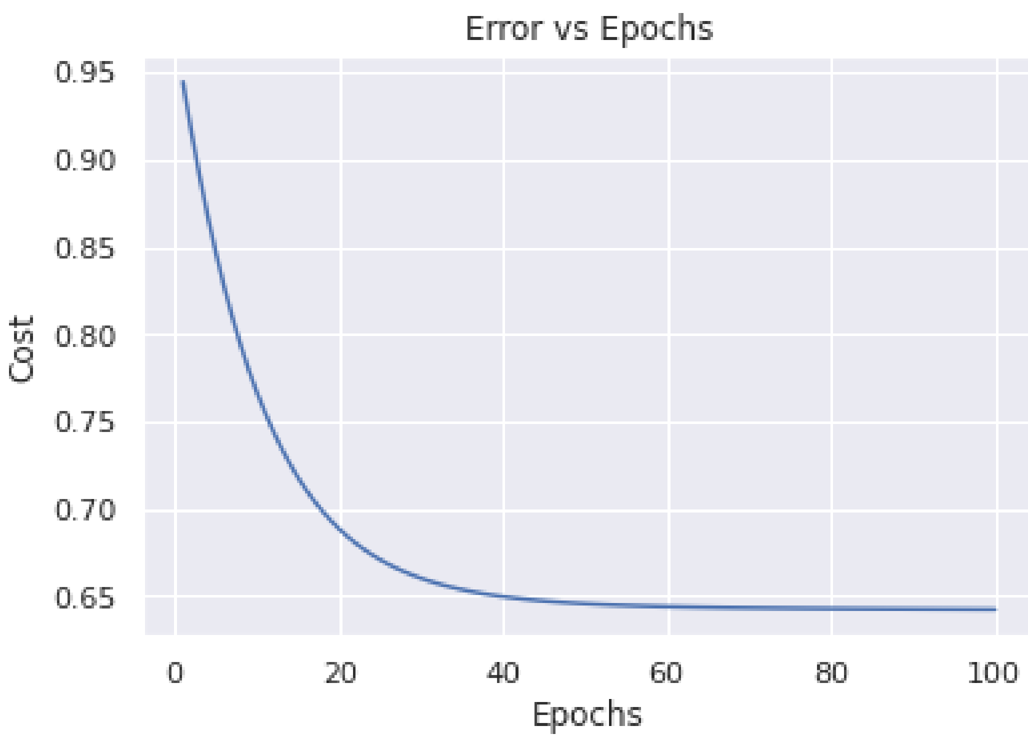



```
Test Accuracy
The accuracy is: 70.37037037037037%
Confusion Matrix:
```

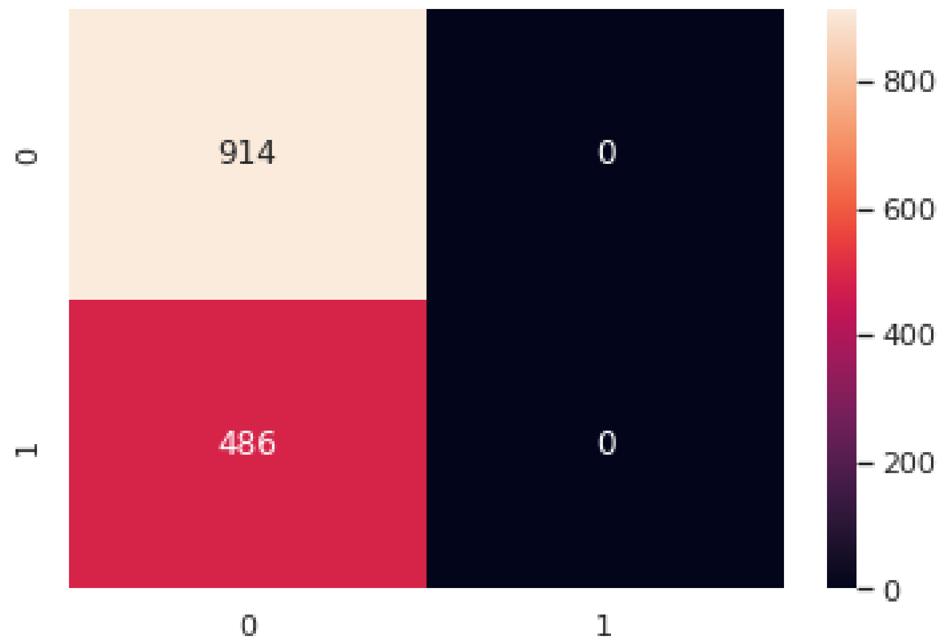


3.4.2 Sigmoid Activation Function

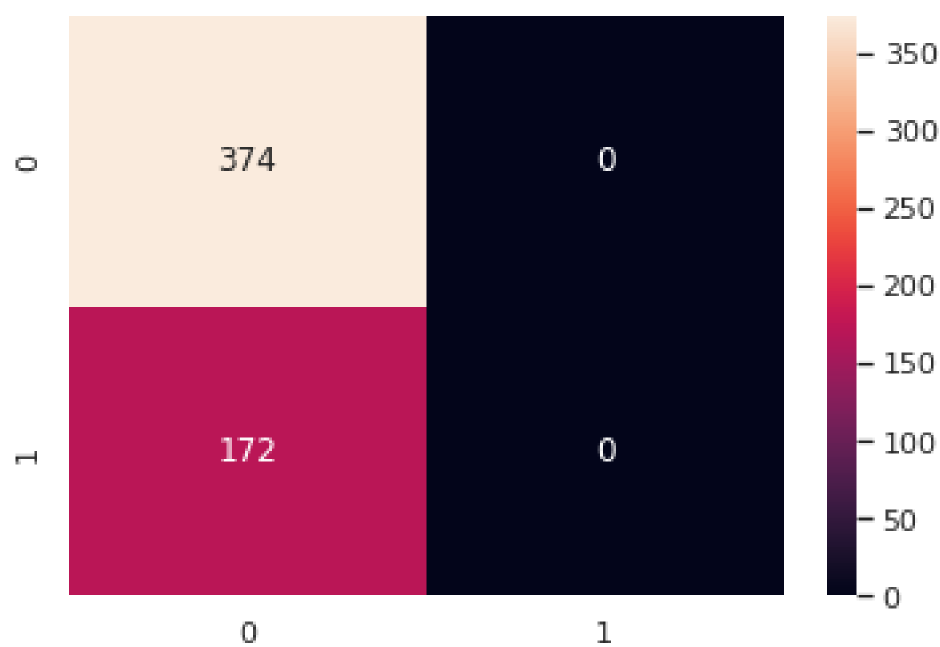
[ ]:
```
SigWeights, SigEpochs, SigError, SigActivations =␣
↪FitNN(trainx,trainy,2,[2,2],1,["sigmoid","sigmoid","sigmoid"],0.1,0,100)
print("Number of epochs until convergence:"+str(SigEpochs)+"\n")
print("Training Accuracy")
Sig_Acc=Predict(trainx,trainy,SigWeights,SigActivations)
print("Validation Accuracy")
Sig_Acc_Val=Predict(validationx,validationy,SigWeights,SigActivations)
print("Test Accuracy")
Sig_Acc_Test=Predict(testx,testy,SigWeights,SigActivations)
```



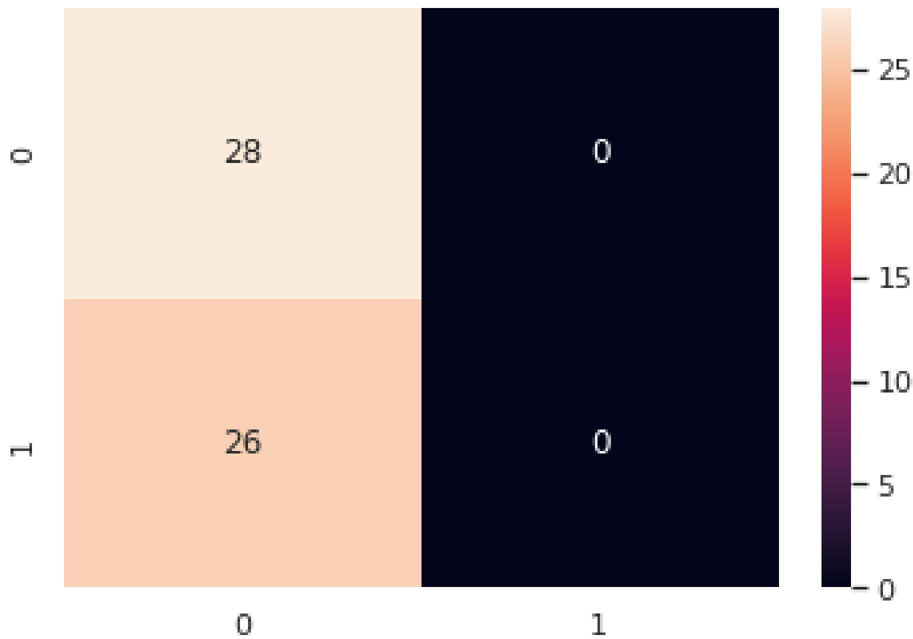

```
Number of epochs until convergence:100

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```




```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```

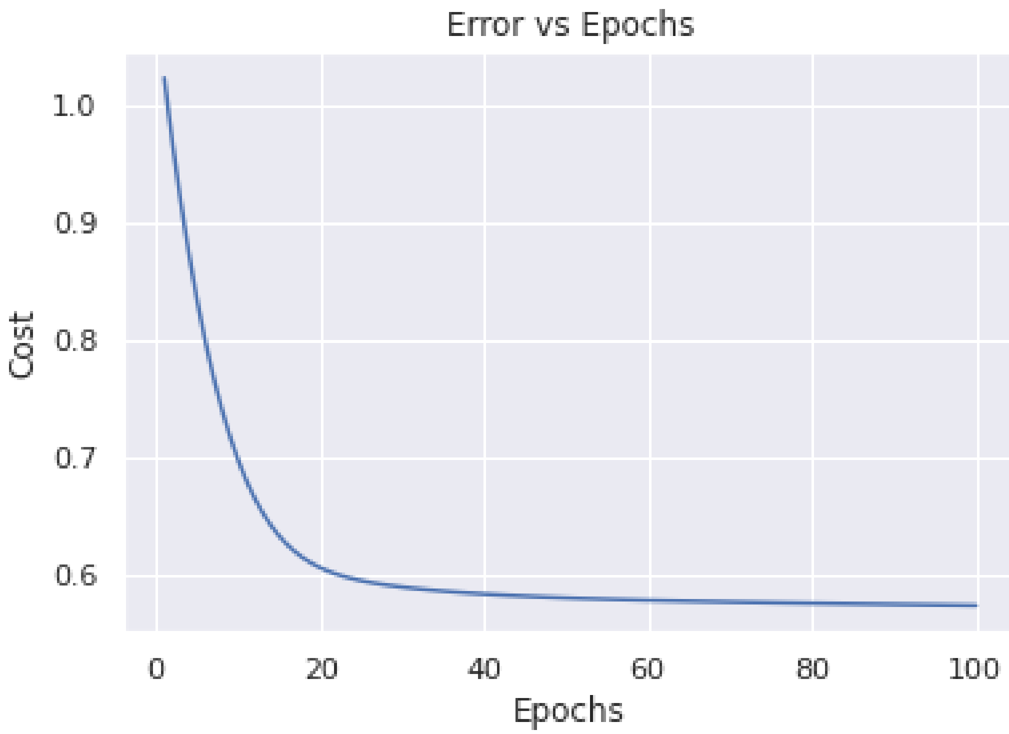


```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```

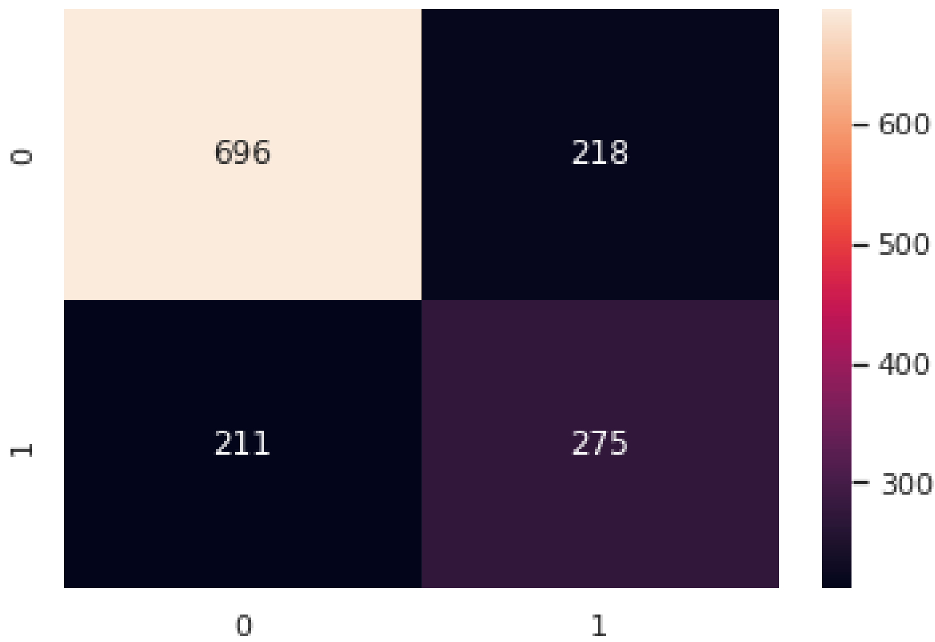


3.4.3 Tanh Activation Function

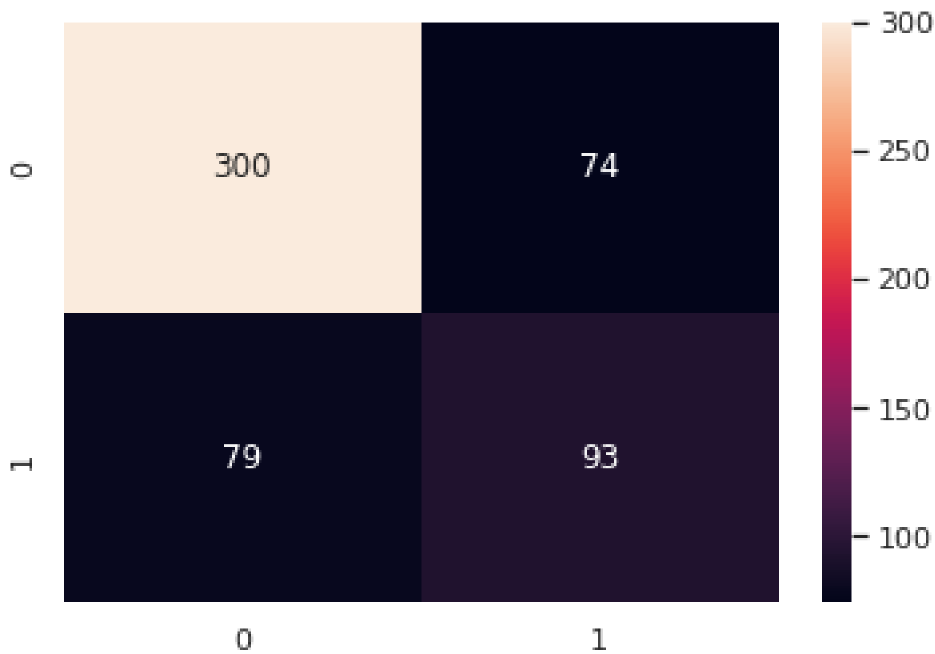
[ ]:
```
TanhWeights, TanhEpochs, TanhError, TanhActivations =␣
 ↪FitNN(trainx,trainy,2,[2,2],1,["tanh","tanh","tanh"],0.1,0,100)
print("Number of epochs until convergence:"+str(TanhEpochs)+"\n")
print("Training Accuracy")
Tanh_Acc=Predict(trainx,trainy,TanhWeights,TanhActivations)
print("Validation Accuracy")
Tanh_Acc_Val=Predict(validationx,validationy,TanhWeights,TanhActivations)
print("Test Accuracy")
Tanh_Acc_Test=Predict(testx,testy,TanhWeights,TanhActivations)
```



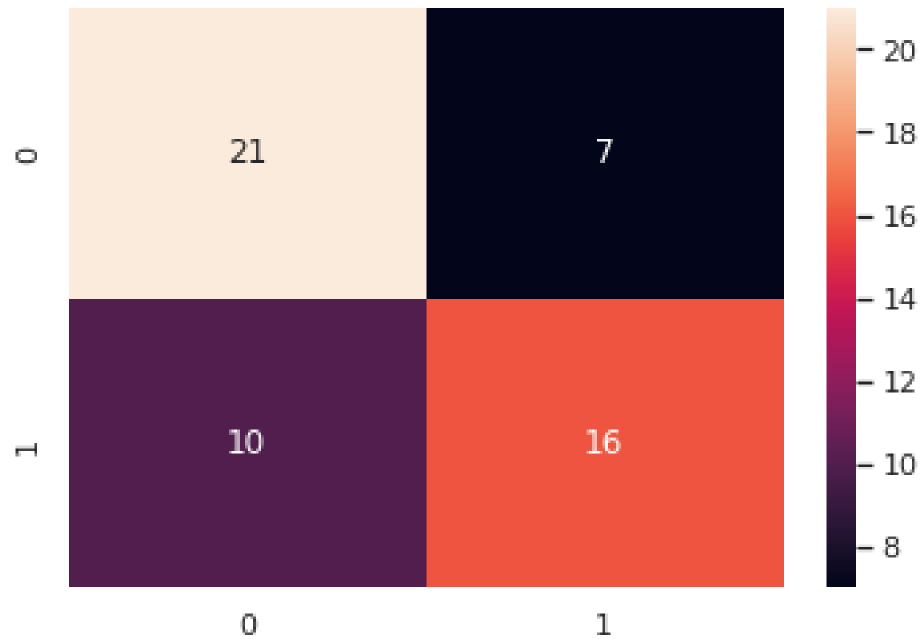

```
Number of epochs until convergence:100

Training Accuracy
The accuracy is: 69.35714285714286%
Confusion Matrix:
```




```
Validation Accuracy
The accuracy is: 71.97802197802197%
Confusion Matrix:
```



```
Test Accuracy
The accuracy is: 68.51851851851852%
Confusion Matrix:
```




```
[ ]: InitialResults = PrettyTable(["Activation Function","Epochs to train","Training␣
↪Accuracy","Validation Accuracy","Testing Accuracy"])

InitialResults.add_row(["ReLu",ReluEpochs,np.round(Relu_Acc*100,2),np.
↪round(Relu_Acc_Val*100,2),np.round(Relu_Acc_Test*100,2)])
InitialResults.add_row(["Sigmoid",SigEpochs,np.round(Sig_Acc*100,2),np.
↪round(Sig_Acc_Val*100,2),np.round(Sig_Acc_Test*100,2)])
InitialResults.add_row(["Tanh",TanhEpochs,np.round(Tanh_Acc*100,2),np.
↪round(Tanh_Acc_Val*100,2),np.round(Tanh_Acc_Test*100,2)])
print(InitialResults)
```

```
+---------------------+-----------------+-------------------+-------------------
--+------------------+
| Activation Function | Epochs to train | Training Accuracy | Validation
Accuracy | Testing Accuracy |
+---------------------+-----------------+-------------------+-------------------
--+------------------+
|         ReLu        |       100       |       72.64       |        74.54
|      70.37       |
|       Sigmoid       |       100       |       65.29       |         68.5
|      51.85       |
|         Tanh        |       100       |       69.36       |        71.98
```

```
|      68.52       |
+---------------------+-----------------+-------------------+-------------------
--+------------------+
```

3.5 Testing different network sizes(Number of hidden layers and number of neurons)

3.5.1 Relu

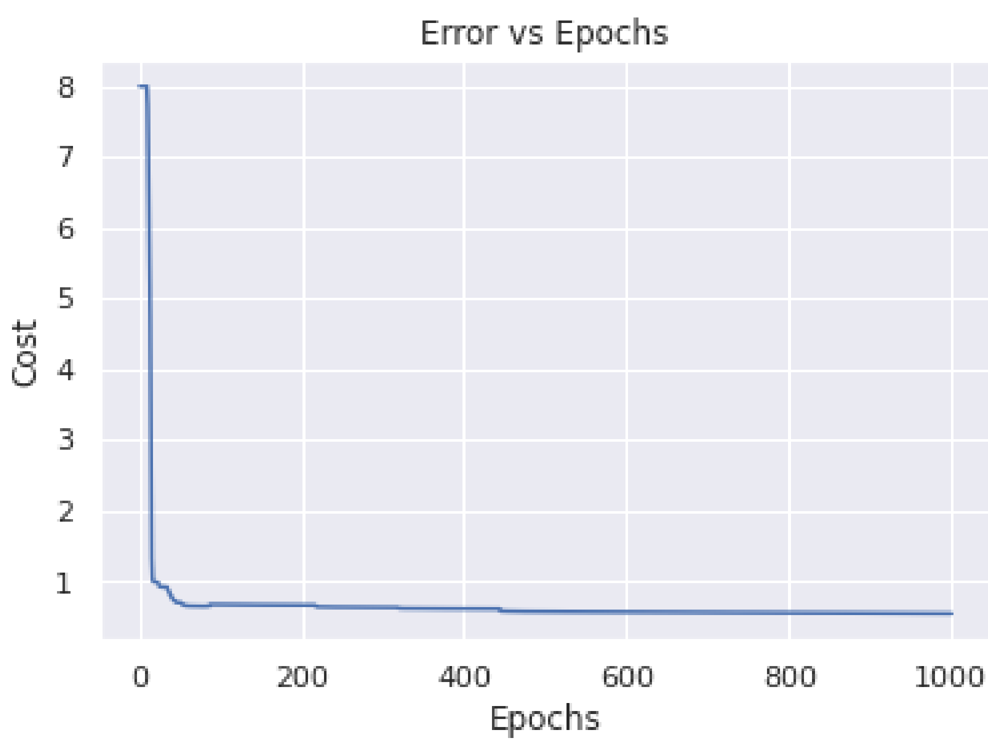
3.5.2 1 Hidden Layers vs 2 Hidden Layers

8 Neurons per layer vs 4 Neurons per layer

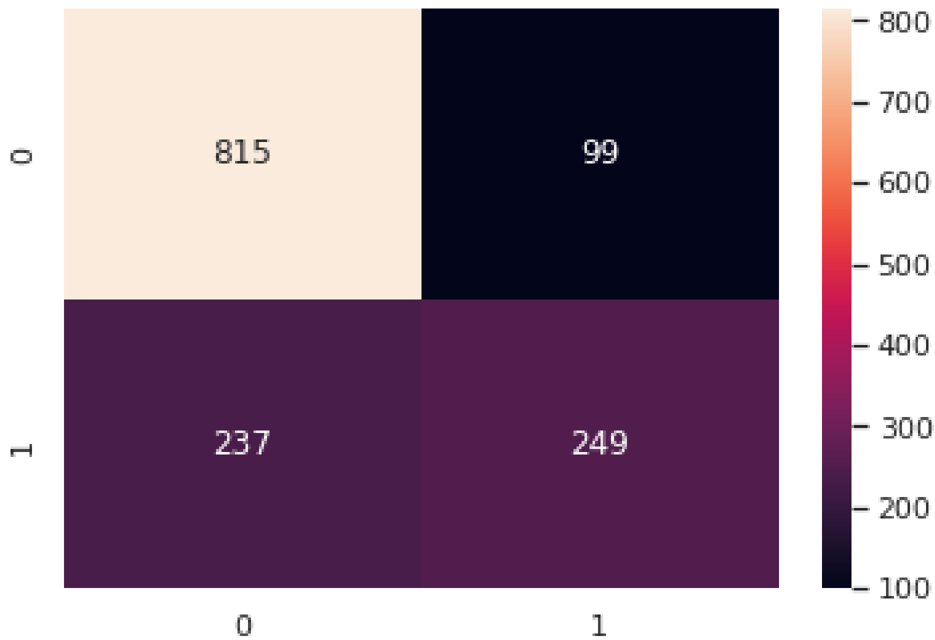
[ ]:
```python
print("1 Layer with 8 Neurons")
R18Weights, R18Epochs, R18Error, R18Activations =␣
 ↪FitNN(trainx,trainy,1,[8],1,["relu","relu"],0.1,0,1000)
print("Number of epochs until convergence:"+str(R18Epochs)+"\n")
print("Training Accuracy")
R18_Acc=Predict(trainx,trainy,R18Weights,R18Activations)
print("Validation Accuracy")
R18_Acc_Val=Predict(validationx,validationy,R18Weights,R18Activations)
print("Test Accuracy")
R18_Acc_Test=Predict(testx,testy,R18Weights,R18Activations)

print("1 Layer with 4 Neurons")
R110Weights, R110Epochs, R110Error, R110Activations =␣
 ↪FitNN(trainx,trainy,1,[4],1,["relu","relu"],0.1,0,1000)
print("Number of epochs until convergence:"+str(R110Epochs)+"\n")
print("Training Accuracy")
R110_Acc=Predict(trainx,trainy,R110Weights,R110Activations)
print("Validation Accuracy")
R110_Acc_Val=Predict(validationx,validationy,R110Weights,R110Activations)
print("Test Accuracy")
R110_Acc_Test=Predict(testx,testy,R110Weights,R110Activations)

print("2 Layers with 8 Neurons")
R28Weights, R28Epochs, R28Error, R28Activations =␣
 ↪FitNN(trainx,trainy,2,[8,8],1,["relu","relu","relu"],0.1,0,1000)
print("Number of epochs until convergence:"+str(R28Epochs)+"\n")
print("Training Accuracy")
R28_Acc=Predict(trainx,trainy,R28Weights,R28Activations)
print("Validation Accuracy")
R28_Acc_Val=Predict(validationx,validationy,R28Weights,R28Activations)
print("Test Accuracy")
R28_Acc_Test=Predict(testx,testy,R28Weights,R28Activations)

print("2 Layers with 4 Neurons")
R210Weights, R210Epochs, R210Error, R210Activations =␣
 ↪FitNN(trainx,trainy,2,[4,4],1,["relu","relu","relu"],0.1,0,1000)
```

```
print("Number of epochs until convergence:"+str(R210Epochs)+"\n")
print("Training Accuracy")
R210_Acc=Predict(trainx,trainy,R210Weights,R210Activations)
print("Validation Accuracy")
R210_Acc_Val=Predict(validationx,validationy,R210Weights,R210Activations)
print("Test Accuracy")
R210_Acc_Test=Predict(testx,testy,R210Weights,R210Activations)


ReluGen = PrettyTable(["Hidden Layers","Neurons in layers","Epochs to␣
↪train","Training Accuracy","Validation Accuracy","Testing Accuracy"])

ReluGen.add_row(["1","8",R18Epochs,np.round(R18_Acc*100,2),np.
↪round(R18_Acc_Val*100,2),np.round(R18_Acc_Test*100,2)])
ReluGen.add_row(["1","4",R110Epochs,np.round(R110_Acc*100,2),np.
↪round(R110_Acc_Val*100,2),np.round(R110_Acc_Test*100,2)])
ReluGen.add_row(["2","8",R28Epochs,np.round(R28_Acc*100,2),np.
↪round(R28_Acc_Val*100,2),np.round(R28_Acc_Test*100,2)])
ReluGen.add_row(["2","4",R210Epochs,np.round(R210_Acc*100,2),np.
↪round(R210_Acc_Val*100,2),np.round(R210_Acc_Test*100,2)])
print(ReluGen)
```

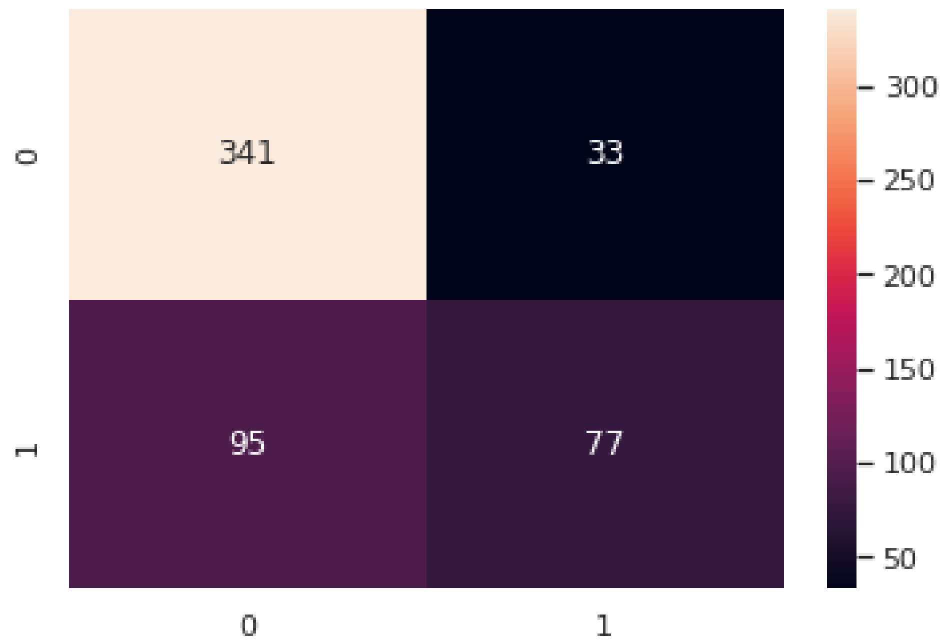
```
1 Layer with 8 Neurons
```



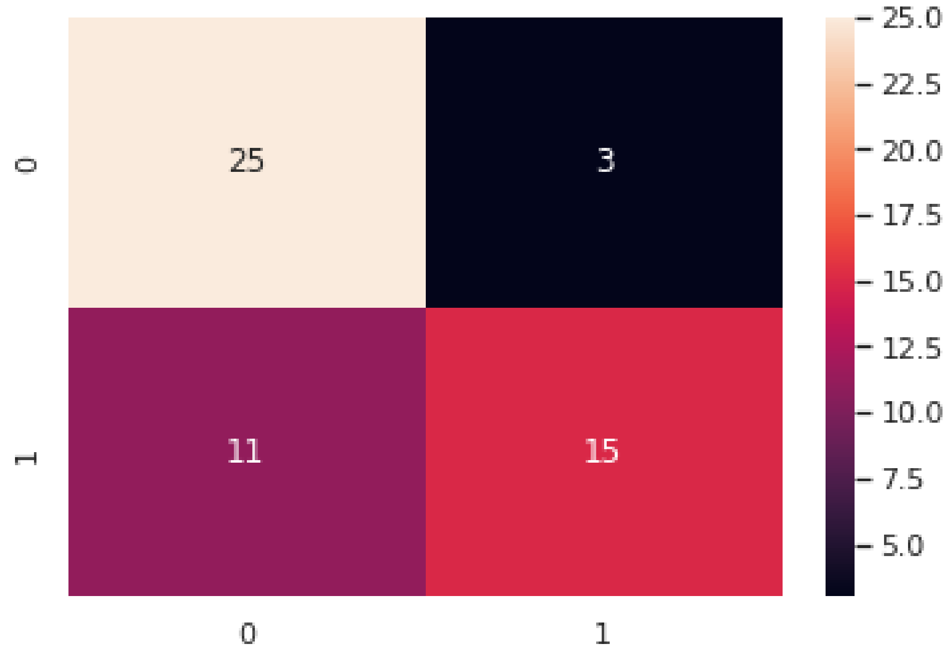
```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 76.0%
Confusion Matrix:
```



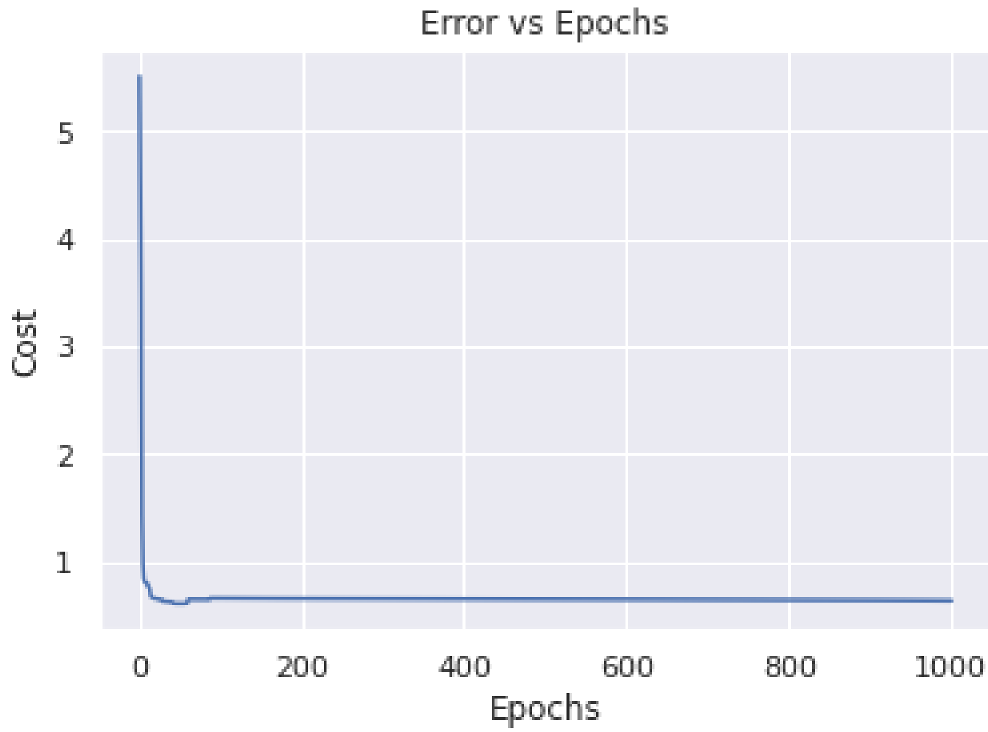

```
Validation Accuracy
The accuracy is: 76.55677655677655%
Confusion Matrix:
```



Test Accuracy
The accuracy is: 74.07407407407408%
Confusion Matrix:

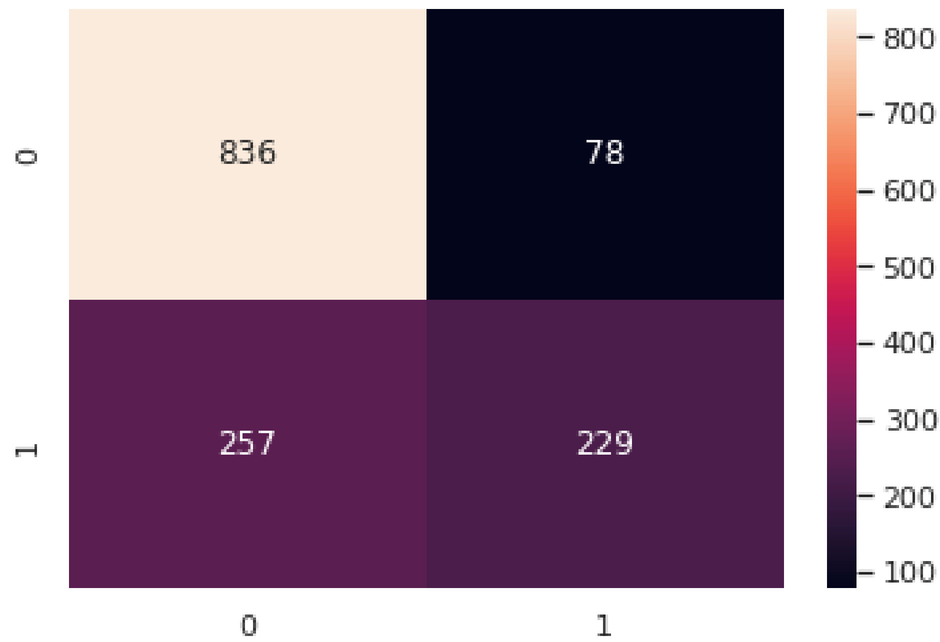


1 Layer with 4 Neurons

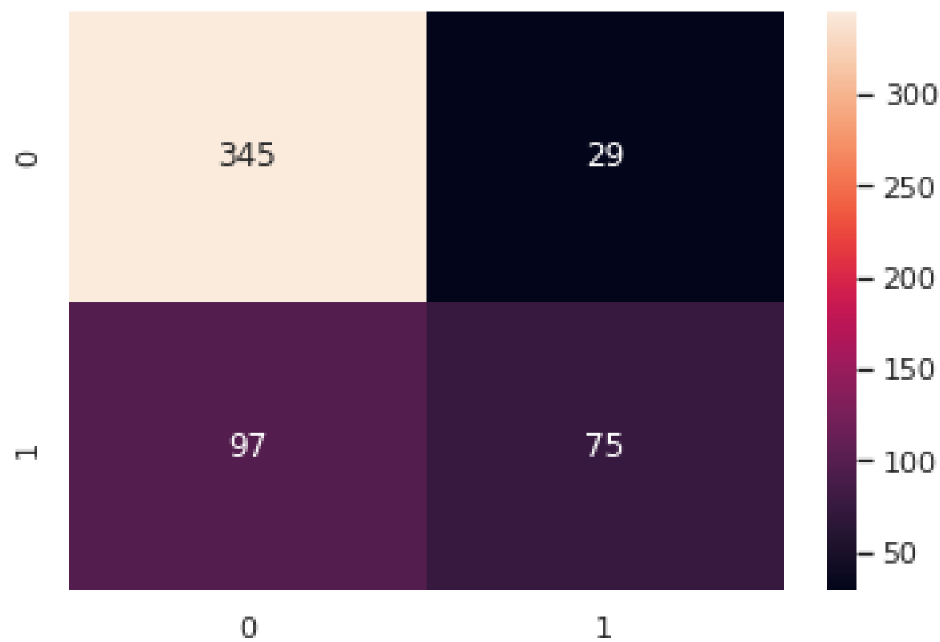


Number of epochs until convergence:1000

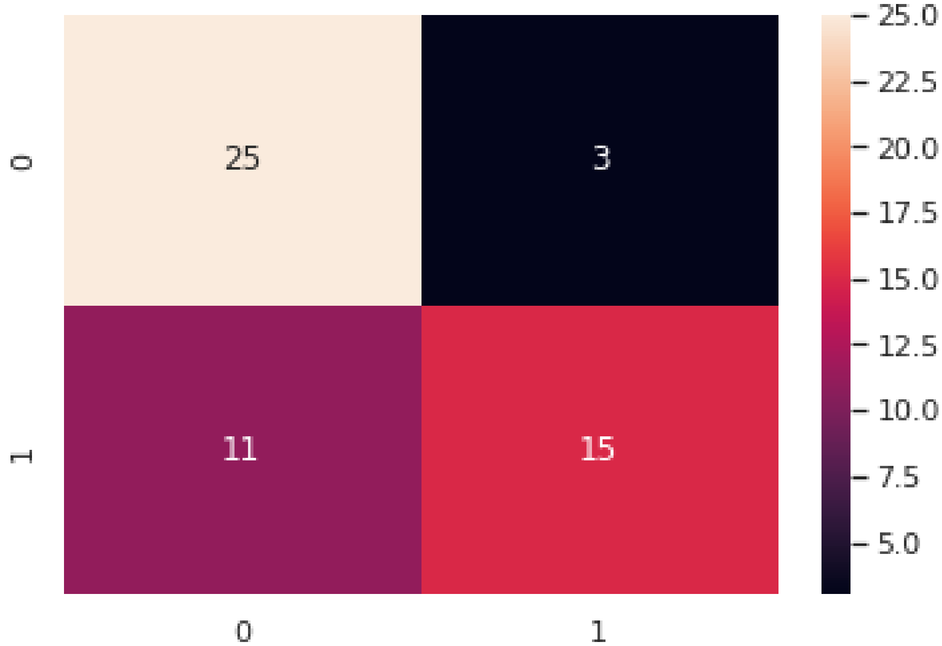
Training Accuracy
The accuracy is: 76.07142857142857%
Confusion Matrix:




```
Validation Accuracy
The accuracy is: 76.92307692307693%
Confusion Matrix:
```

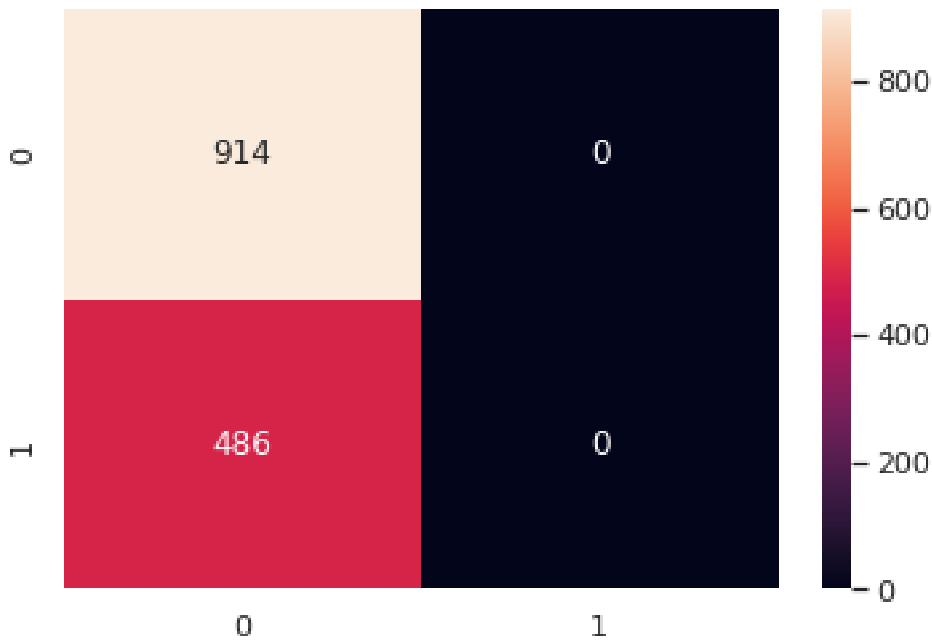


```
Test Accuracy
The accuracy is: 74.07407407407408%
Confusion Matrix:
```

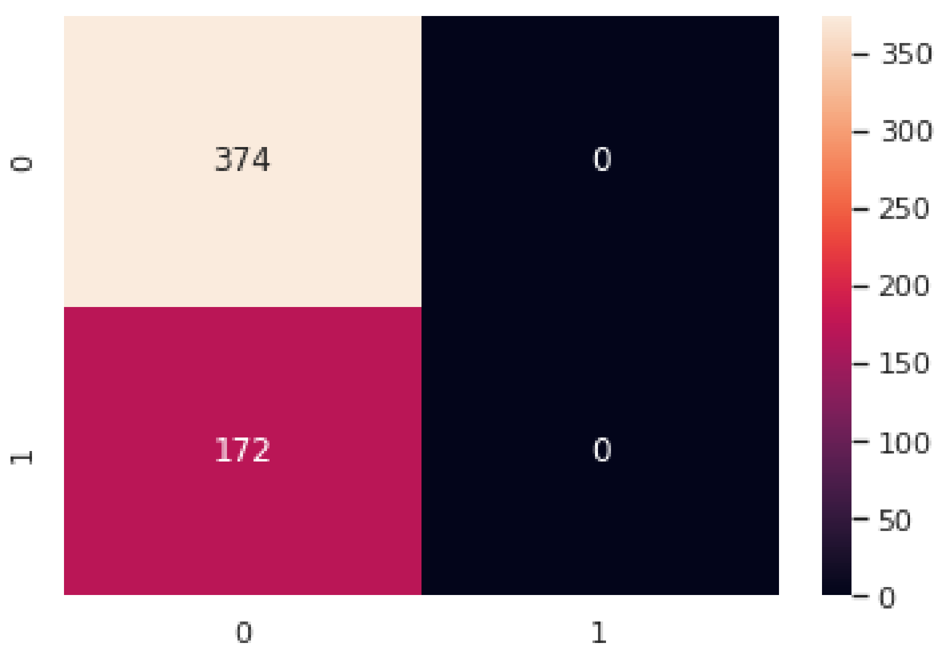



```
2 Layers with 8 Neurons
```

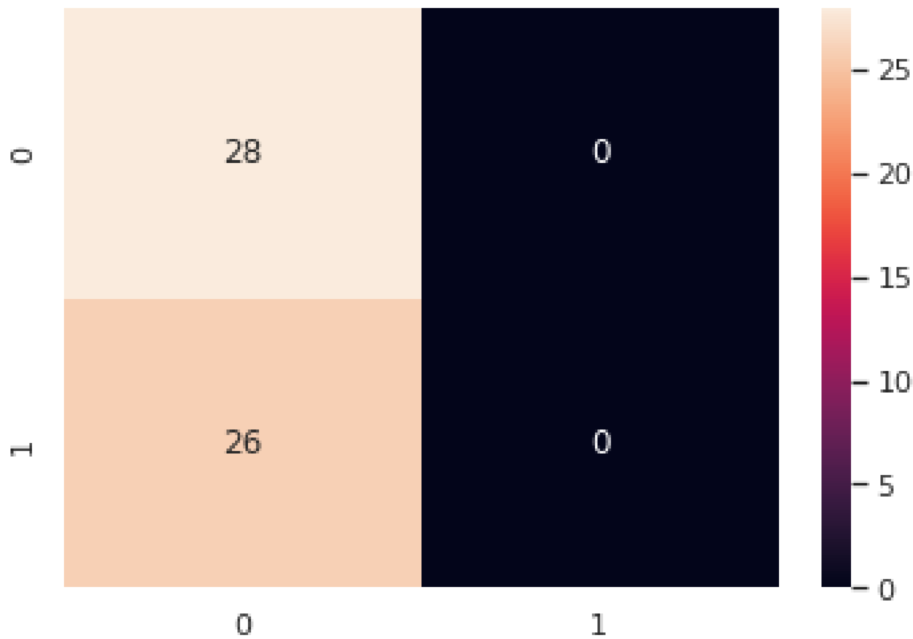

```
Number of epochs until convergence:4

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



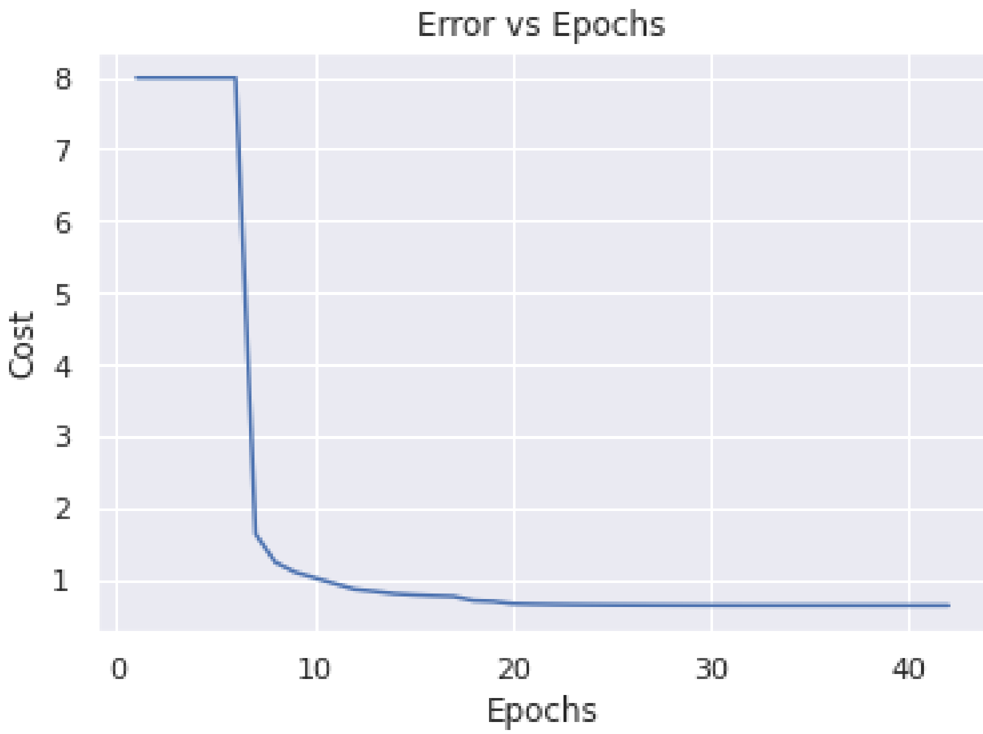
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:



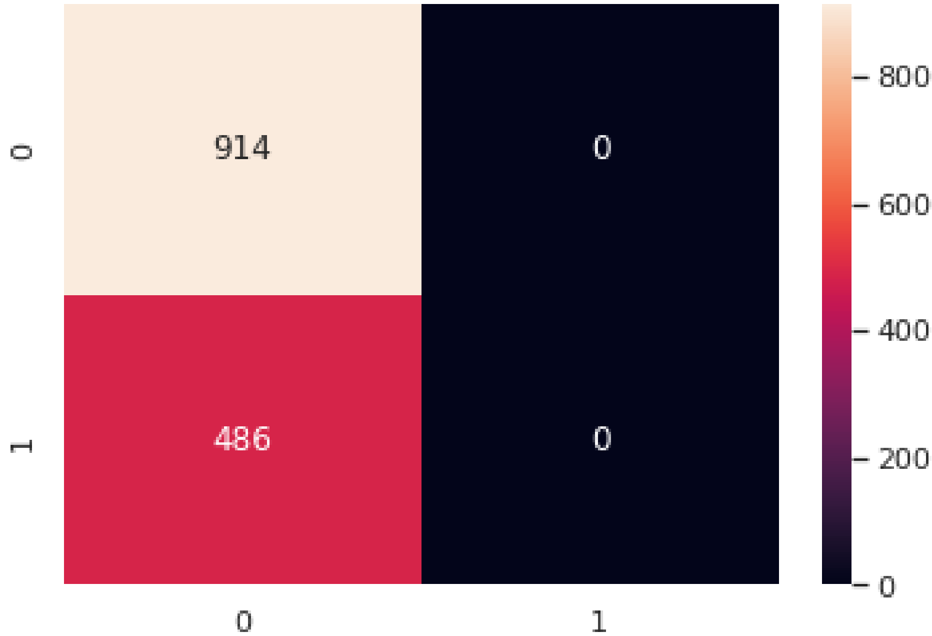
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



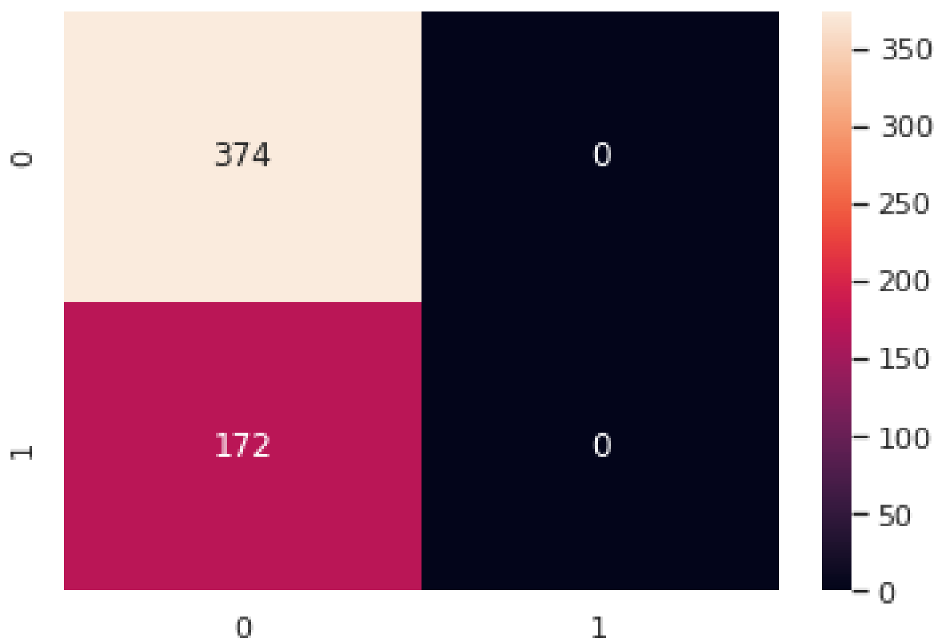

```
2 Layers with 4 Neurons
```



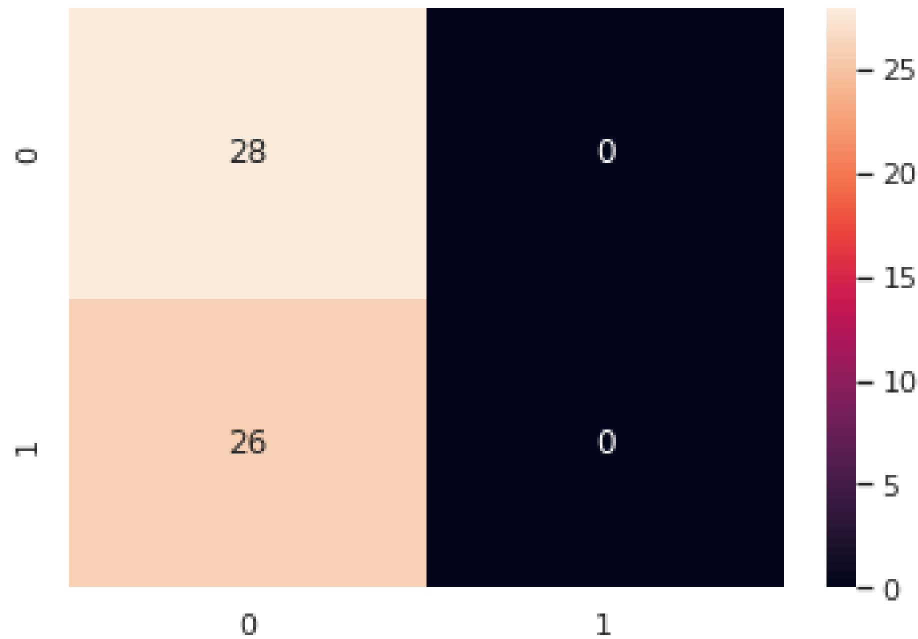

```
Number of epochs until convergence:42

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```




```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



Hidden Layers	Neurons in layers	Epochs to train	Training Accuracy	Validation Accuracy	Testing Accuracy
1	8	1000	76.0	76.56	74.07
1	4	1000	76.07	76.92	74.07
2	8	4	65.29	68.5	51.85
2	4	42	65.29	68.5	51.85

3.5.3 Sigmoid

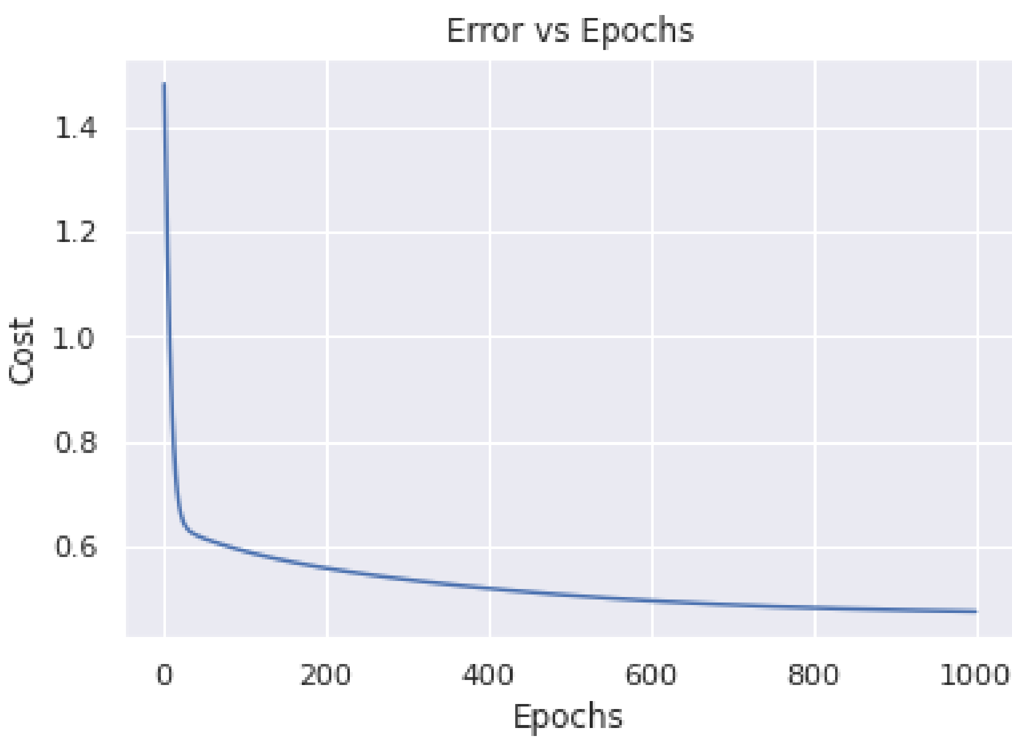
1 layer vs 2 layers

8 Neurons vs 9 Neurons

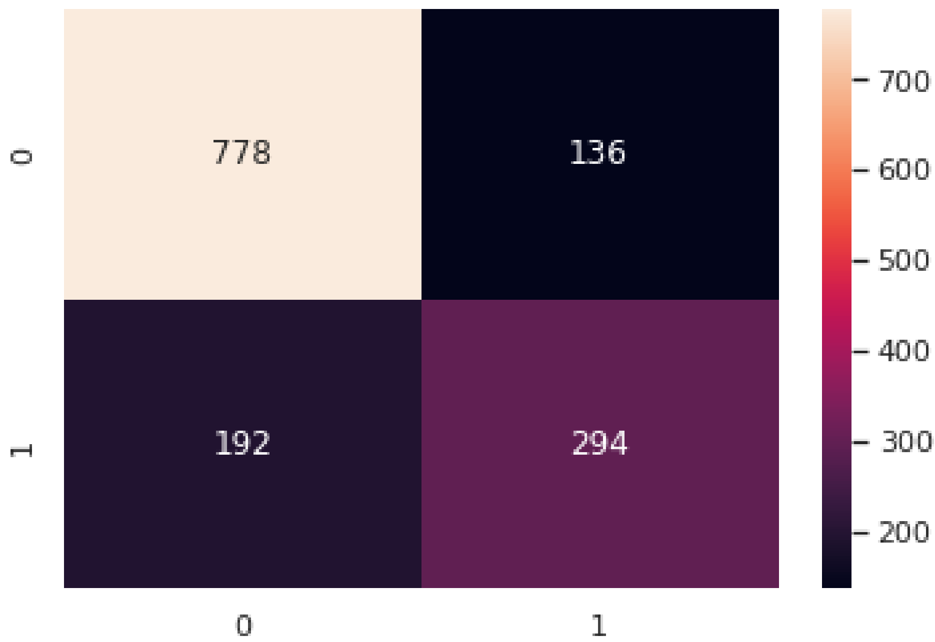
```
[ ]: print("1 Layer with 8 Neurons")
S18Weights, S18Epochs, S18Error, S18Activations =␣
 ↪FitNN(trainx,trainy,1,[8],1,["sigmoid","sigmoid"],0.1,0,1000)
print("Number of epochs until convergence:"+str(S18Epochs)+"\n")
print("Training Accuracy")
S18_Acc=Predict(trainx,trainy,S18Weights,S18Activations)
print("Validation Accuracy")
S18_Acc_Val=Predict(validationx,validationy,S18Weights,S18Activations)
print("Test Accuracy")
S18_Acc_Test=Predict(testx,testy,S18Weights,S18Activations)

print("1 Layer with 9 Neurons")
S110Weights, S110Epochs, S110Error, S110Activations =␣
 ↪FitNN(trainx,trainy,1,[9],1,["sigmoid","sigmoid"],0.1,0,1000)
print("Number of epochs until convergence:"+str(S110Epochs)+"\n")
print("Training Accuracy")
S110_Acc=Predict(trainx,trainy,S110Weights,S110Activations)
print("Validation Accuracy")
S110_Acc_Val=Predict(validationx,validationy,S110Weights,S110Activations)
print("Test Accuracy")
S110_Acc_Test=Predict(testx,testy,S110Weights,S110Activations)

print("2 Layers with 8 Neurons")
S28Weights, S28Epochs, S28Error, S28Activations =␣
 ↪FitNN(trainx,trainy,2,[8,8],1,["sigmoid","sigmoid","sigmoid"],0.1,0,1000)
print("Number of epochs until convergence:"+str(S28Epochs)+"\n")
print("Training Accuracy")
S28_Acc=Predict(trainx,trainy,S28Weights,S28Activations)
print("Validation Accuracy")
S28_Acc_Val=Predict(validationx,validationy,S28Weights,S28Activations)
print("Test Accuracy")
S28_Acc_Test=Predict(testx,testy,S28Weights,S28Activations)

print("2 Layers with 9 Neurons")
S210Weights, S210Epochs, S210Error, S210Activations =␣
 ↪FitNN(trainx,trainy,2,[9,9],1,["sigmoid","sigmoid","sigmoid"],0.1,0,1000)
print("Number of epochs until convergence:"+str(S210Epochs)+"\n")
print("Training Accuracy")
S210_Acc=Predict(trainx,trainy,S210Weights,S210Activations)
print("Validation Accuracy")
S210_Acc_Val=Predict(validationx,validationy,S210Weights,S210Activations)
print("Test Accuracy")
S210_Acc_Test=Predict(testx,testy,S210Weights,S210Activations)



SigmoidGen = PrettyTable(["Hidden Layers","Neurons in layers","Epochs to␣
 ↪train","Training Accuracy","Validation Accuracy","Testing Accuracy"])
```

```
SigmoidGen.add_row(["1","8",S18Epochs,np.round(S18_Acc*100,2),np.
 ↪round(S18_Acc_Val*100,2),np.round(S18_Acc_Test*100,2)])
SigmoidGen.add_row(["1","9",S110Epochs,np.round(S110_Acc*100,2),np.
 ↪round(S110_Acc_Val*100,2),np.round(S110_Acc_Test*100,2)])
SigmoidGen.add_row(["2","8",S28Epochs,np.round(S28_Acc*100,2),np.
 ↪round(S28_Acc_Val*100,2),np.round(S28_Acc_Test*100,2)])
SigmoidGen.add_row(["2","9",S210Epochs,np.round(S210_Acc*100,2),np.
 ↪round(S210_Acc_Val*100,2),np.round(S210_Acc_Test*100,2)])
print(SigmoidGen)
```

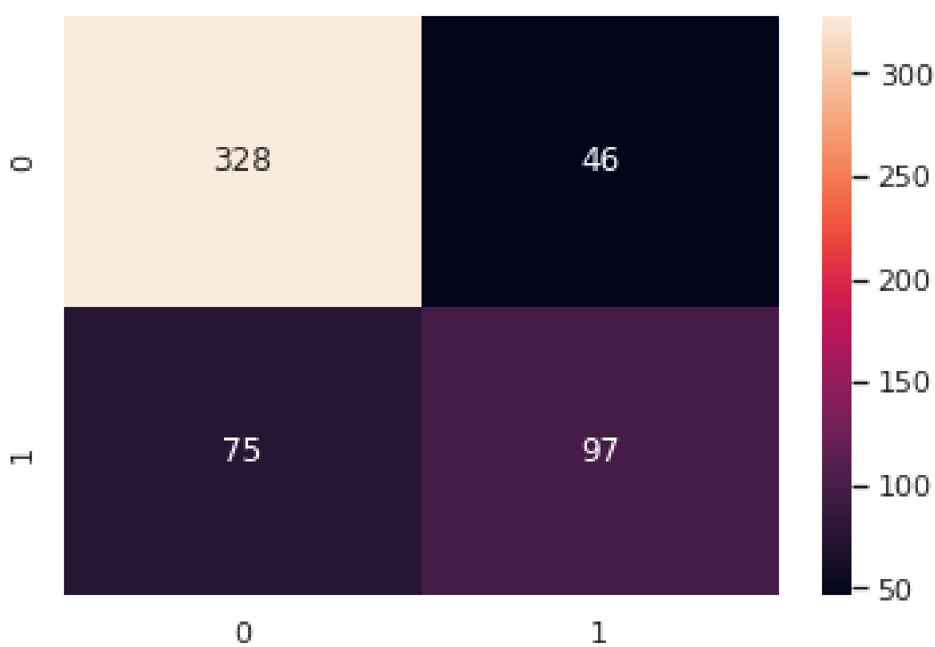
```
1 Layer with 8 Neurons
```



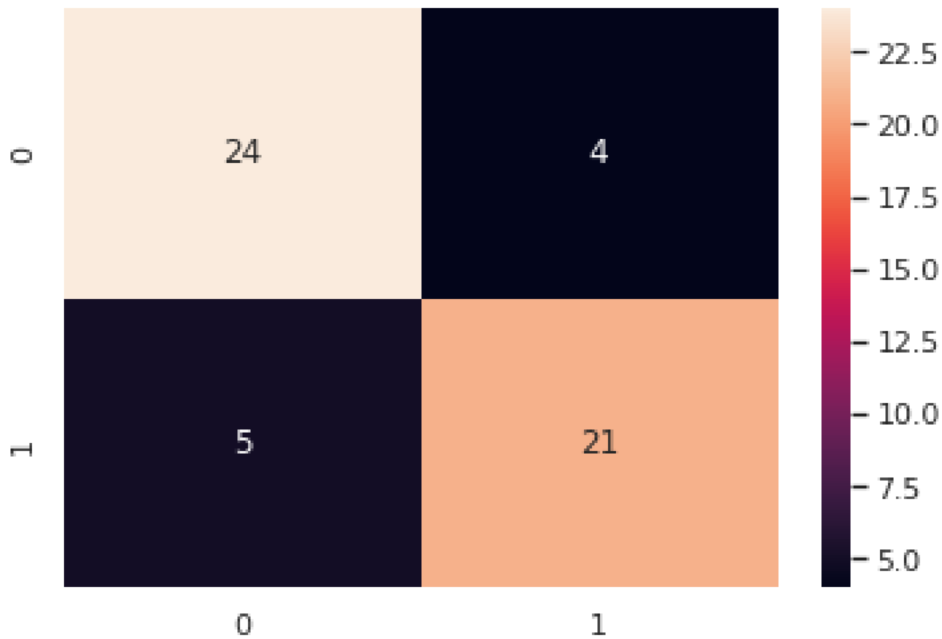

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 76.57142857142857%
Confusion Matrix:
```



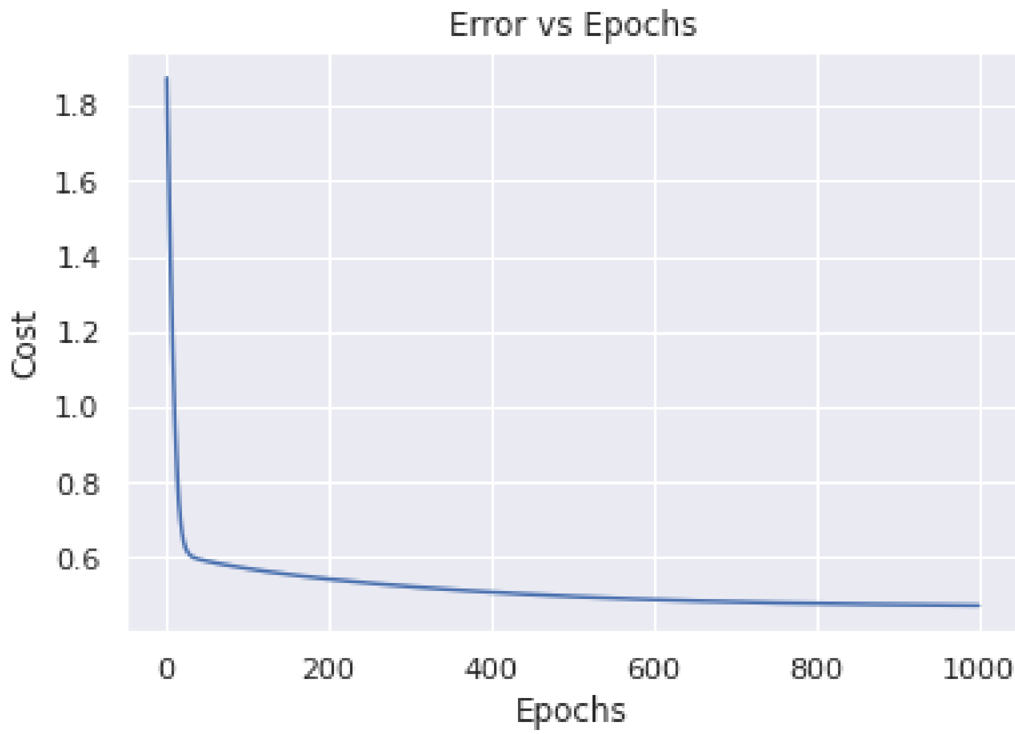

```
Validation Accuracy
The accuracy is: 77.83882783882784%
Confusion Matrix:
```



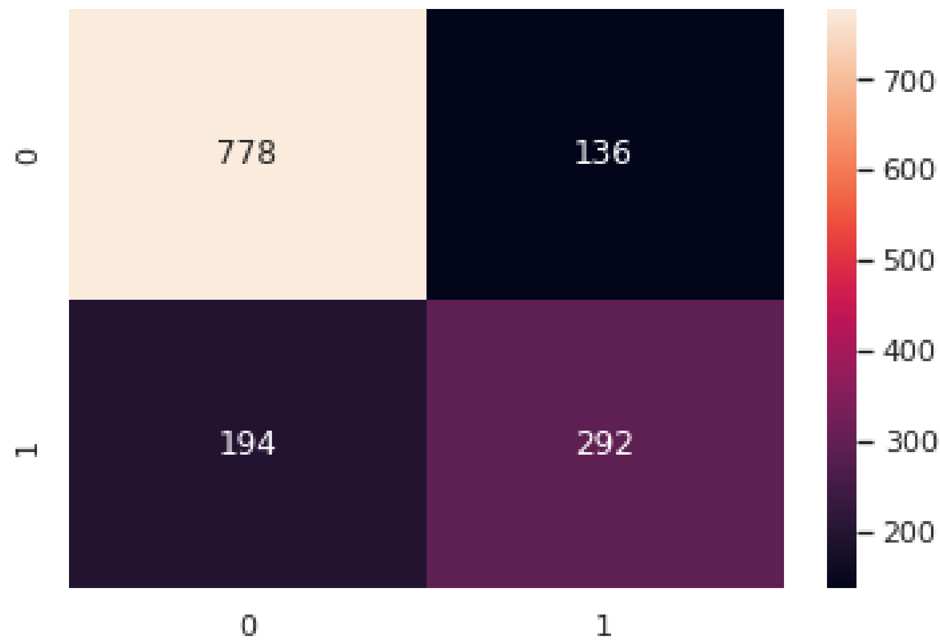
```
Test Accuracy
The accuracy is: 83.33333333333334%
Confusion Matrix:
```



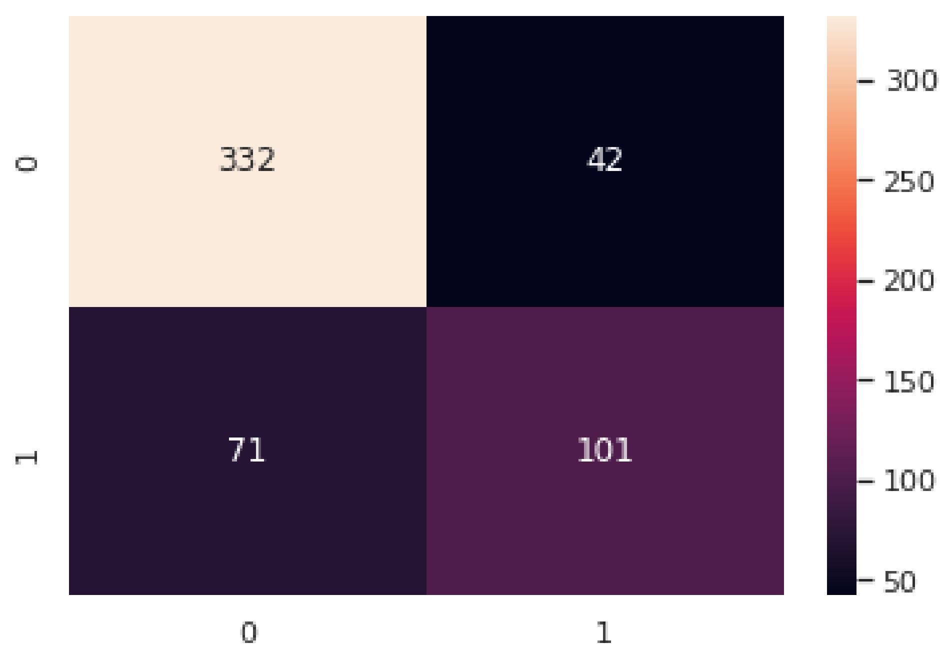

```
1 Layer with 9 Neurons
```



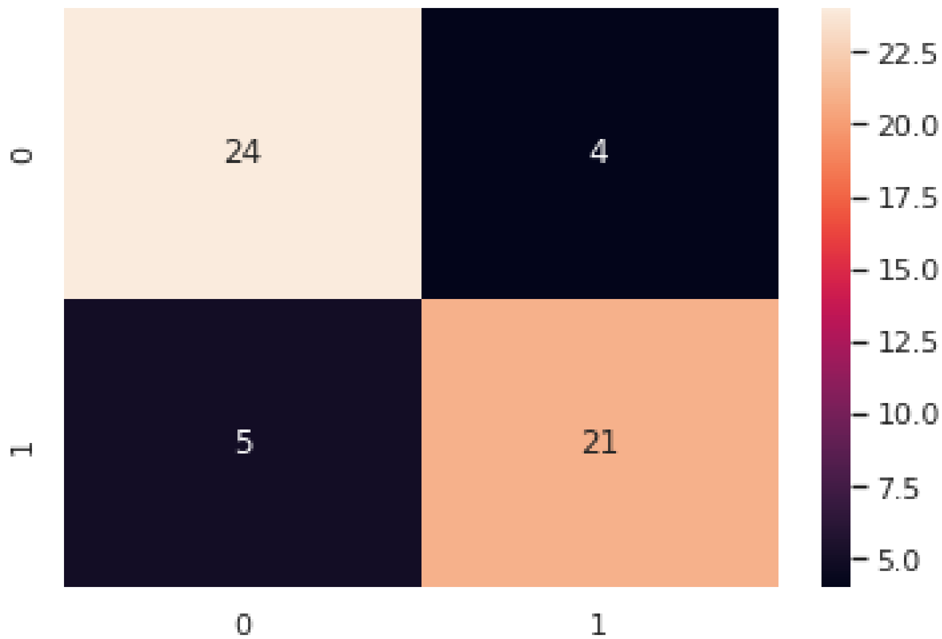

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 76.42857142857142%
Confusion Matrix:
```



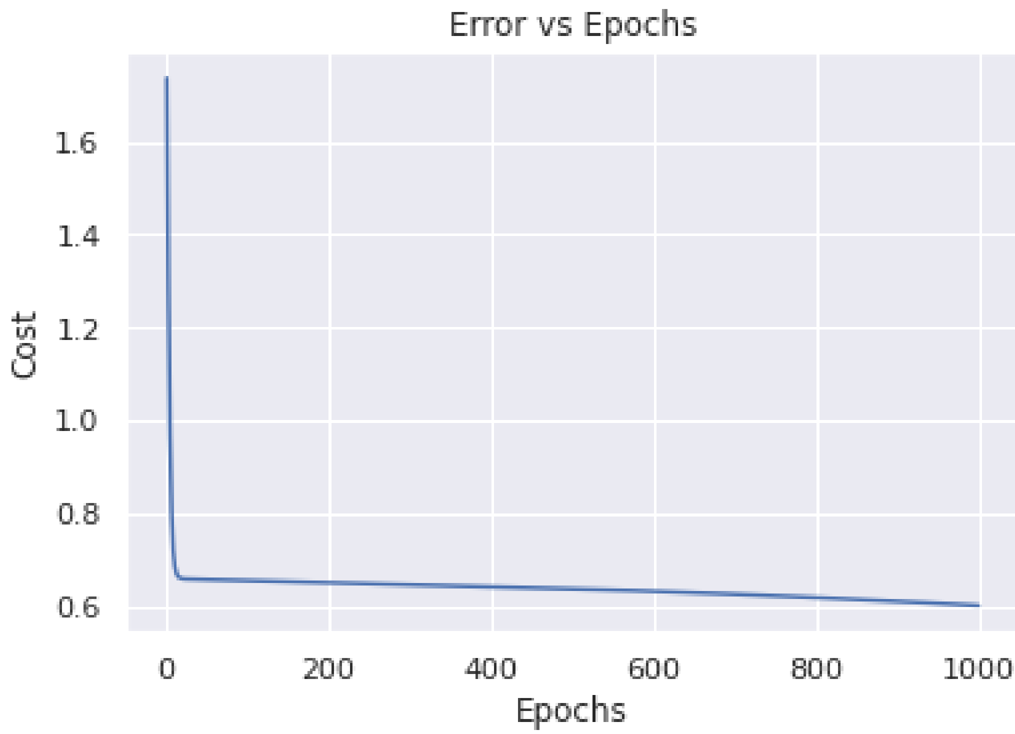

```
Validation Accuracy
The accuracy is: 79.3040293040293%
Confusion Matrix:
```



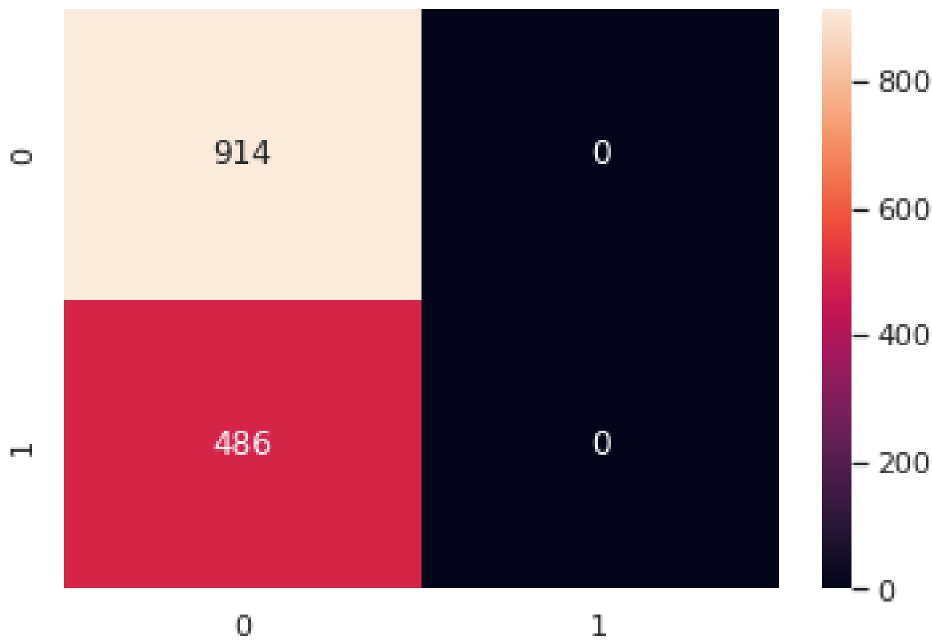
```
Test Accuracy
The accuracy is: 83.33333333333334%
Confusion Matrix:
```



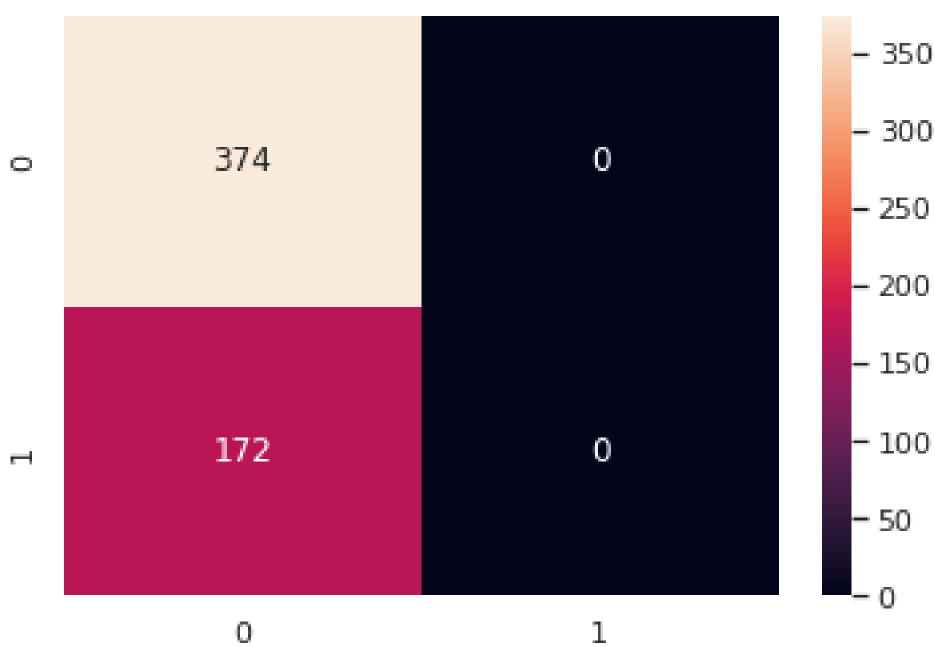

```
2 Layers with 8 Neurons
```



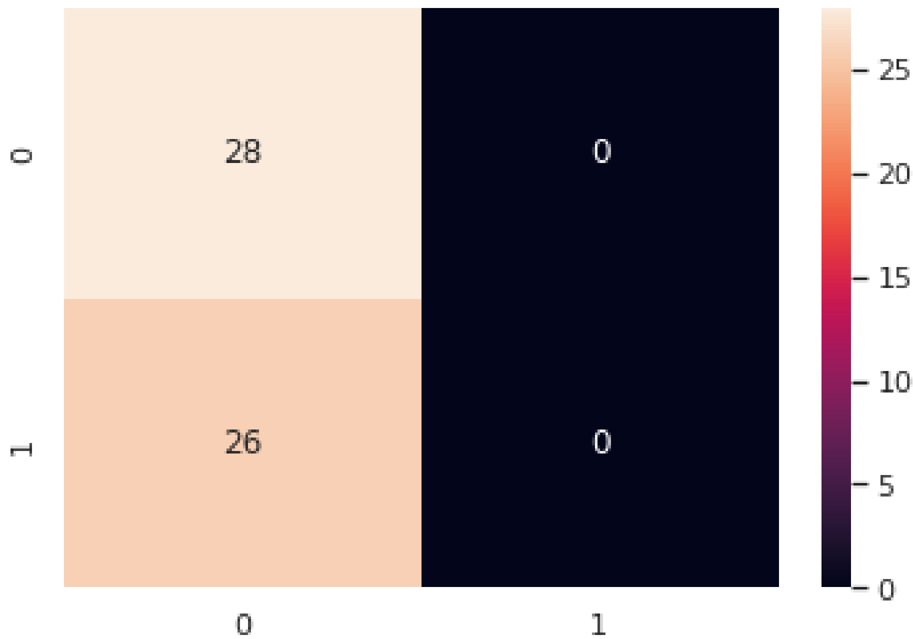

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



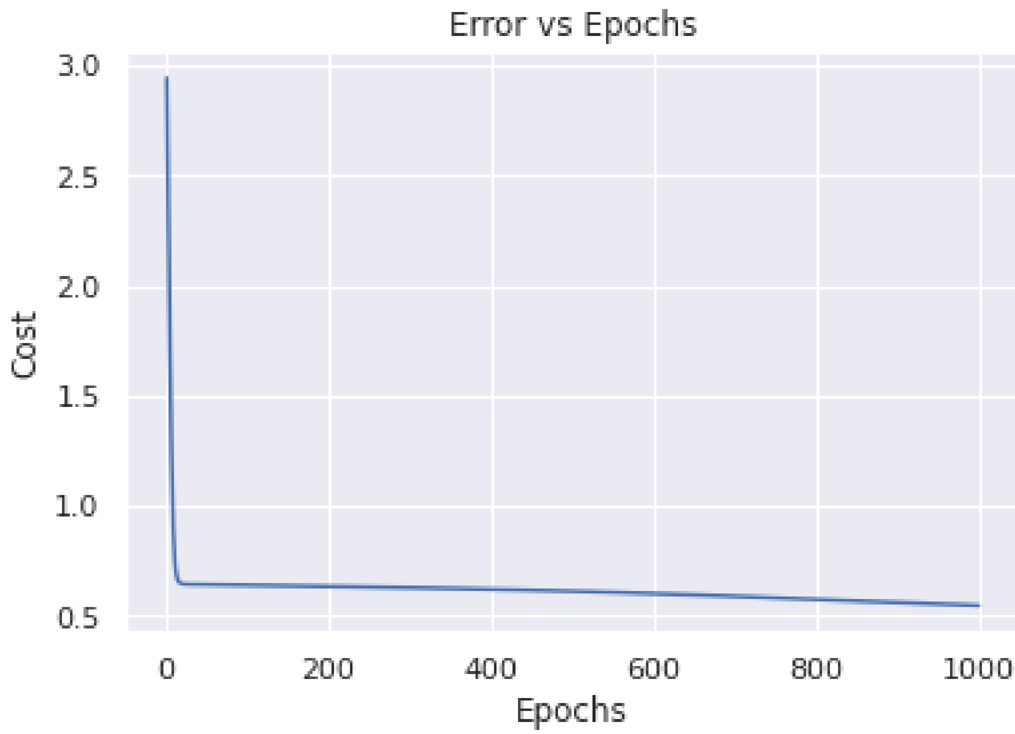

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



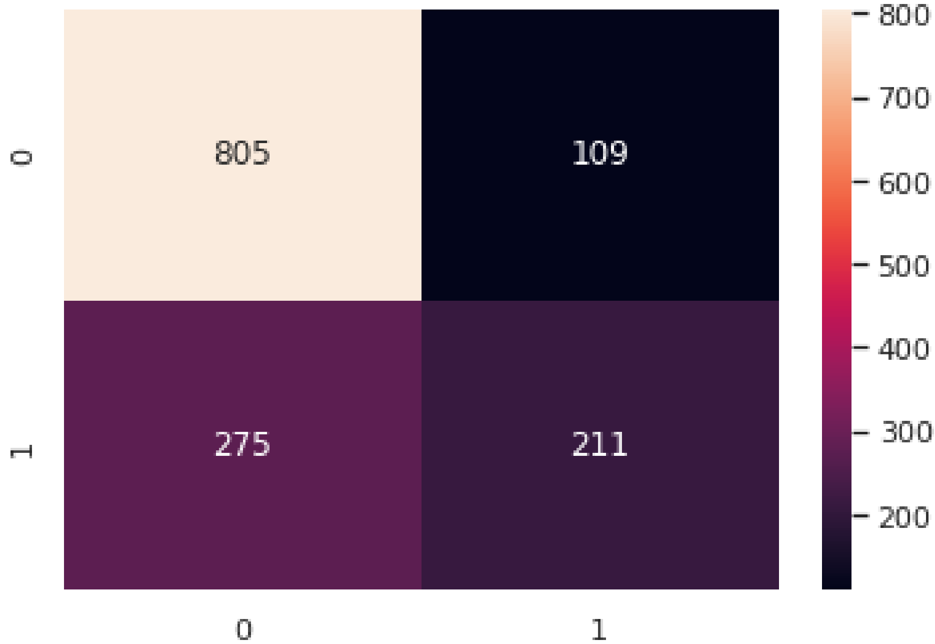
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



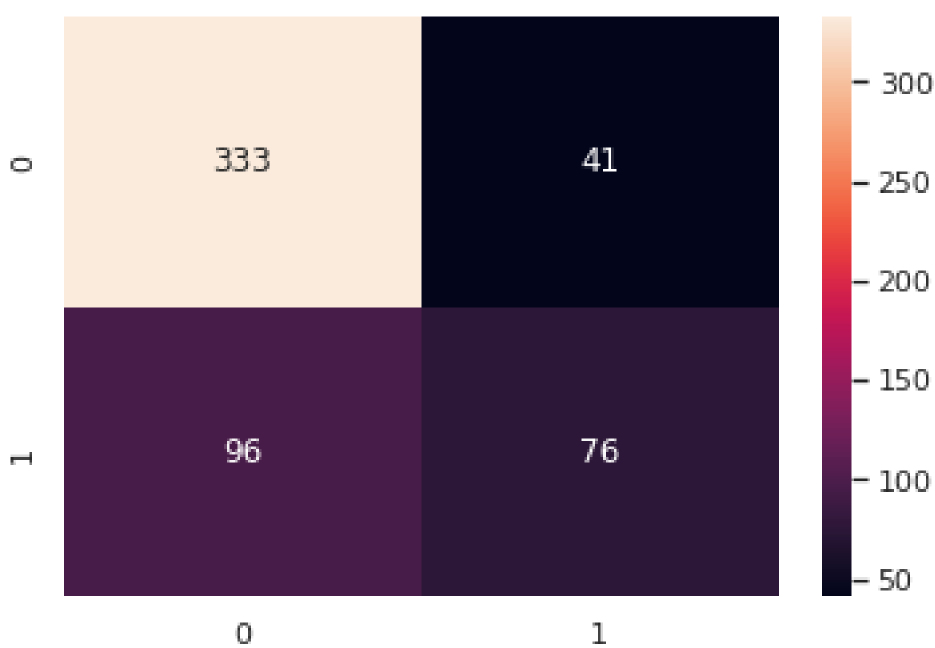

```
2 Layers with 9 Neurons
```



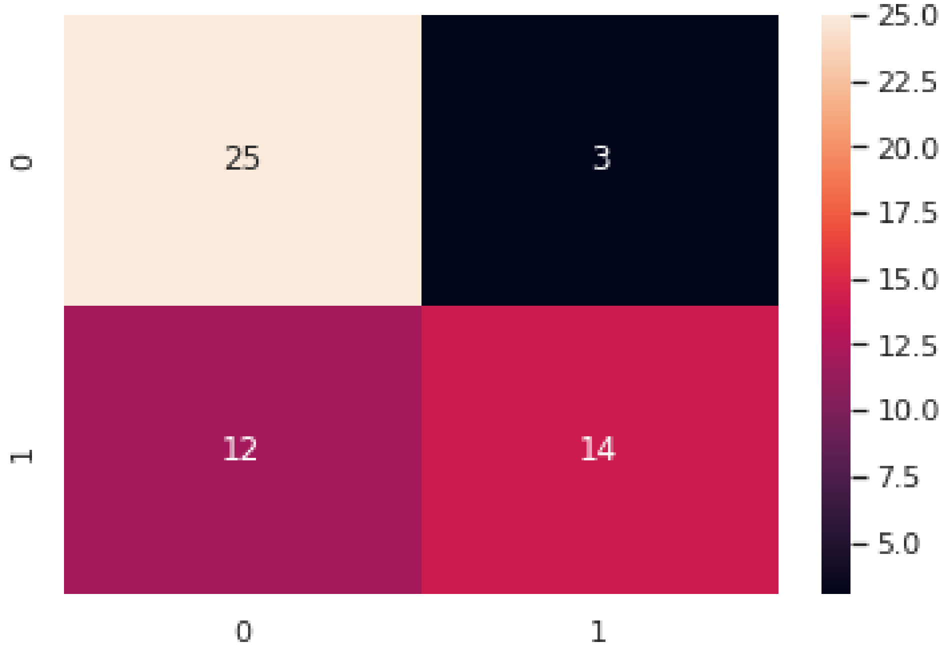

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 72.57142857142857%
Confusion Matrix:
```




```
Validation Accuracy
The accuracy is: 74.9084249084249%
Confusion Matrix:
```



```
Test Accuracy
The accuracy is: 72.22222222222221%
Confusion Matrix:
```



Hidden Layers	Neurons in layers	Epochs to train	Training Accuracy	Validation Accuracy	Testing Accuracy
1	8	1000	76.57	77.84	83.33
1	9	1000	76.43	79.3	83.33
2	8	1000	65.29	68.5	51.85
2	9	1000	72.57	74.91	72.22

3.5.4 Tanh

1 layer vs 2 layers

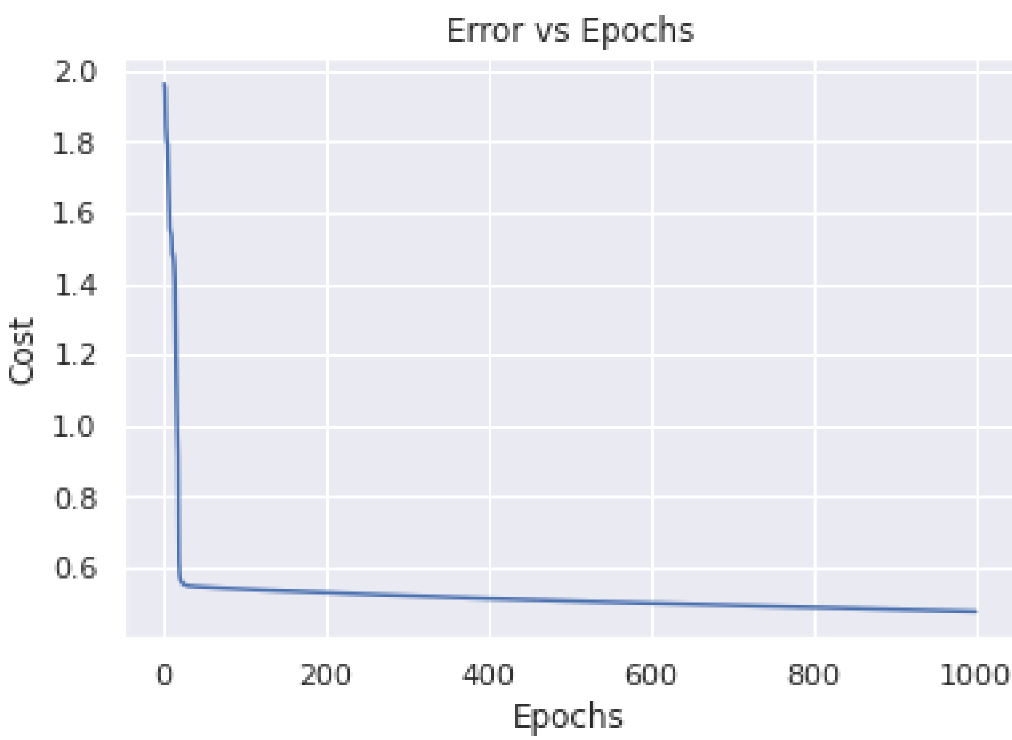
3 Neurons per layer vs 18 Neurons per layer

[ ]:

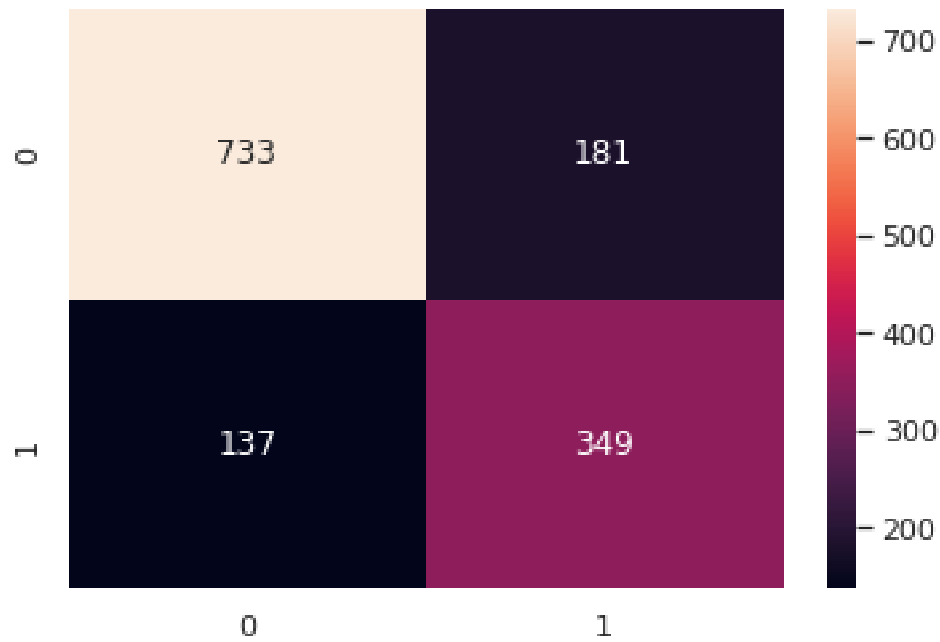
```
print("1 Layer with 3 Neurons")
T18Weights, T18Epochs, T18Error, T18Activations =␣
↪FitNN(trainx,trainy,1,[3],1,["tanh","tanh"],0.1,0,1000)
print("Number of epochs until convergence:"+str(T18Epochs)+"\n")
print("Training Accuracy")
T18_Acc=Predict(trainx,trainy,T18Weights,T18Activations)
print("Validation Accuracy")
T18_Acc_Val=Predict(validationx,validationy,T18Weights,T18Activations)
print("Test Accuracy")
T18_Acc_Test=Predict(testx,testy,T18Weights,T18Activations)

print("1 Layer with 18 Neurons")
T110Weights, T110Epochs, T110Error, T110Activations =␣
↪FitNN(trainx,trainy,1,[18],1,["tanh","tanh"],0.1,0,1000)
print("Number of epochs until convergence:"+str(T110Epochs)+"\n")
print("Training Accuracy")
T110_Acc=Predict(trainx,trainy,T110Weights,T110Activations)
print("Validation Accuracy")
T110_Acc_Val=Predict(validationx,validationy,T110Weights,T110Activations)
print("Test Accuracy")
T110_Acc_Test=Predict(testx,testy,T110Weights,T110Activations)

print("2 Layers with 3 Neurons")
T28Weights, T28Epochs, T28Error, T28Activations =␣
↪FitNN(trainx,trainy,2,[3,3],1,["tanh","tanh","tanh"],0.1,0,1000)
print("Number of epochs until convergence:"+str(T28Epochs)+"\n")
print("Training Accuracy")
T28_Acc=Predict(trainx,trainy,T28Weights,T28Activations)
print("Validation Accuracy")
T28_Acc_Val=Predict(validationx,validationy,T28Weights,T28Activations)
print("Test Accuracy")
T28_Acc_Test=Predict(testx,testy,T28Weights,T28Activations)

print("2 Layers with 18 Neurons")
T210Weights, T210Epochs, T210Error, T210Activations =␣
↪FitNN(trainx,trainy,2,[18,18],1,["tanh","tanh","tanh"],0.1,0,1000)
print("Number of epochs until convergence:"+str(T210Epochs)+"\n")
print("Training Accuracy")
T210_Acc=Predict(trainx,trainy,T210Weights,T210Activations)
print("Validation Accuracy")
T210_Acc_Val=Predict(validationx,validationy,T210Weights,T210Activations)
print("Test Accuracy")
T210_Acc_Test=Predict(testx,testy,T210Weights,T210Activations)



TanhGen = PrettyTable(["Hidden Layers","Neurons in layers","Epochs to␣
↪train","Training Accuracy","Validation Accuracy","Testing Accuracy"])
```

```
TanhGen.add_row(["1","3",T18Epochs,np.round(T18_Acc*100,2),np.
 ↪round(T18_Acc_Val*100,2),np.round(T18_Acc_Test*100,2)])
TanhGen.add_row(["1","18",T110Epochs,np.round(T110_Acc*100,2),np.
 ↪round(T110_Acc_Val*100,2),np.round(T110_Acc_Test*100,2)])
TanhGen.add_row(["2","3",T28Epochs,np.round(T28_Acc*100,2),np.
 ↪round(T28_Acc_Val*100,2),np.round(T28_Acc_Test*100,2)])
TanhGen.add_row(["2","18",T210Epochs,np.round(T210_Acc*100,2),np.
 ↪round(T210_Acc_Val*100,2),np.round(T210_Acc_Test*100,2)])
print(TanhGen)
```

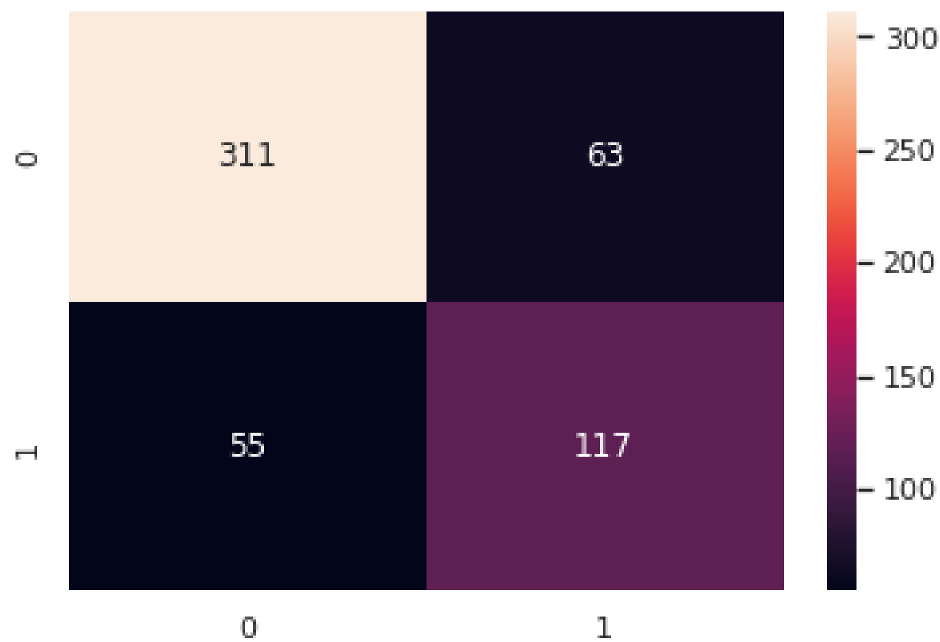
```
1 Layer with 3 Neurons
```



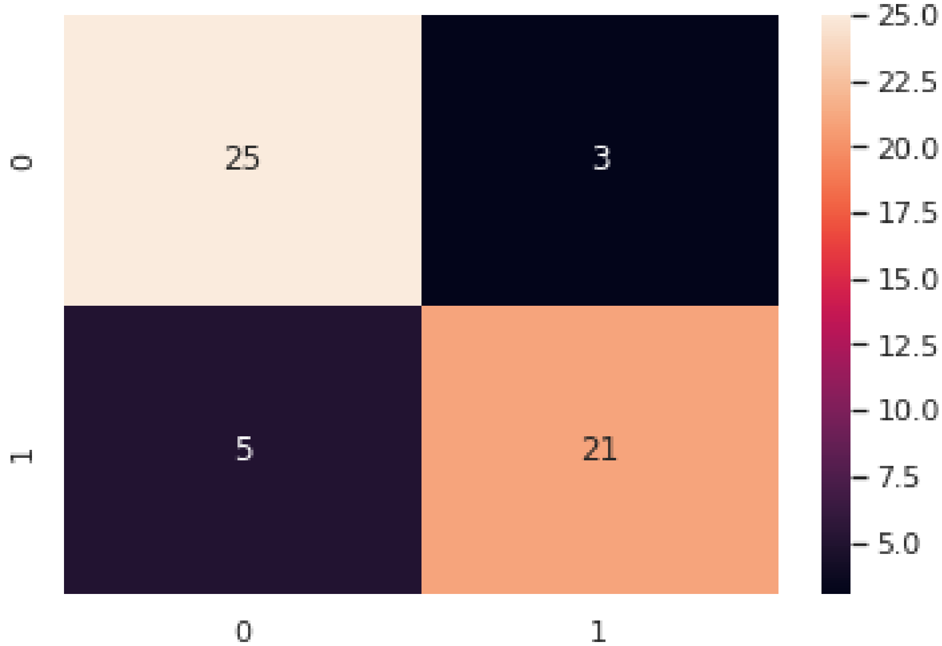

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 77.28571428571429%
Confusion Matrix:
```



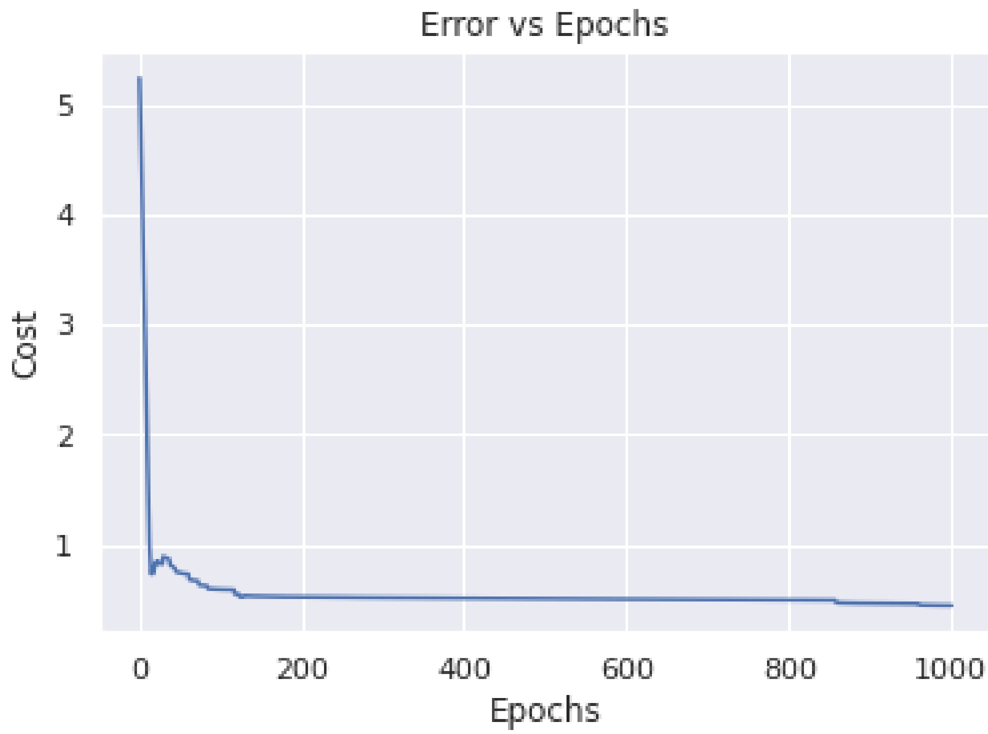

```
Validation Accuracy
The accuracy is: 78.3882783882784%
Confusion Matrix:
```



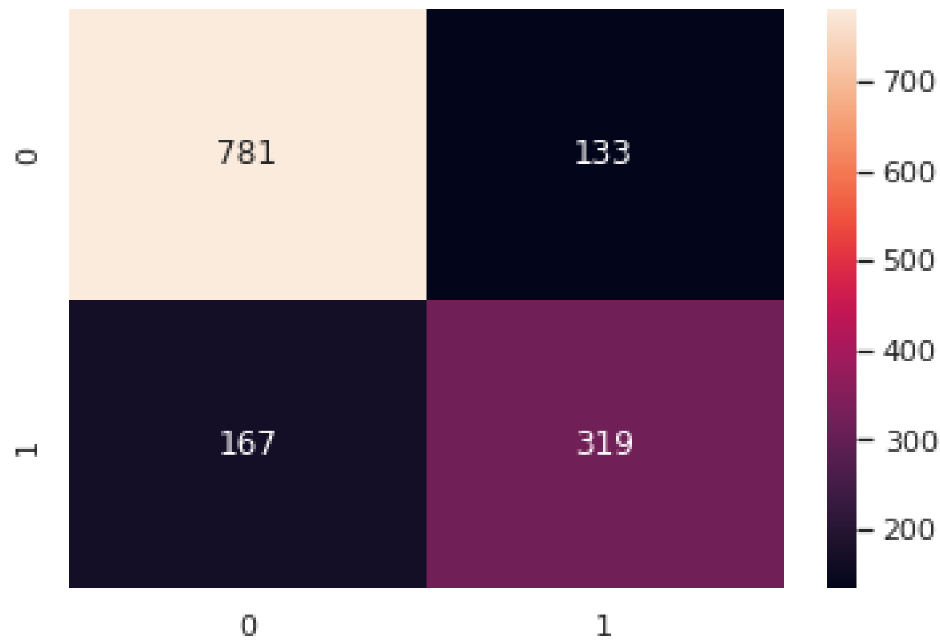
```
Test Accuracy
The accuracy is: 85.18518518518519%
Confusion Matrix:
```



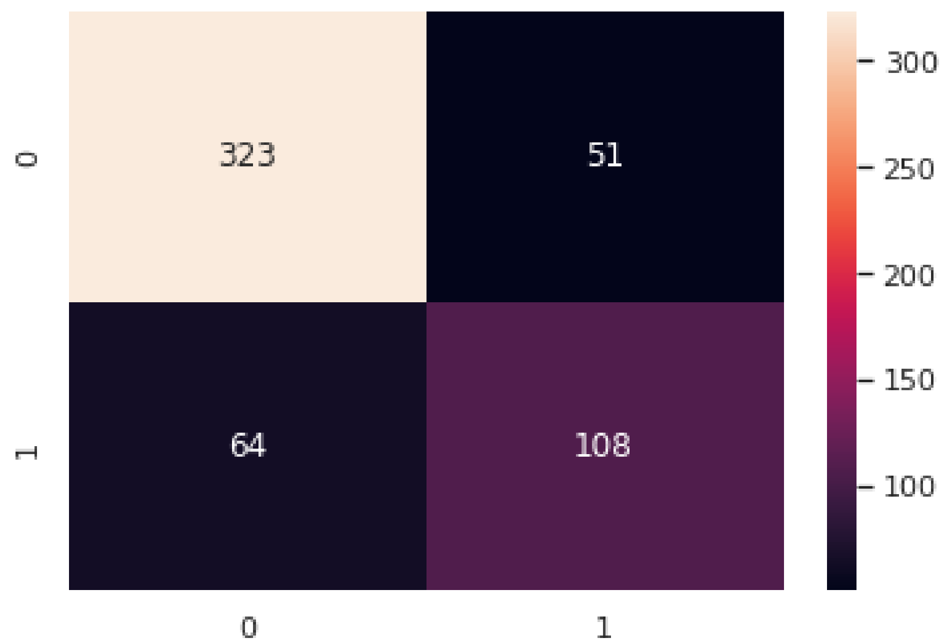

```
1 Layer with 18 Neurons
```



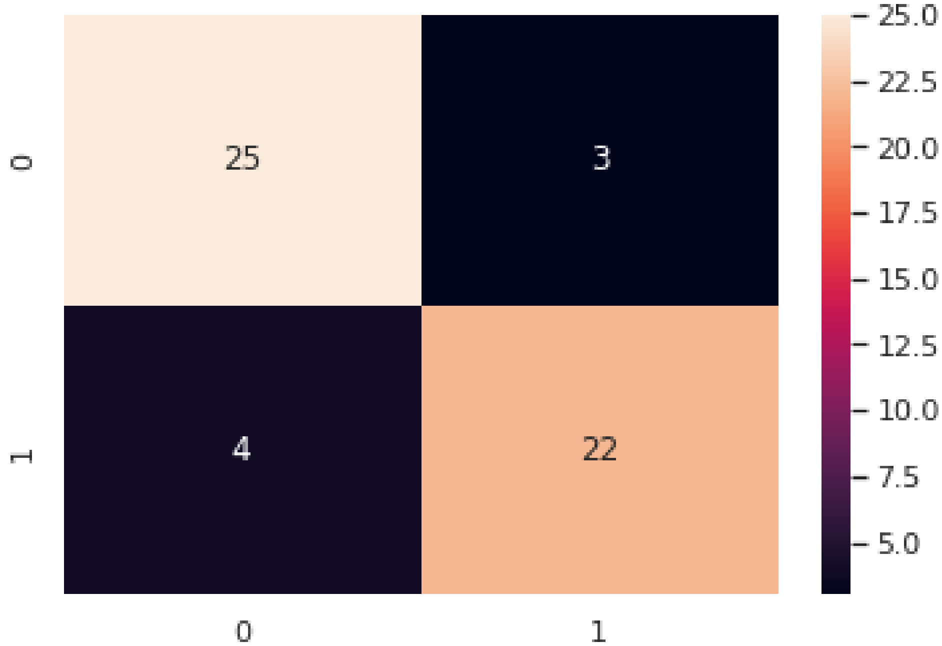

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 78.57142857142857%
Confusion Matrix:
```



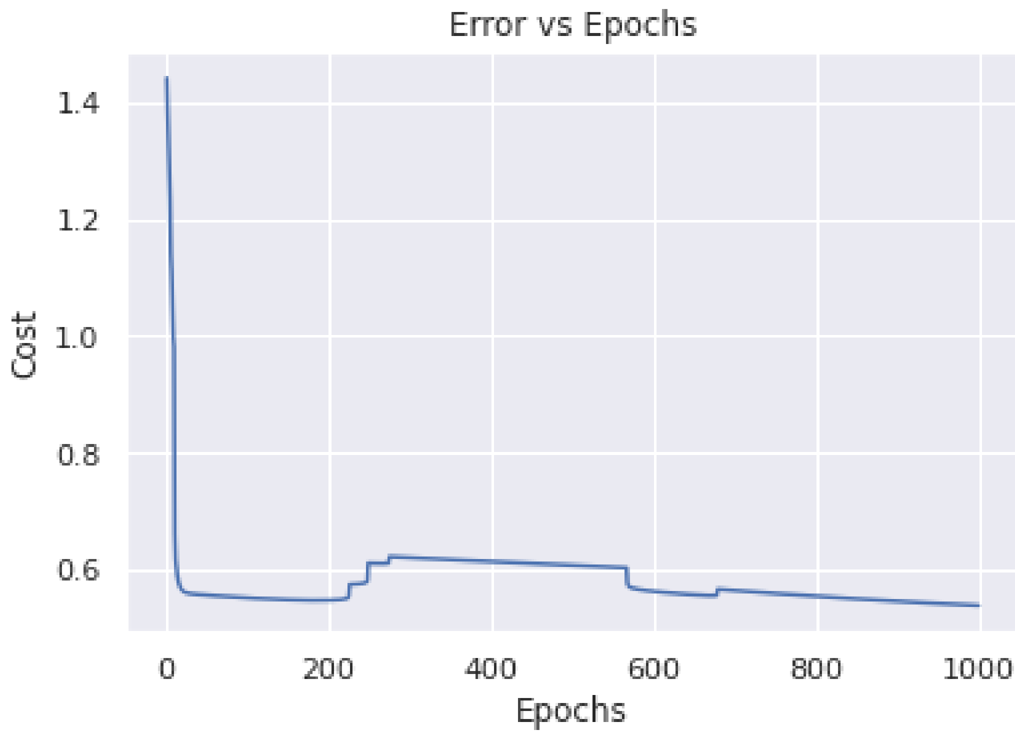
Validation Accuracy
The accuracy is: 78.93772893772893%
Confusion Matrix:



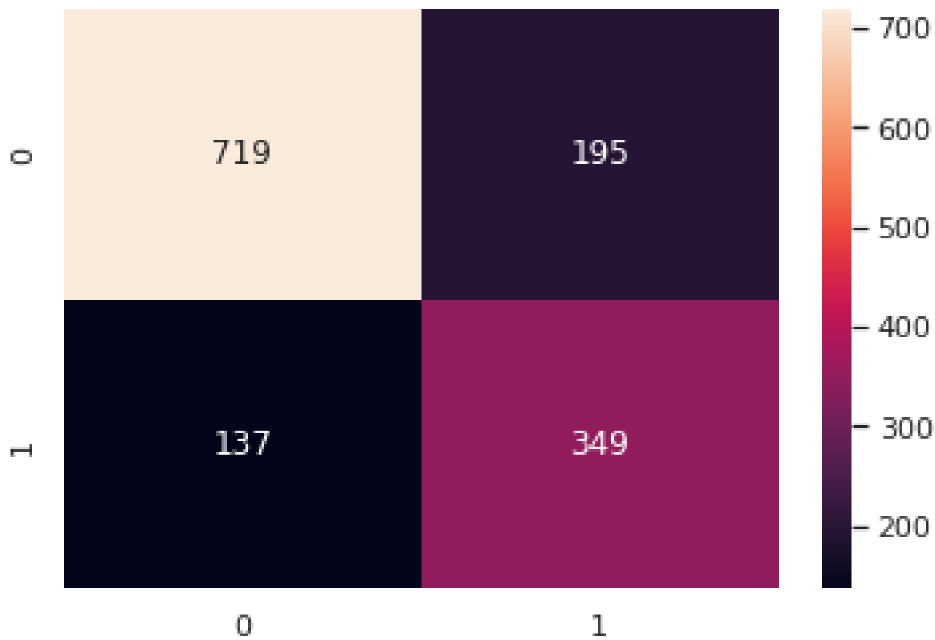
```
Test Accuracy
The accuracy is: 87.03703703703704%
Confusion Matrix:
```



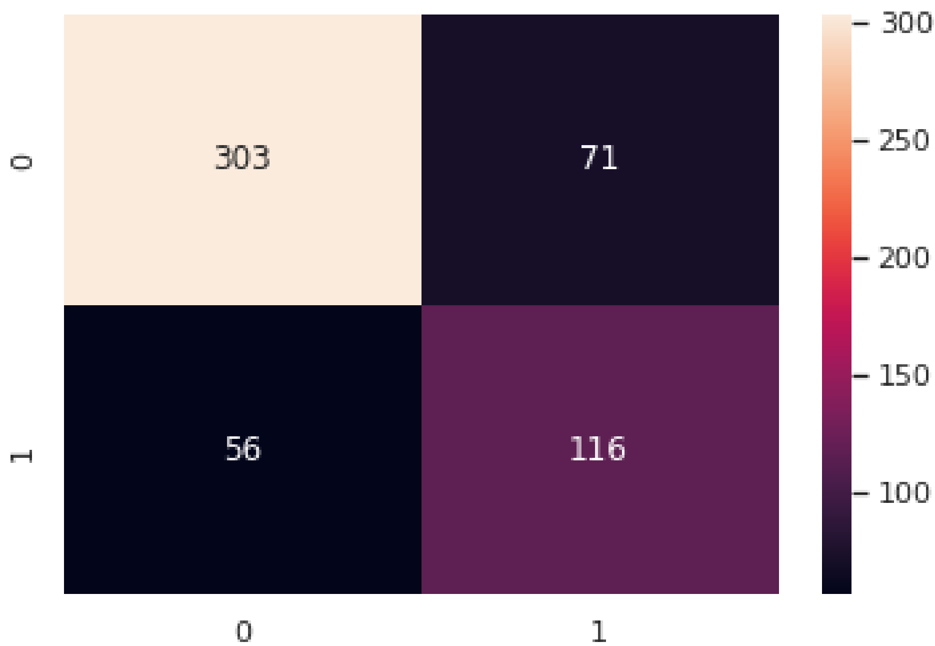

```
2 Layers with 3 Neurons
```



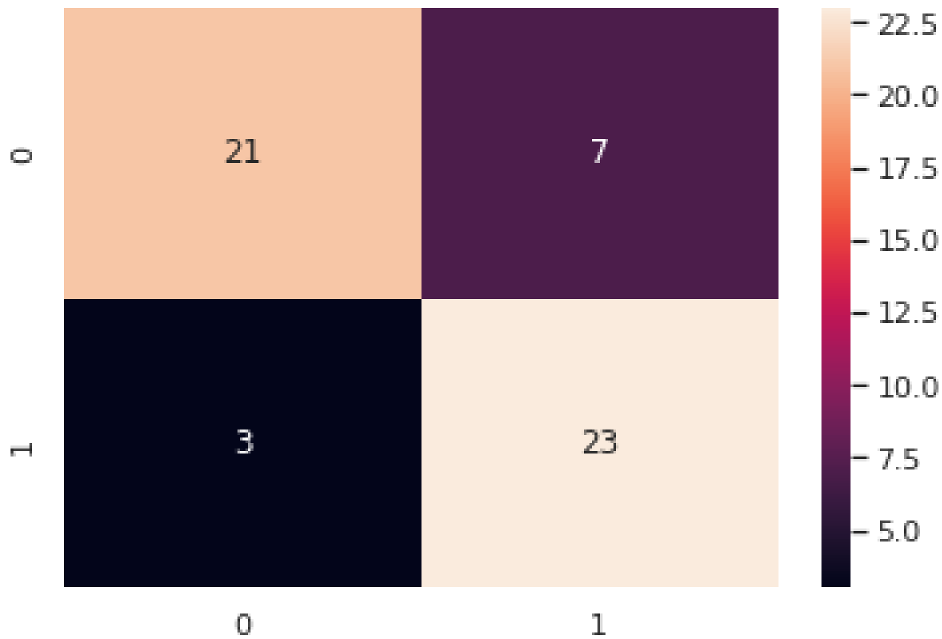

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 76.28571428571429%
Confusion Matrix:
```



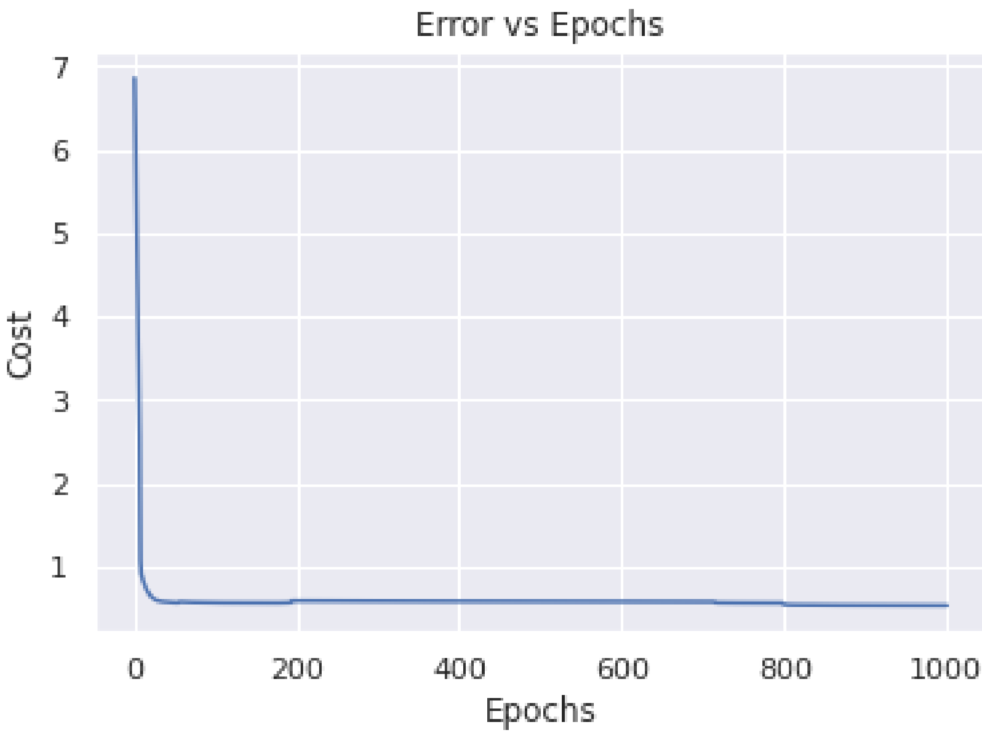

```
Validation Accuracy
The accuracy is: 76.73992673992674%
Confusion Matrix:
```



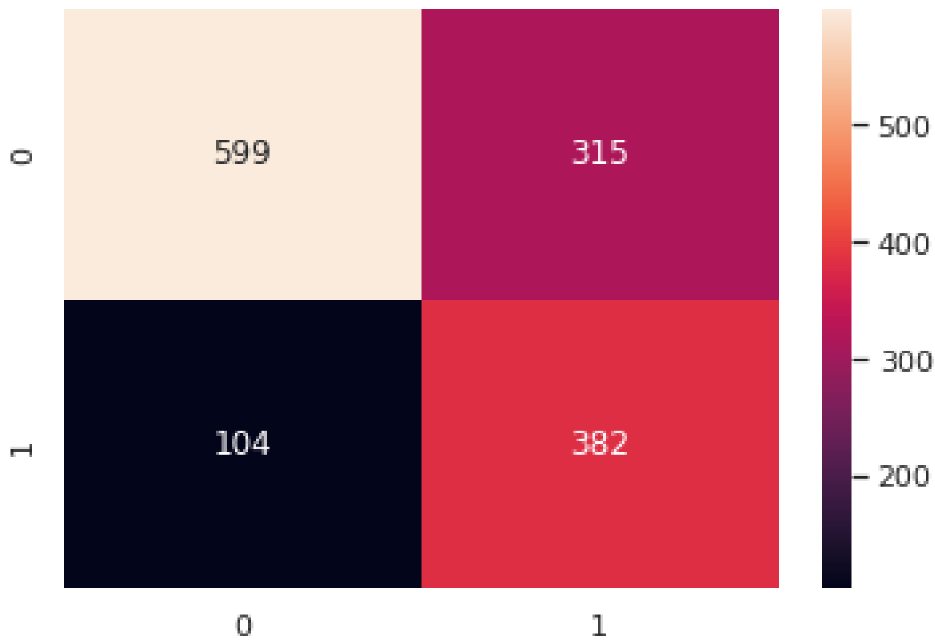
```
Test Accuracy
The accuracy is: 81.48148148148148%
Confusion Matrix:
```



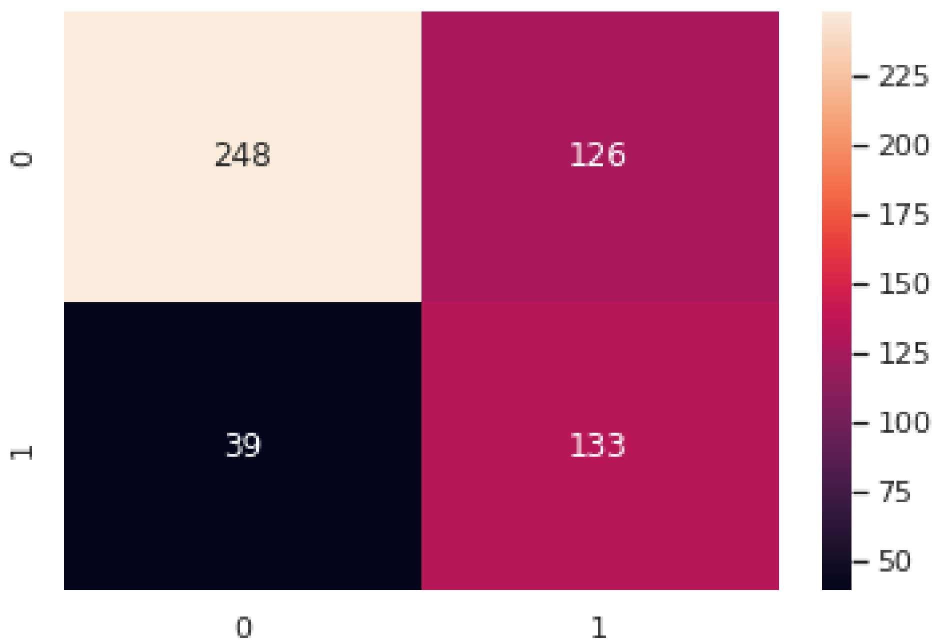

```
2 Layers with 18 Neurons
```



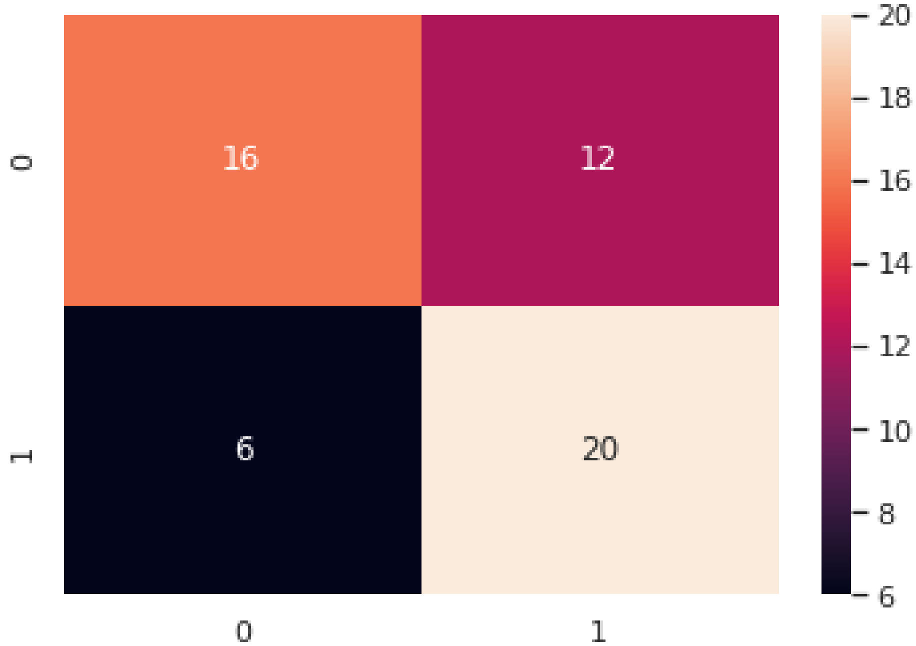

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 70.07142857142857%
Confusion Matrix:
```




```
Validation Accuracy
The accuracy is: 69.78021978021978%
Confusion Matrix:
```



```
Test Accuracy
The accuracy is: 66.66666666666666%
Confusion Matrix:
```



Hidden Layers	Neurons in layers	Epochs to train	Training Accuracy	Validation Accuracy	Testing Accuracy
1	3	1000	77.29	78.39	85.19
1	18	1000	78.57	78.94	87.04
2	3	1000	76.29	76.74	81.48
2	18	1000	70.07	69.78	66.67

4 Discussing results

[ ]:
```
print("Initial results with 2 layers with 2 neurons each")
print(InitialResults)
```

```
Initial results with 2 layers with 2 neurons each
+---------------------+-----------------+-------------------+-------------------
--+------------------+
| Activation Function | Epochs to train | Training Accuracy | Validation
Accuracy | Testing Accuracy |
+---------------------+-----------------+-------------------+-------------------
--+------------------+
|         ReLu        |       100       |       72.64       |        74.54
|      70.37       |
|       Sigmoid       |       100       |       65.29       |         68.5
|      51.85       |
|         Tanh        |       100       |       69.36       |        71.98
|      68.52       |
+---------------------+-----------------+-------------------+-------------------
--+------------------+
```

[ ]:
```
print("Relu activation function with different network sizes")
print(ReluGen)
```

```
Relu activation function with different network sizes
+---------------+-------------------+-----------------+-------------------+-----
---------------+------------------+
| Hidden Layers | Neurons in layers | Epochs to train | Training Accuracy |
Validation Accuracy | Testing Accuracy |
+---------------+-------------------+-----------------+-------------------+-----
---------------+------------------+
|       1       |         8         |       1000      |        76.0       |
76.56         |      74.07       |
|       1       |         4         |       1000      |       76.07       |
76.92         |      74.07       |
|       2       |         8         |        4        |       65.29       |
68.5         |      51.85       |
|       2       |         4         |        42       |       65.29       |
68.5         |      51.85       |
+---------------+-------------------+-----------------+-------------------+-----
---------------+------------------+
```

[ ]:
```
print("Sigmoid activation function with different network sizes")
print(SigmoidGen)
```

```
Sigmoid activation function with different network sizes
+---------------+-------------------+-----------------+-------------------+-----
---------------+------------------+
```

```
| Hidden Layers | Neurons in layers | Epochs to train | Training Accuracy |
Validation Accuracy | Testing Accuracy |
+---------------+-------------------+-----------------+-------------------+-----
----------------+------------------+
|       1       |         8         |       1000      |       76.57       |
77.84         |      83.33       |
|       1       |         9         |       1000      |       76.43       |
79.3          |      83.33       |
|       2       |         8         |       1000      |       65.29       |
68.5          |      51.85       |
|       2       |         9         |       1000      |       72.57       |
74.91         |      72.22       |
+---------------+-------------------+-----------------+-------------------+-----
----------------+------------------+
```

[ ]:

```
print("Tanh activation function with different network sizes")
print(TanhGen)
```

```
Tanh activation function with different network sizes
+---------------+-------------------+-----------------+-------------------+-----
----------------+------------------+
| Hidden Layers | Neurons in layers | Epochs to train | Training Accuracy |
Validation Accuracy | Testing Accuracy |
+---------------+-------------------+-----------------+-------------------+-----
----------------+------------------+
|       1       |         3         |       1000      |       77.29       |
78.39         |      85.19       |
|       1       |         18        |       1000      |       78.57       |
78.94         |      87.04       |
|       2       |         3         |       1000      |       76.29       |
76.74         |      81.48       |
|       2       |         18        |       1000      |       70.07       |
69.78         |      66.67       |
+---------------+-------------------+-----------------+-------------------+-----
----------------+------------------+
```

There has been a use of three activation functions namely: -Relu -Sigmoid -Tanh These have been used to examine the different effects that they have on the same data. When looking at the initial accuracies when using 2 hidden layers with 2 nodes each, the tanh activation function seems to out peform the other two for the training and validation, however the Relu and Sigmoid functions do the best when it comes to the hidden test data. Therefore implying that the relu and sigmoid functions are less fitted to the training data.

Thereafter, for each activation function we have looked at the effect of different network sizes. Each activation function has been provided with different network sizes that seem to provide optimal results.

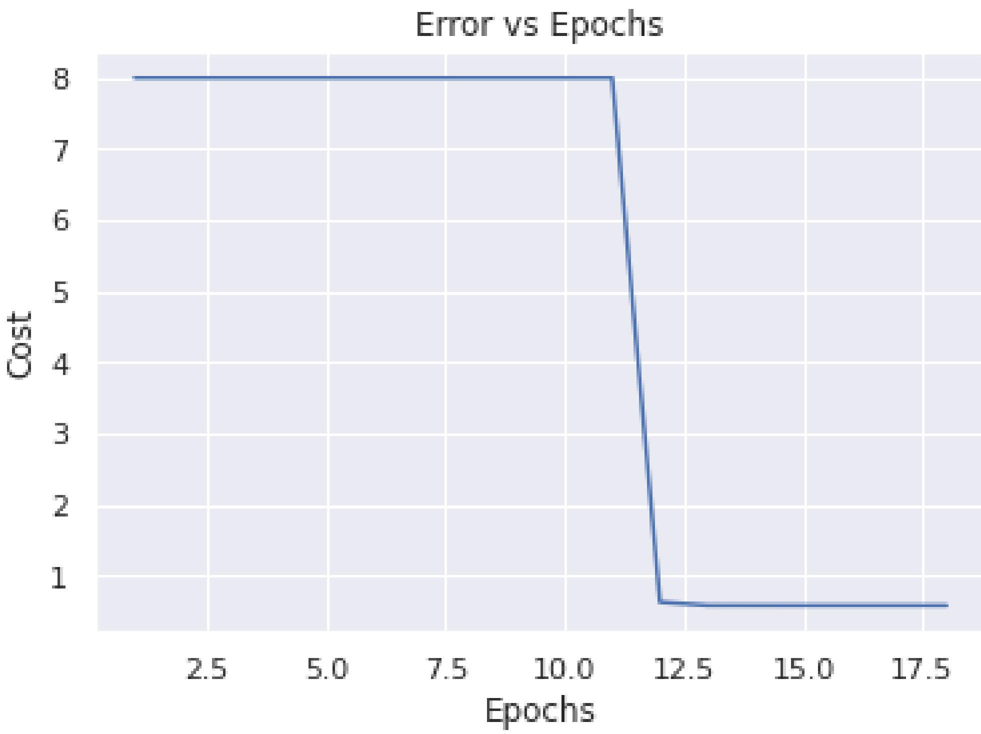
The Relu function with 1 hidden layer consisting of 8 nodes performed the best overall when averaging the accuracies over the training, validation and testing data.

The learning rate and regularization has been consistent throughout, so we shall now study the effect of these using the best performing network from the previous observations.

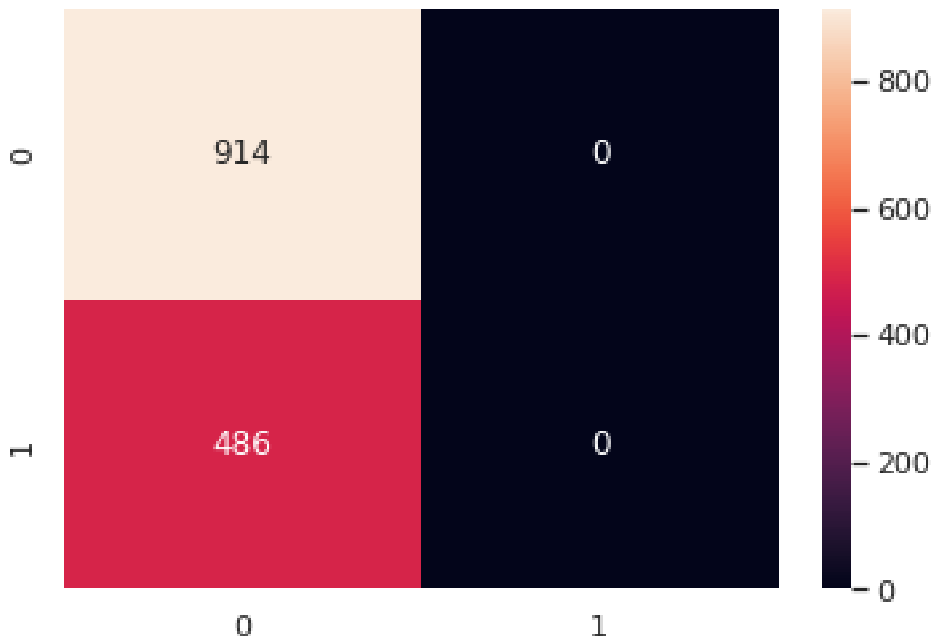
5 Different learning rates

[ ]:
```
LearningResults = PrettyTable(["Learning Rate","Epochs to train","Training␣
↪Accuracy","Validation Accuracy","Testing Accuracy"])

for i in range(10):
    print("Learning Rate:"+str(1/10**i))
    R18Weights, R18Epochs, R18Error, R18Activations =␣
↪FitNN(trainx,trainy,1,[8],1,["relu","relu"],1/10**i,0,1000)
    print("Number of epochs until convergence:"+str(R18Epochs)+"\n")
    print("Training Accuracy")
    R18_Acc=Predict(trainx,trainy,R18Weights,R18Activations)
    print("Validation Accuracy")
    R18_Acc_Val=Predict(validationx,validationy,R18Weights,R18Activations)
    print("Test Accuracy")
    R18_Acc_Test=Predict(testx,testy,R18Weights,R18Activations)
    LearningResults.add_row([1/10**i,R18Epochs,np.round(R18_Acc*100,2),np.
↪round(R18_Acc_Val*100,2),np.round(R18_Acc_Test*100,2)])


print(LearningResults)
```

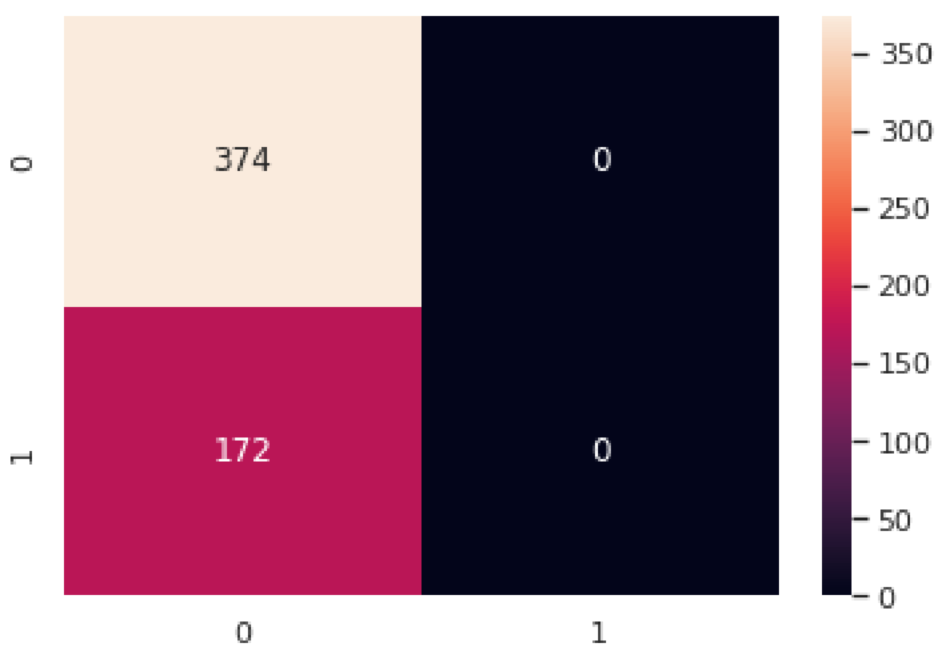
```
Learning Rate:1.0
```



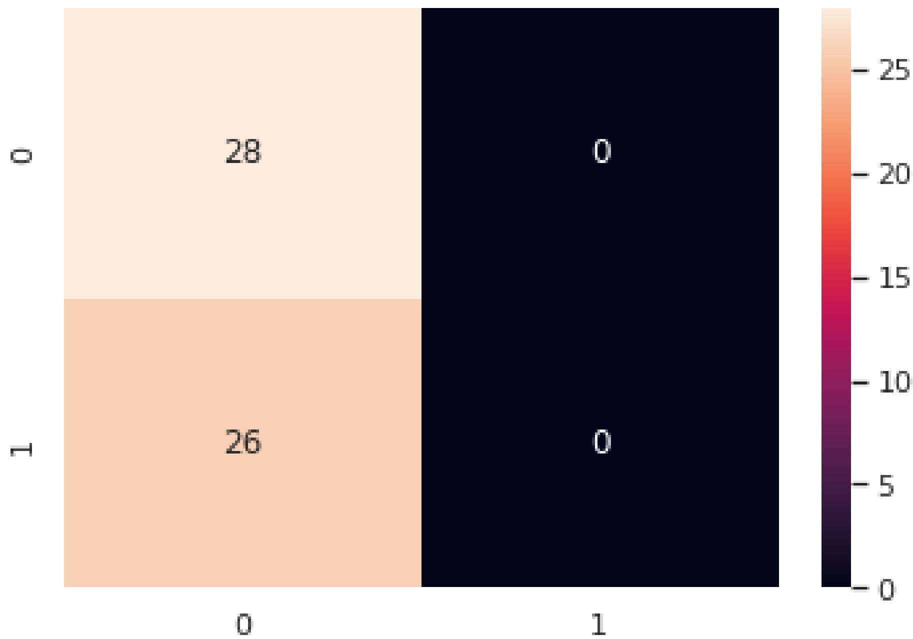

```
Number of epochs until convergence:18

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



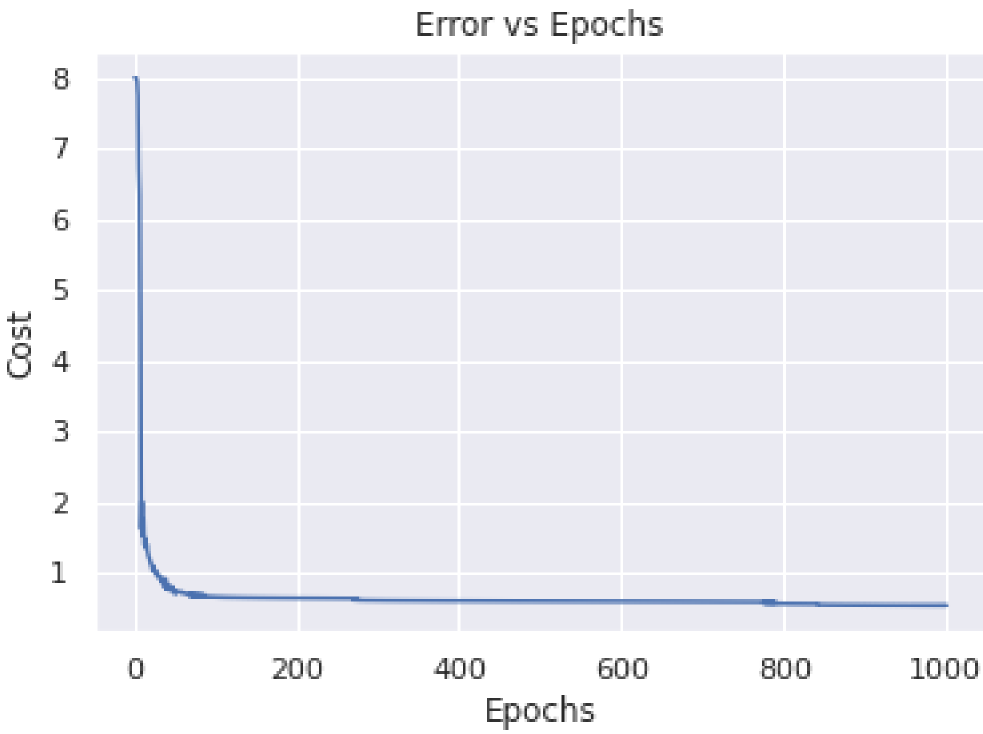

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



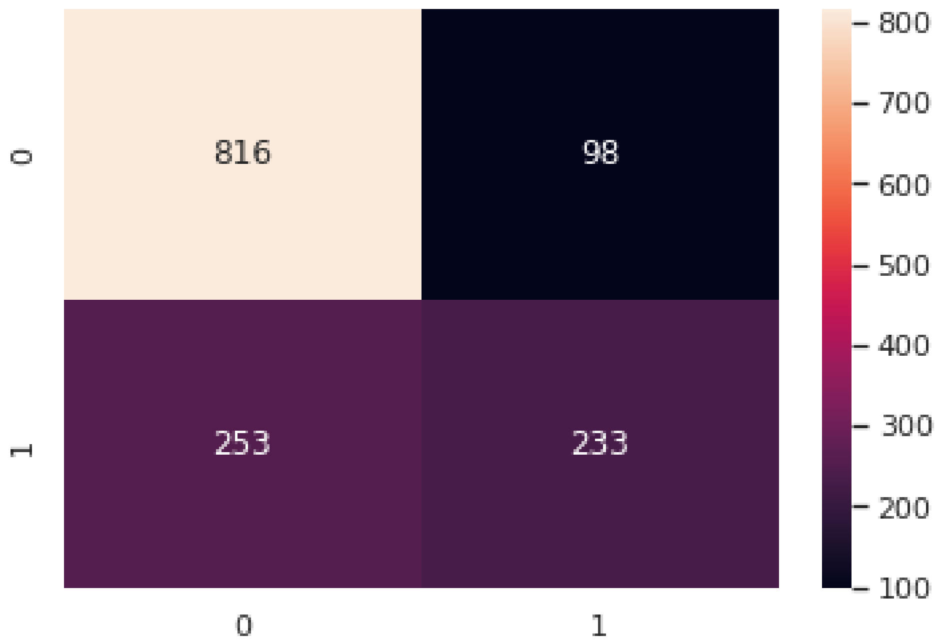
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



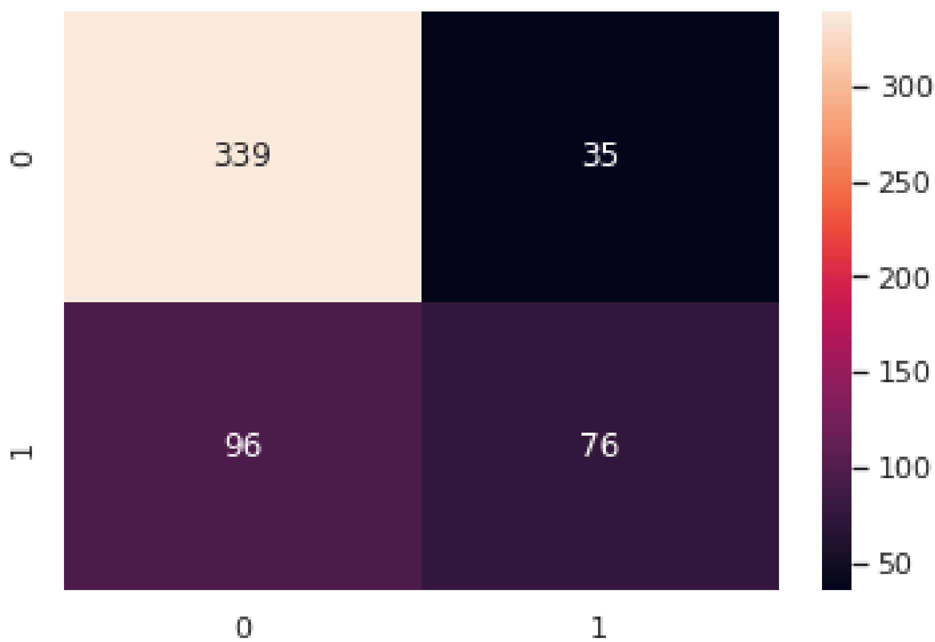

```
Learning Rate:0.1
```



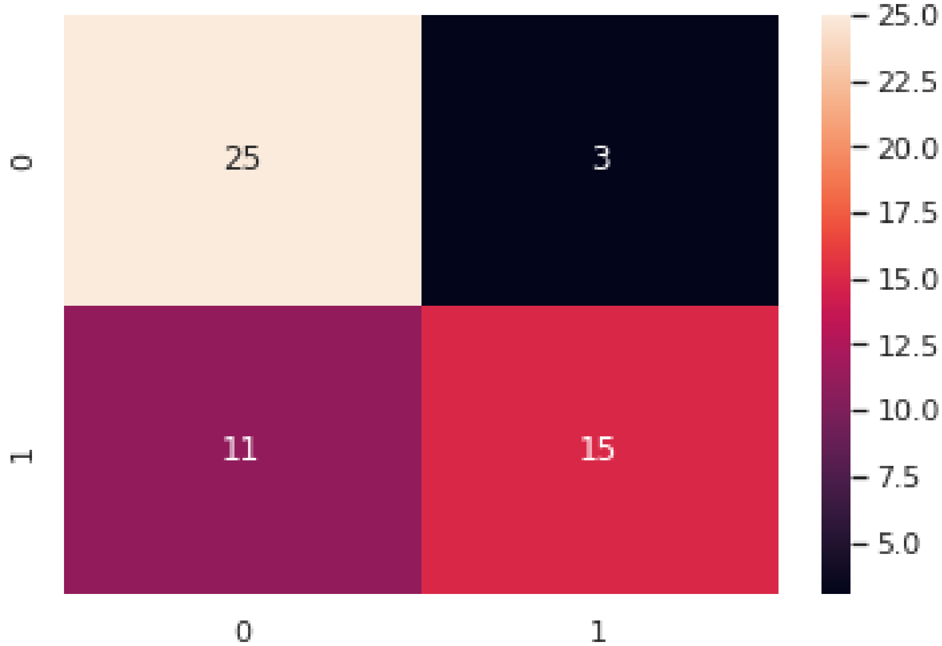

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 74.92857142857143%
Confusion Matrix:
```



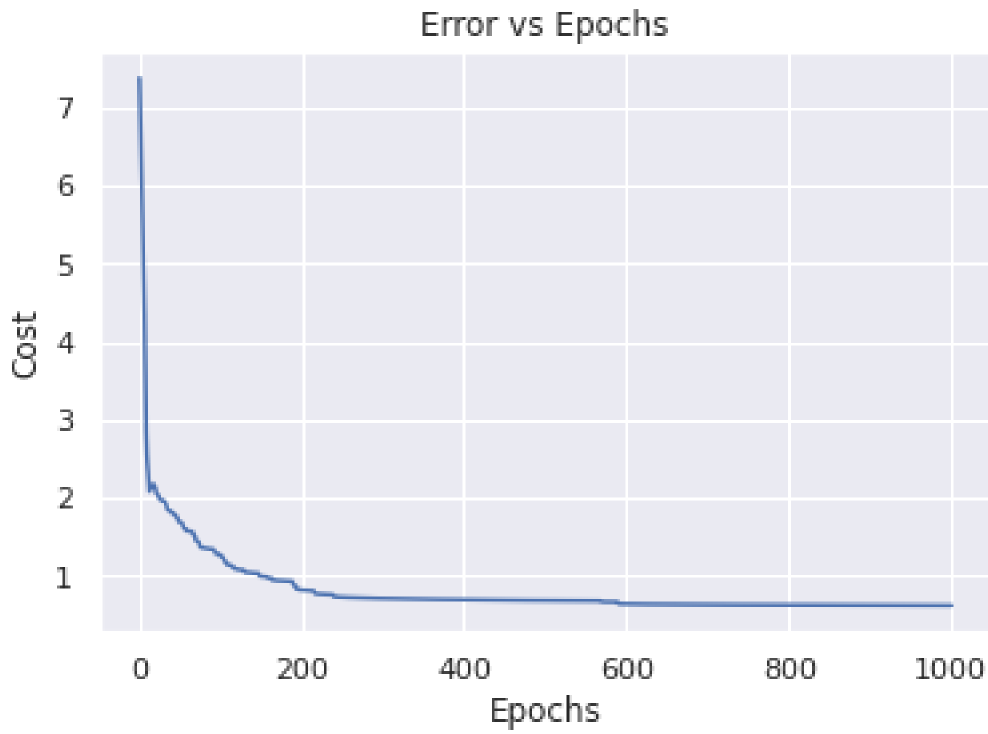
Validation Accuracy
The accuracy is: 76.007326007326%
Confusion Matrix:



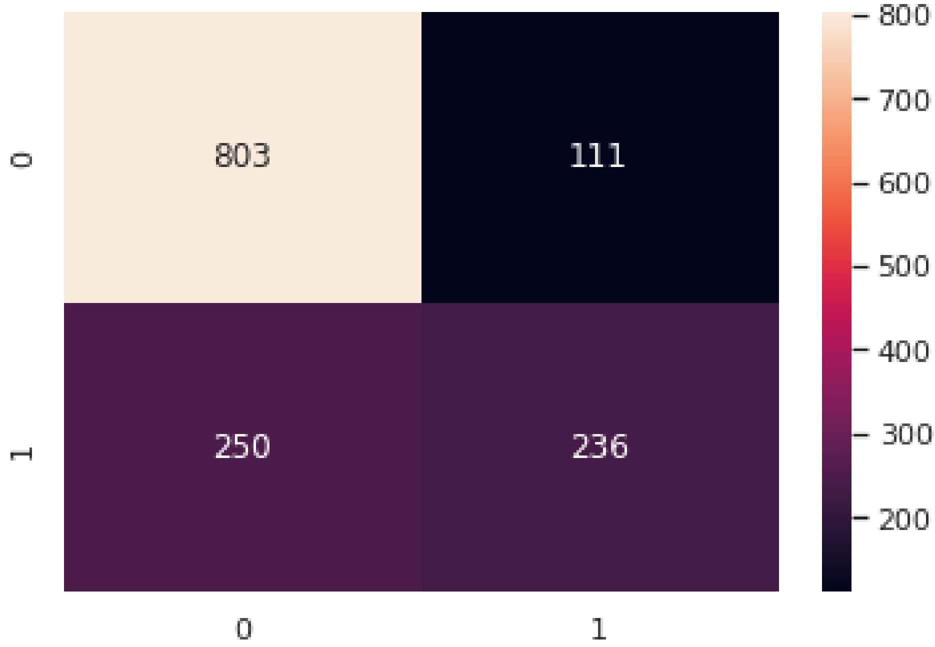
```
Test Accuracy
The accuracy is: 74.07407407407408%
Confusion Matrix:
```



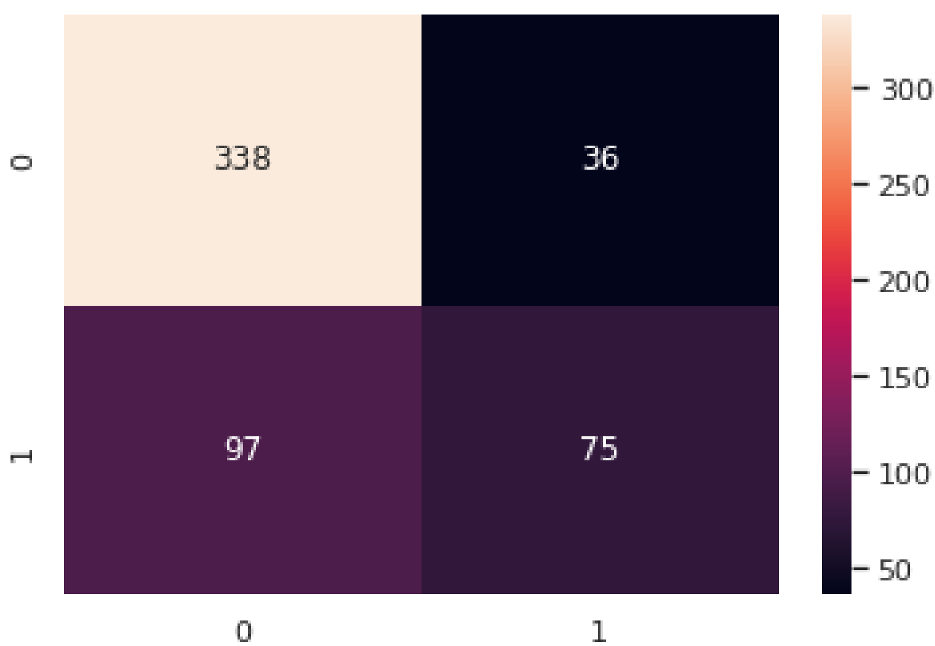

```
Learning Rate:0.01
```



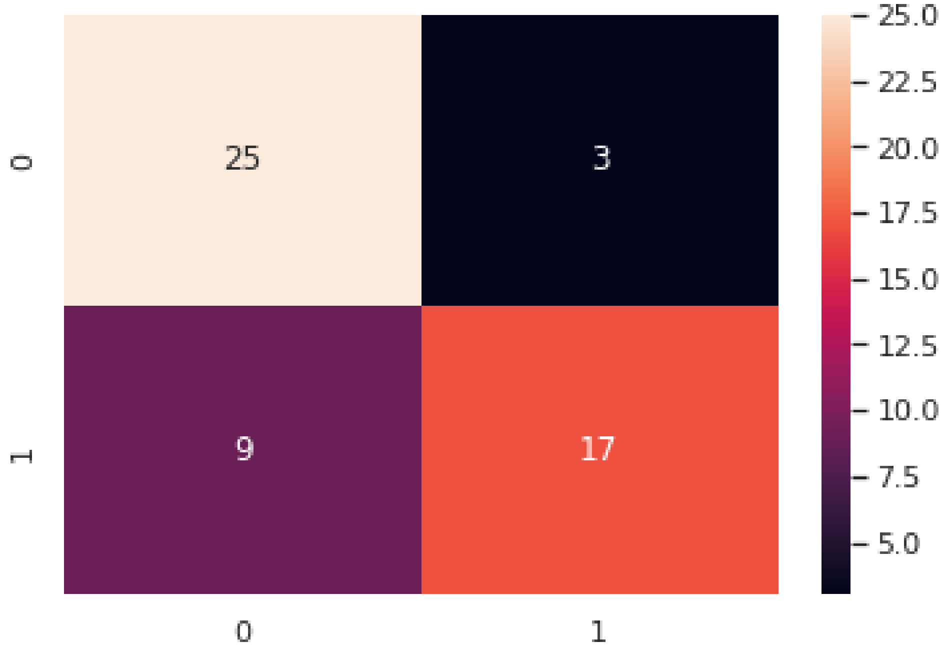

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 74.21428571428571%
Confusion Matrix:
```



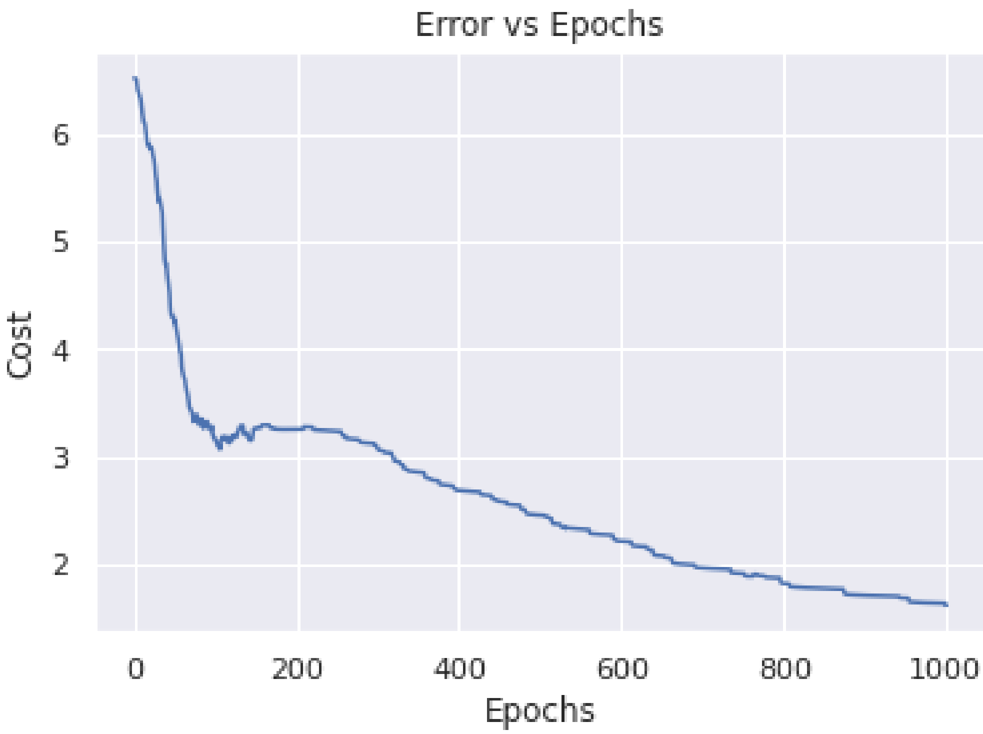

```
Validation Accuracy
The accuracy is: 75.64102564102564%
Confusion Matrix:
```



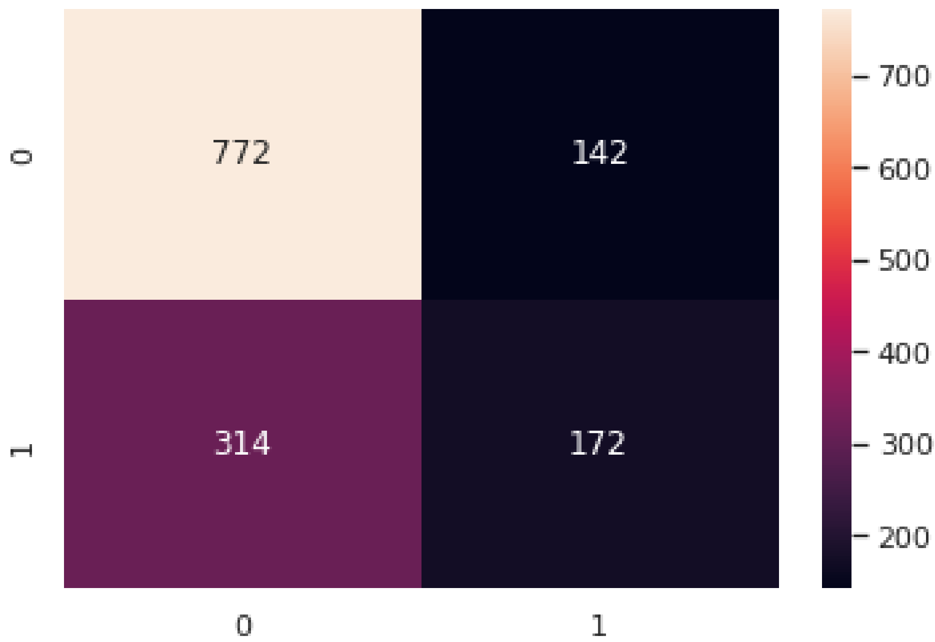
```
Test Accuracy
The accuracy is: 77.77777777777779%
Confusion Matrix:
```



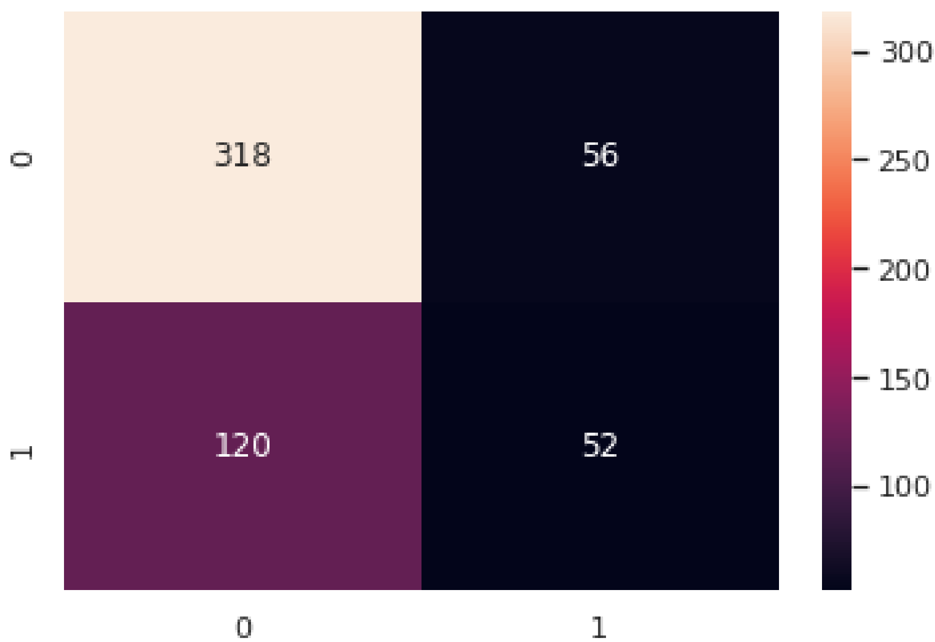

```
Learning Rate:0.001
```



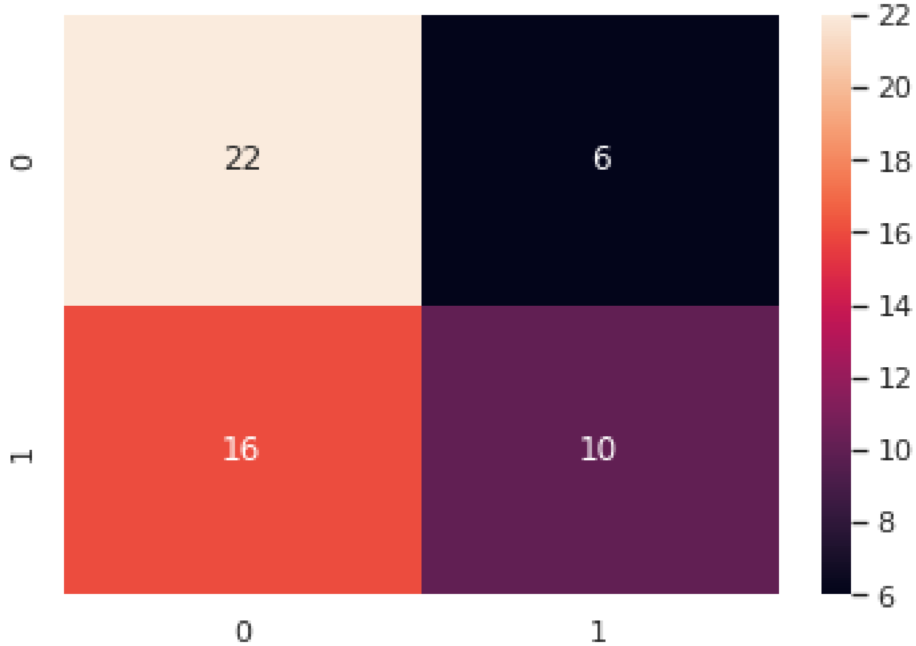

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 67.42857142857143%
Confusion Matrix:
```




```
Validation Accuracy
The accuracy is: 67.76556776556777%
Confusion Matrix:
```

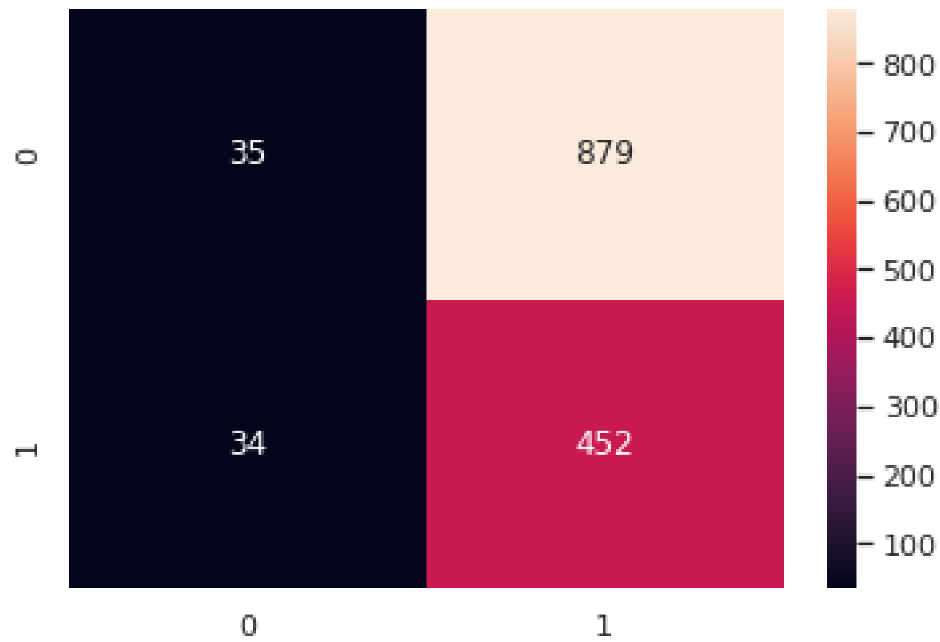


```
Test Accuracy
The accuracy is: 59.25925925925925%
Confusion Matrix:
```

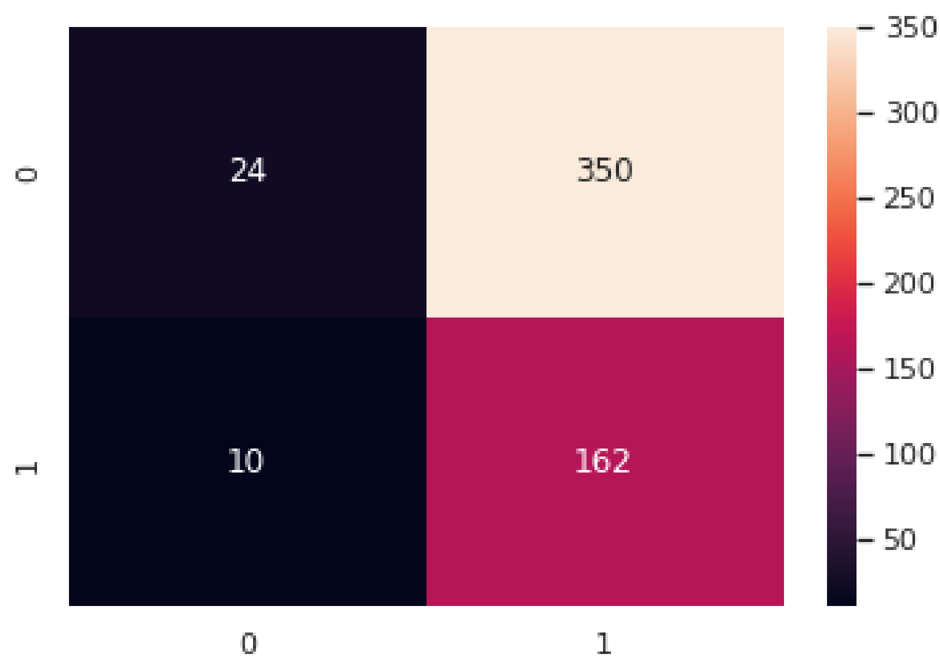



```
Learning Rate:0.0001
```

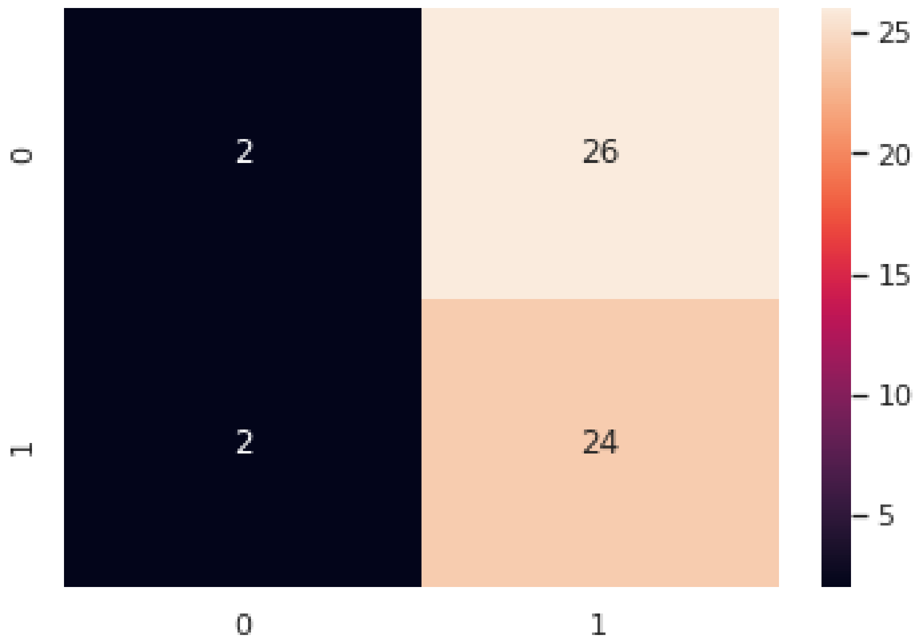

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 34.785714285714285%
Confusion Matrix:
```



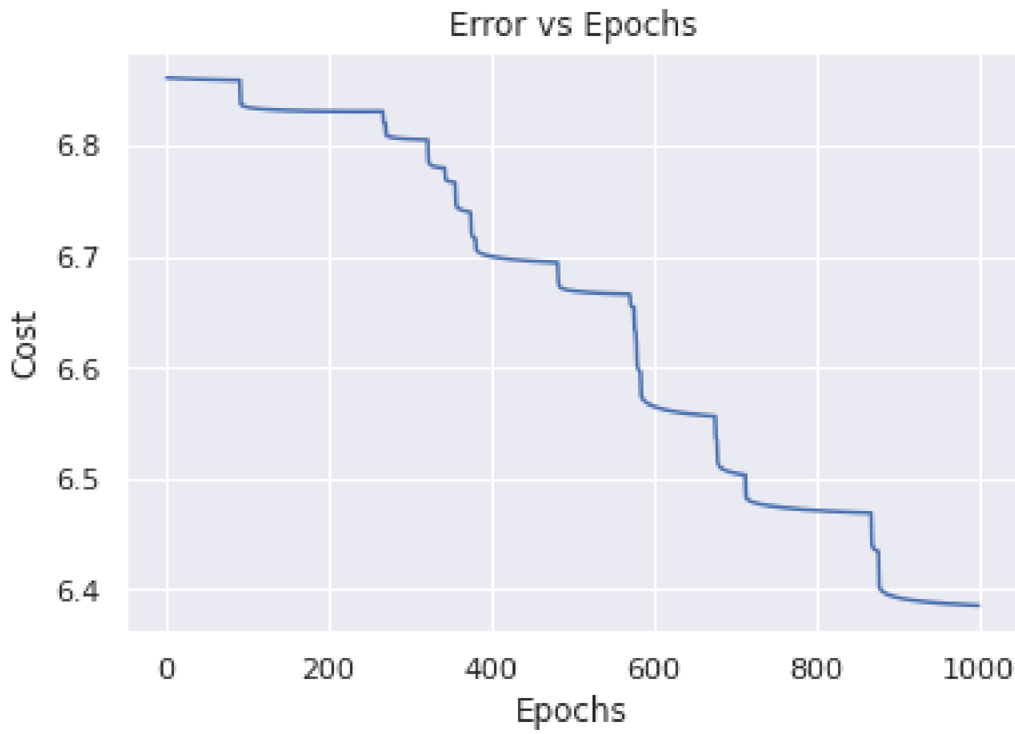

```
Validation Accuracy
The accuracy is: 34.065934065934066%
Confusion Matrix:
```



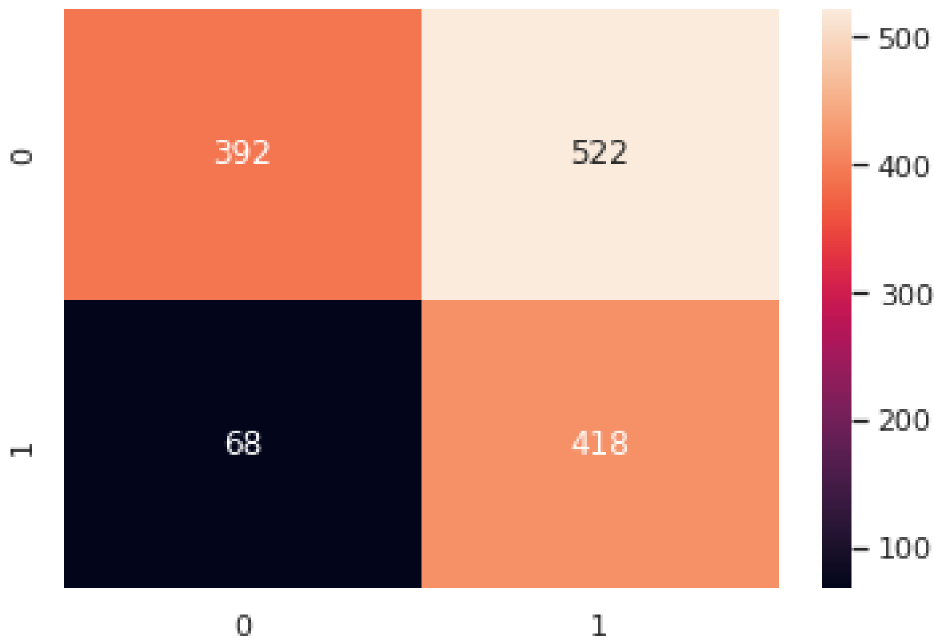
Test Accuracy
The accuracy is: 48.148148148148145%
Confusion Matrix:



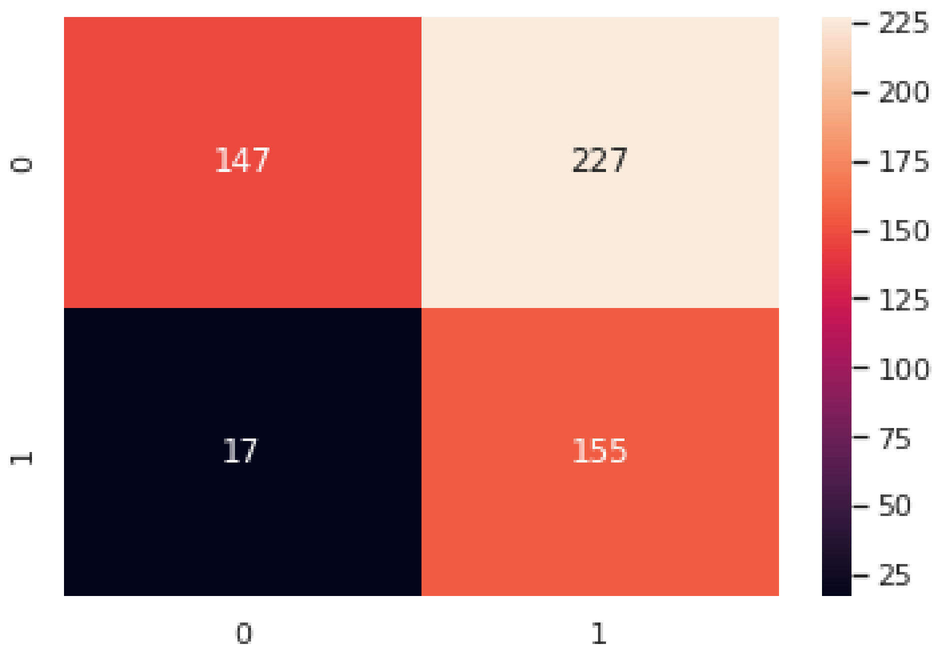
Learning Rate:1e-05



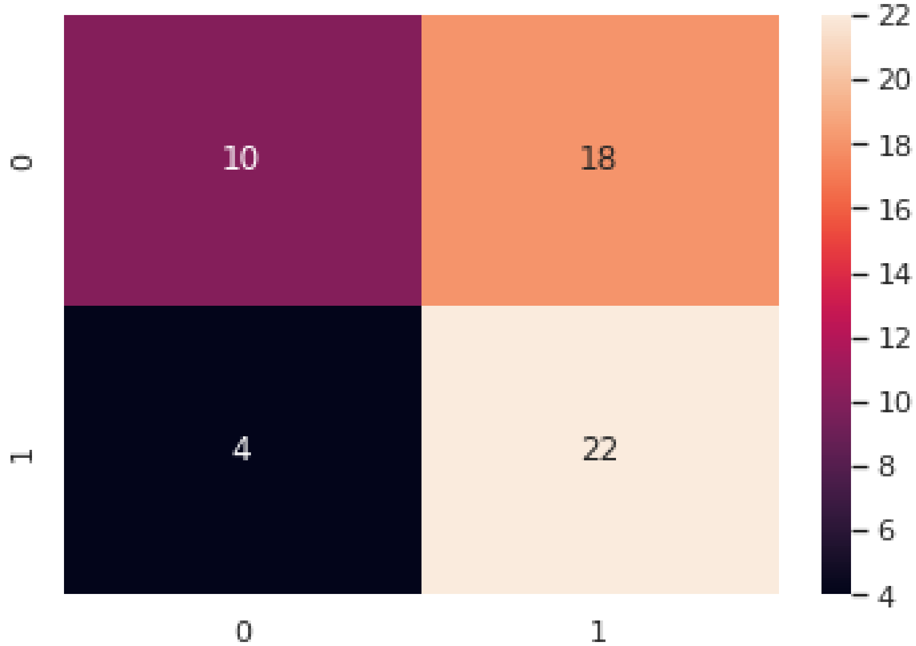

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 57.85714285714286%
Confusion Matrix:
```



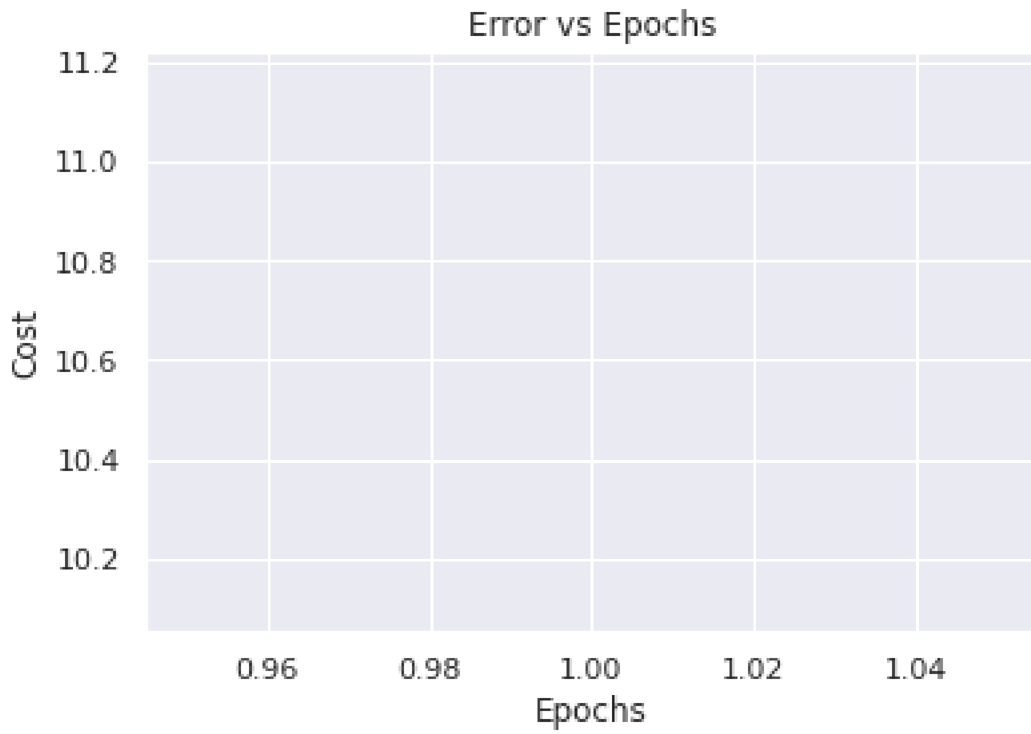
Validation Accuracy
The accuracy is: 55.311355311355314%
Confusion Matrix:



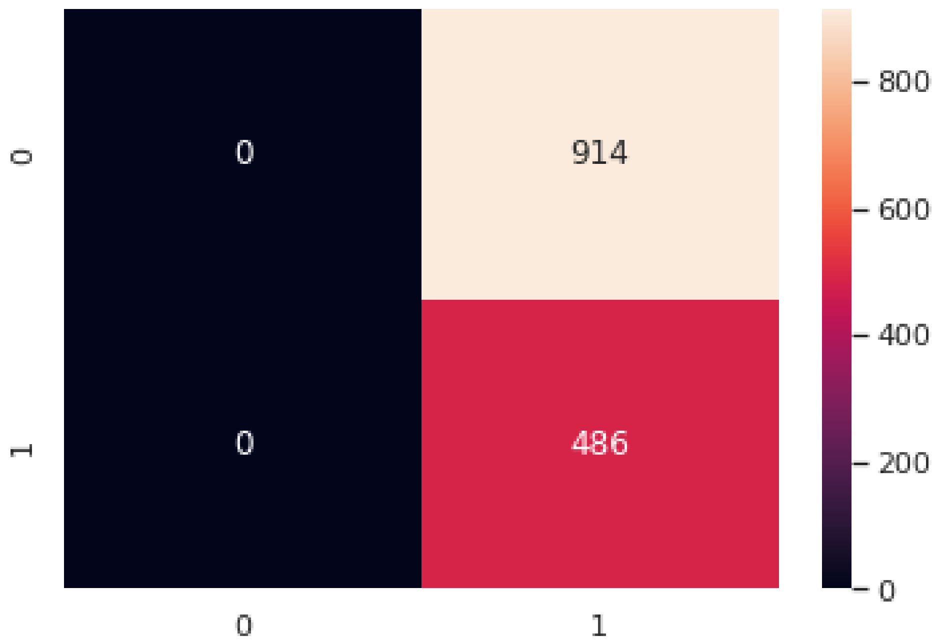
```
Test Accuracy
The accuracy is: 59.25925925925925%
Confusion Matrix:
```



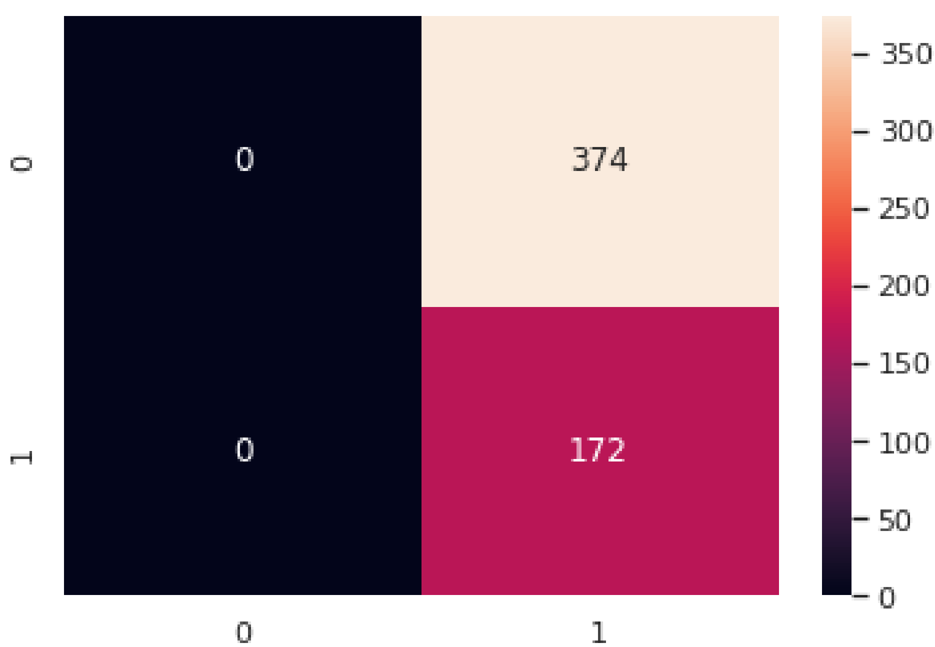

```
Learning Rate:1e-06
```



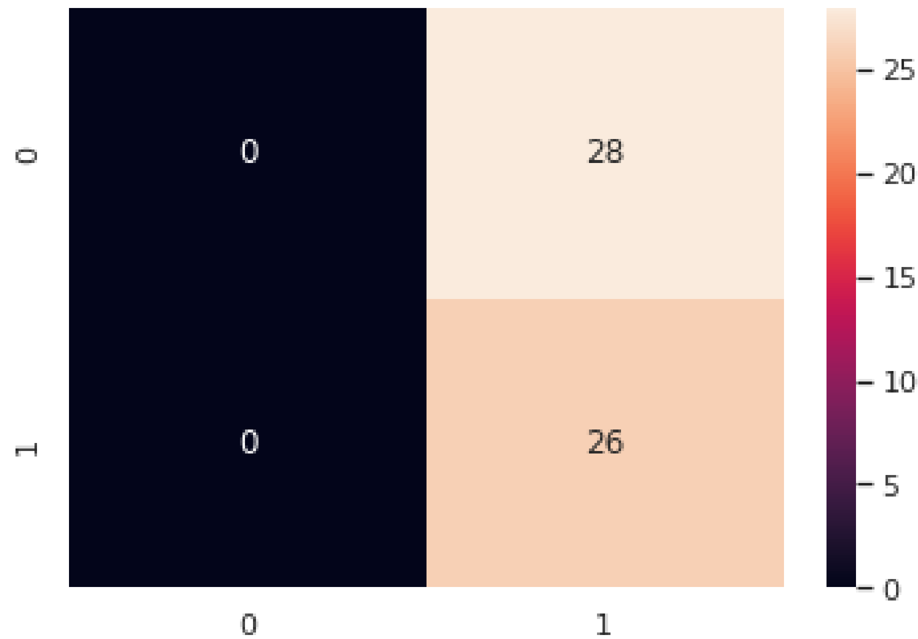

```
Number of epochs until convergence:1

Training Accuracy
The accuracy is: 34.714285714285715%
Confusion Matrix:
```



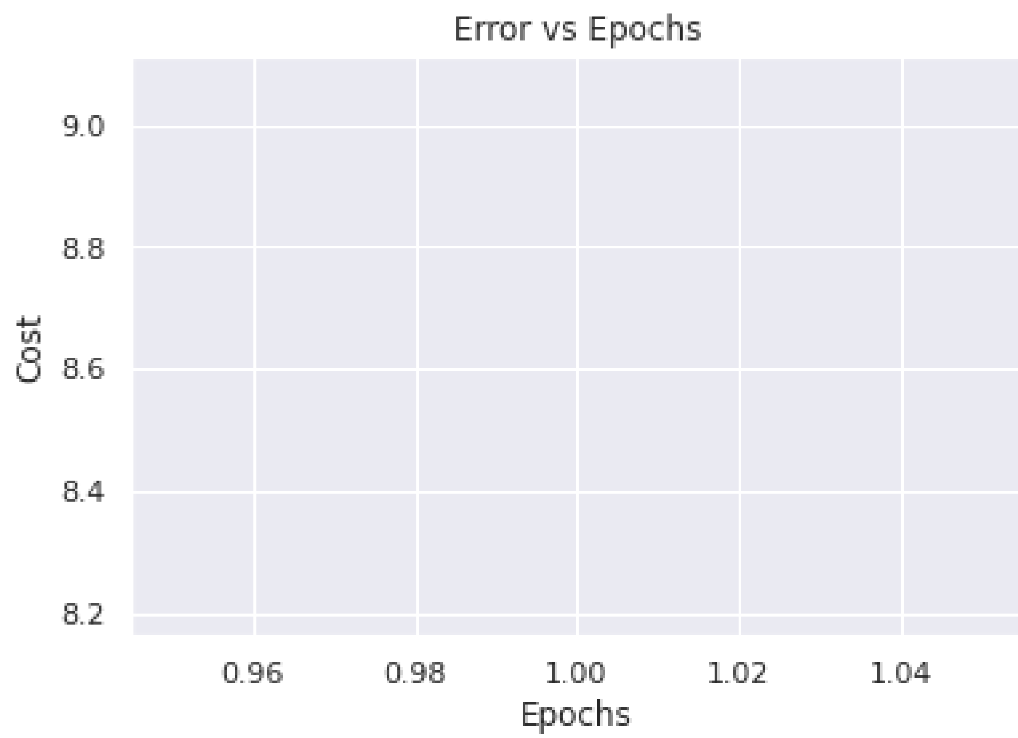

```
Validation Accuracy
The accuracy is: 31.5018315018315%
Confusion Matrix:
```



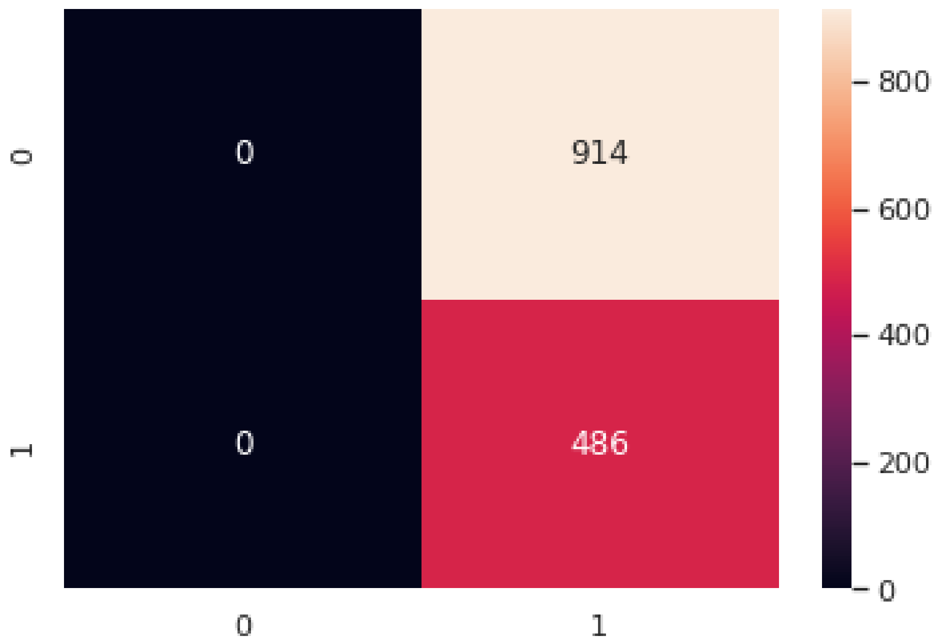
```
Test Accuracy
The accuracy is: 48.148148148148145%
Confusion Matrix:
```



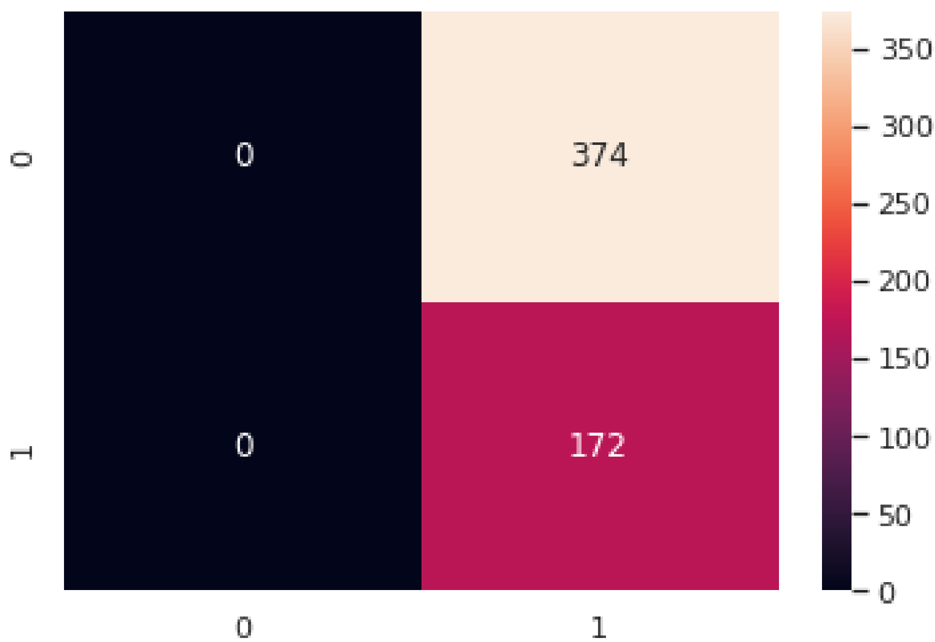

```
Learning Rate:1e-07
```



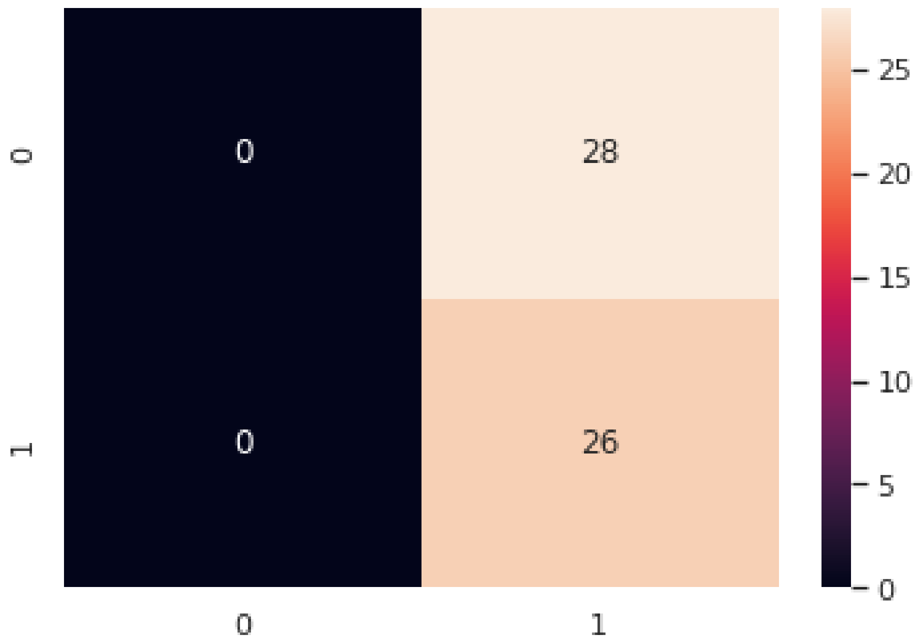

```
Number of epochs until convergence:1

Training Accuracy
The accuracy is: 34.714285714285715%
Confusion Matrix:
```




```
Validation Accuracy
The accuracy is: 31.5018315018315%
Confusion Matrix:
```

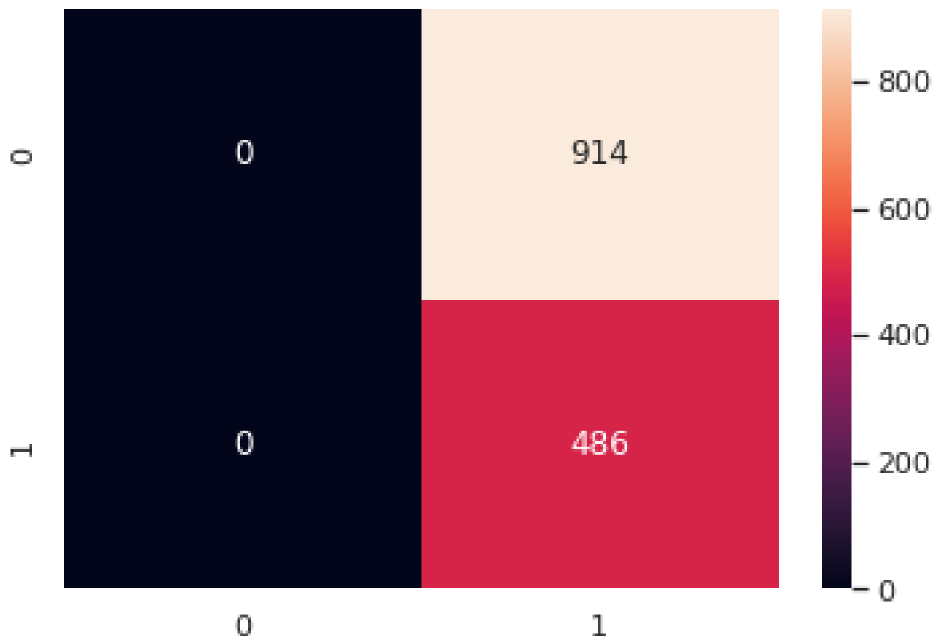


```
Test Accuracy
The accuracy is: 48.148148148148145%
Confusion Matrix:
```

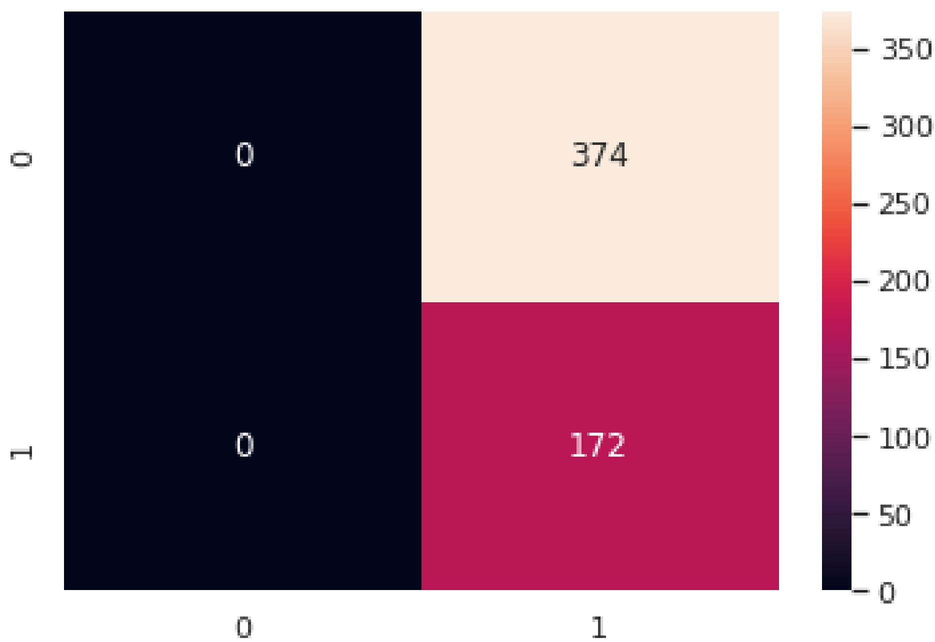



```
Learning Rate:1e-08
```

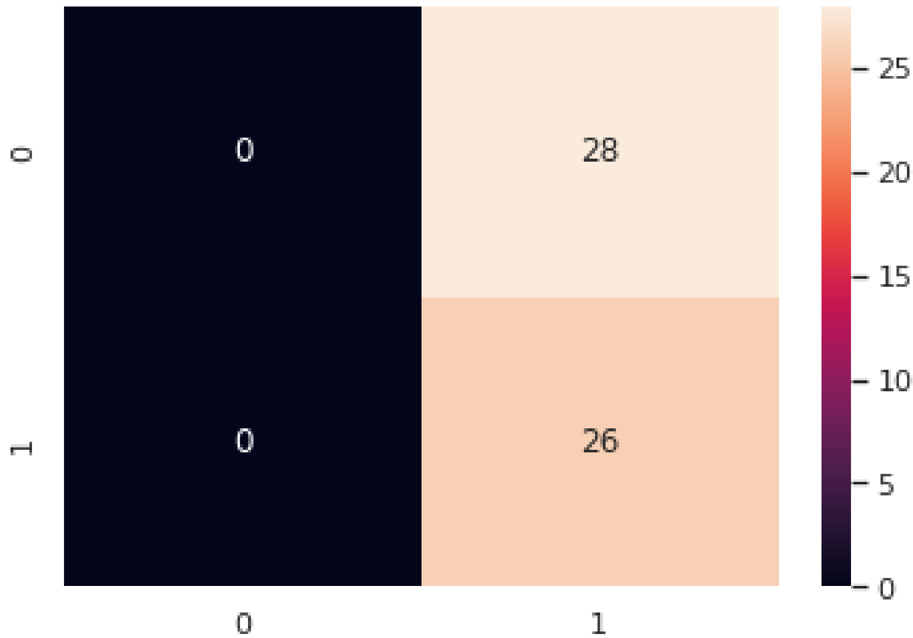

```
Number of epochs until convergence:1

Training Accuracy
The accuracy is: 34.714285714285715%
Confusion Matrix:
```



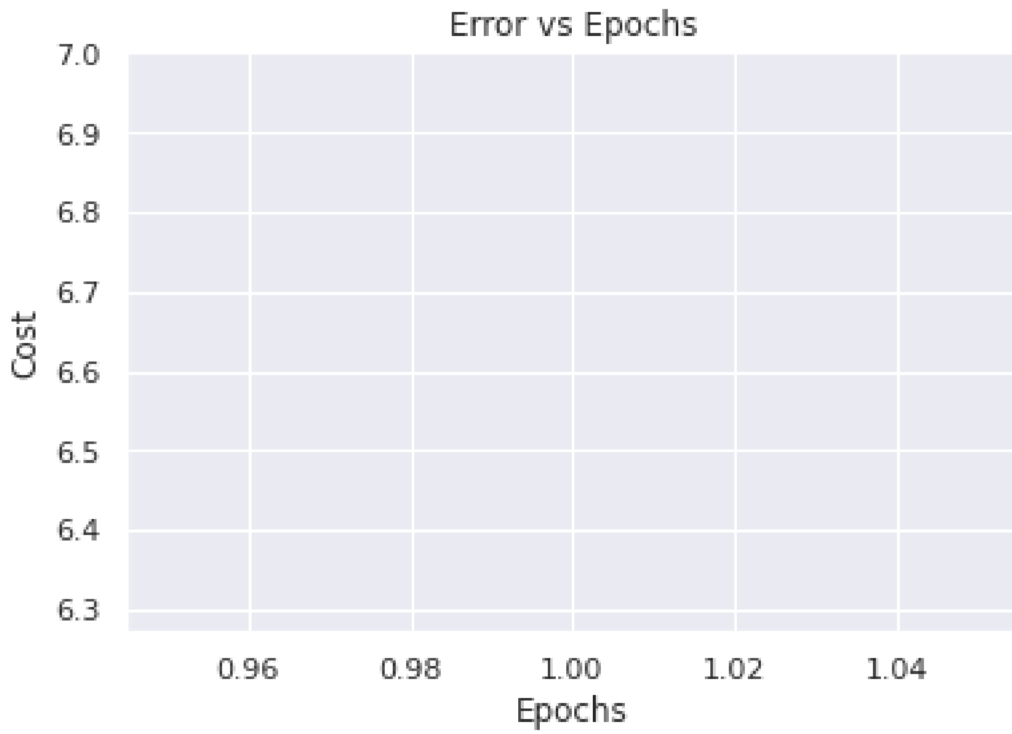
Validation Accuracy
The accuracy is: 31.5018315018315%
Confusion Matrix:



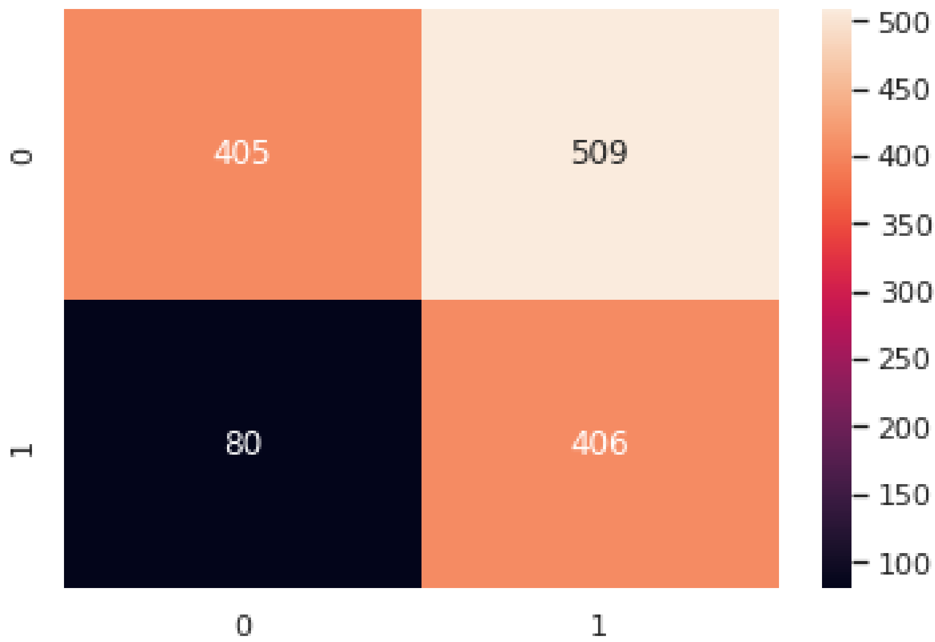
```
Test Accuracy
The accuracy is: 48.148148148148145%
Confusion Matrix:
```



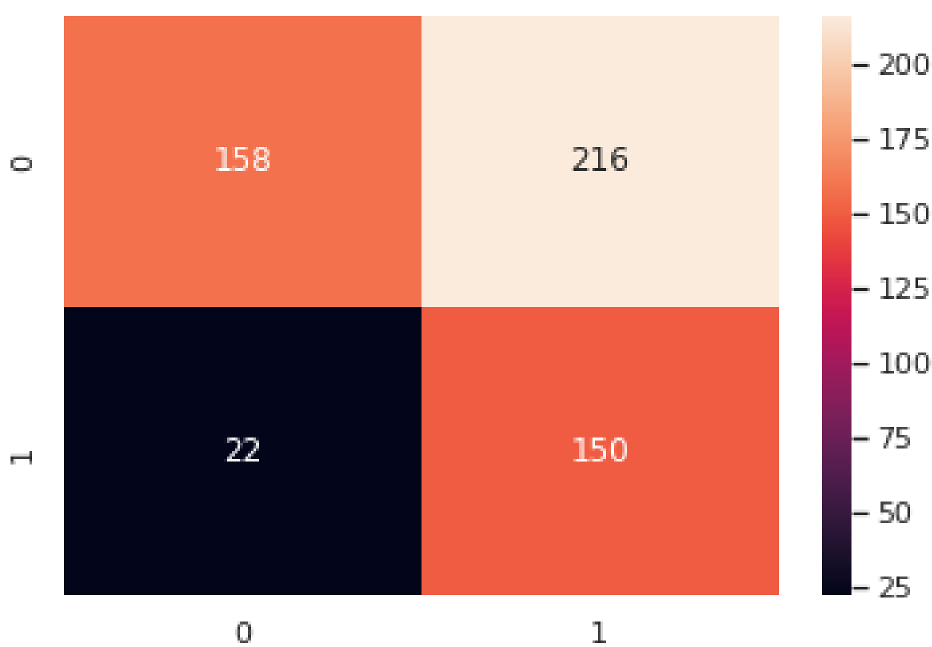

```
Learning Rate:1e-09
```



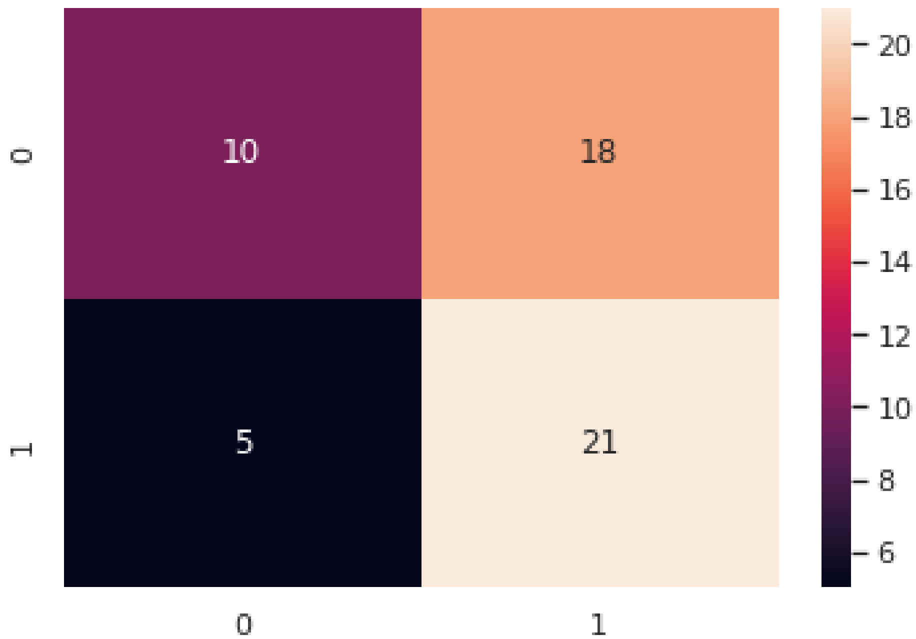

```
Number of epochs until convergence:1

Training Accuracy
The accuracy is: 57.92857142857143%
Confusion Matrix:
```




```
Validation Accuracy
The accuracy is: 56.41025641025641%
Confusion Matrix:
```



Test Accuracy
The accuracy is: 57.407407407407405%
Confusion Matrix:



Learning Rate	Epochs to train	Training Accuracy	Validation Accuracy	Testing Accuracy
1.0	18	65.29	68.5	51.85
0.1	1000	74.93	76.01	74.07
0.01	1000	74.21	75.64	77.78
0.001	1000	67.43	67.77	59.26
0.0001	1000	34.79	34.07	48.15
1e-05	1000	57.86	55.31	59.26
1e-06	1	34.71	31.5	48.15
1e-07	1	34.71	31.5	48.15

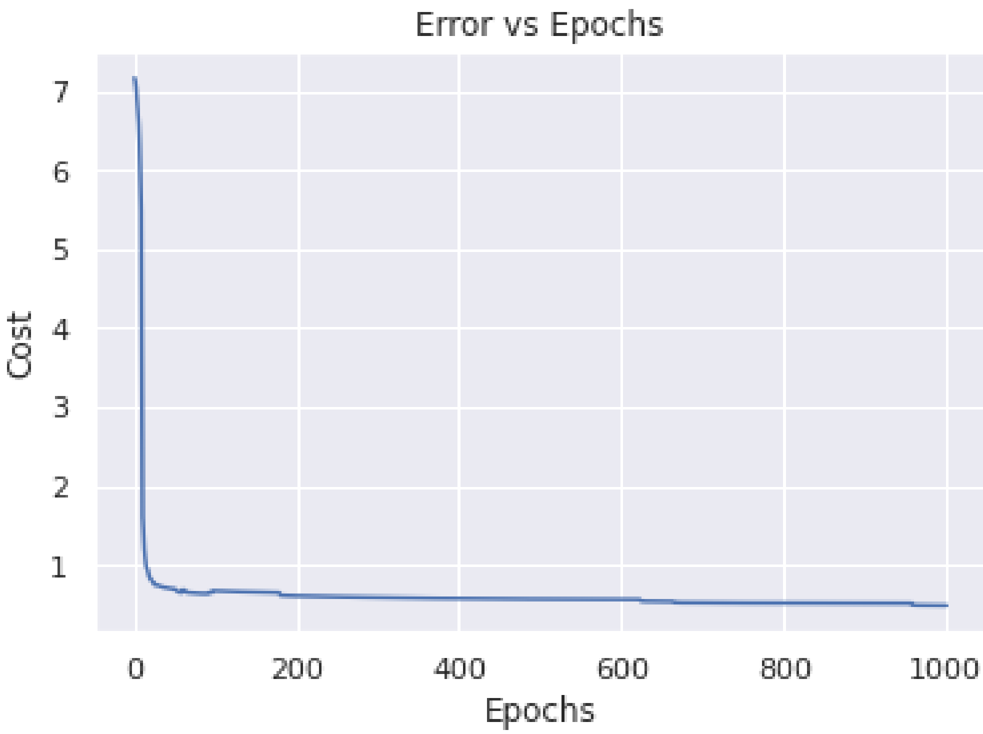
```
|      1e-08      |         1         |        34.71        |          31.5          |
48.15       |
|      1e-09      |         1         |        57.93        |         56.41          |
57.41       |
+----------------+------------------+--------------------+----------------------+---
---------------+
```

As seen by the table above, the learning rates of 0.1 and 0.01 produce the best results. Once the learning rate is 0.000001 or smaller, the results converge after 1 epoch, due to the fact that the learning rate is too low.

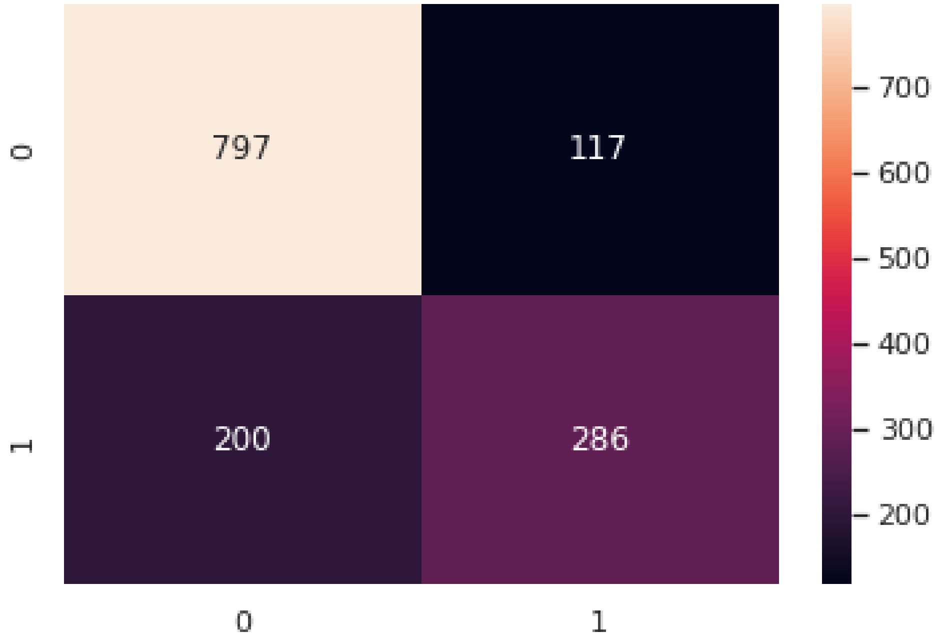
6 Different Regularization

[ ]:
```
RegResults = PrettyTable(["Regularization","Epochs to train","Training␣
↪Accuracy","Validation Accuracy","Testing Accuracy"])

for i in range(20):
    print("Regularization:"+str(0.1*i))
    R18Weights, R18Epochs, R18Error, R18Activations =␣
↪FitNN(trainx,trainy,1,[8],1,["relu","relu"],0.1,0.1*i,1000)
    print("Number of epochs until convergence:"+str(R18Epochs)+"\n")
    print("Training Accuracy")
    R18_Acc=Predict(trainx,trainy,R18Weights,R18Activations)
    print("Validation Accuracy")
    R18_Acc_Val=Predict(validationx,validationy,R18Weights,R18Activations)
    print("Test Accuracy")
    R18_Acc_Test=Predict(testx,testy,R18Weights,R18Activations)
    RegResults.add_row([0.1*i,R18Epochs,np.round(R18_Acc*100,2),np.
↪round(R18_Acc_Val*100,2),np.round(R18_Acc_Test*100,2)])


print(RegResults)
```

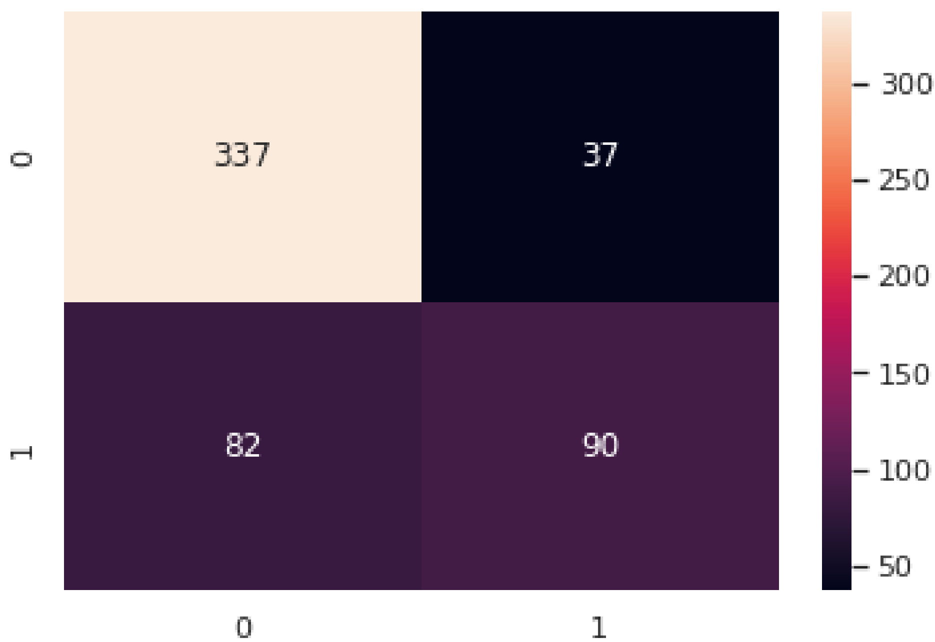
```
Regularization:0.0
```



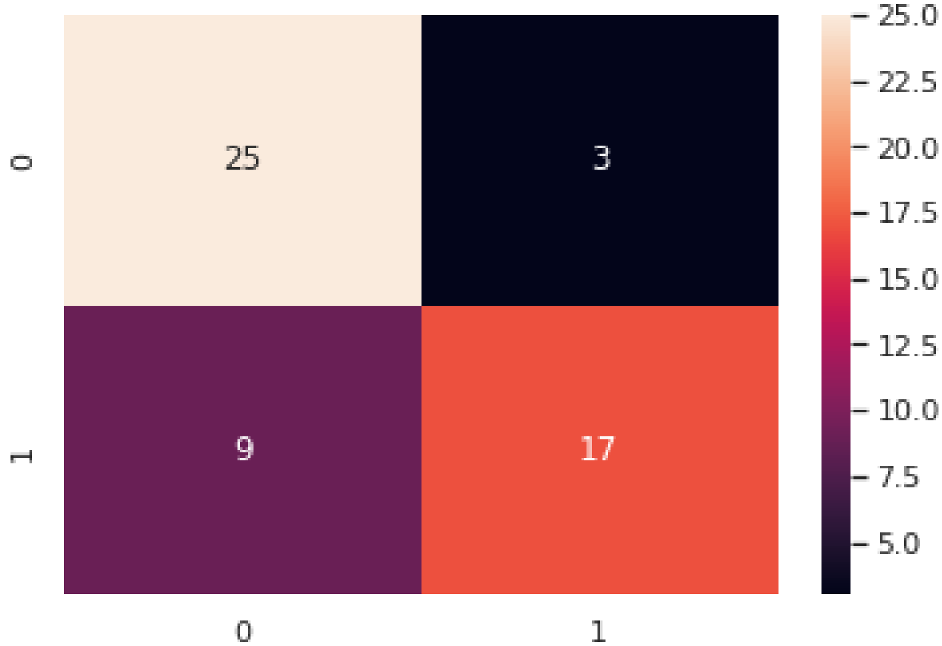

```
Number of epochs until convergence:1000

Training Accuracy
The accuracy is: 77.35714285714286%
Confusion Matrix:
```



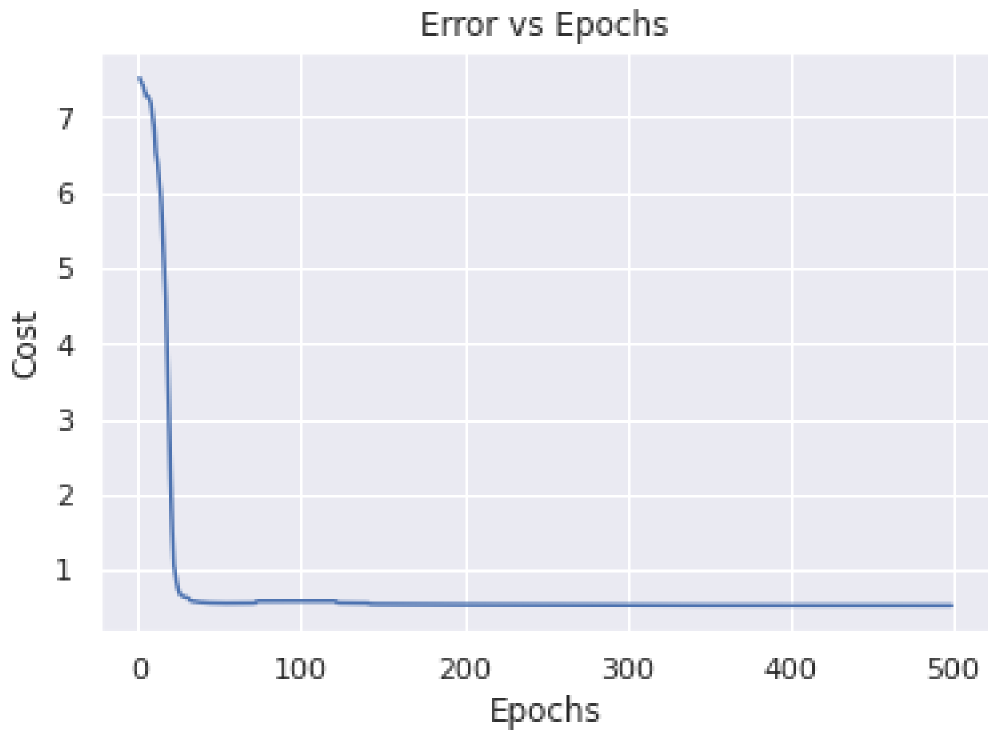

```
Validation Accuracy
The accuracy is: 78.2051282051282%
Confusion Matrix:
```



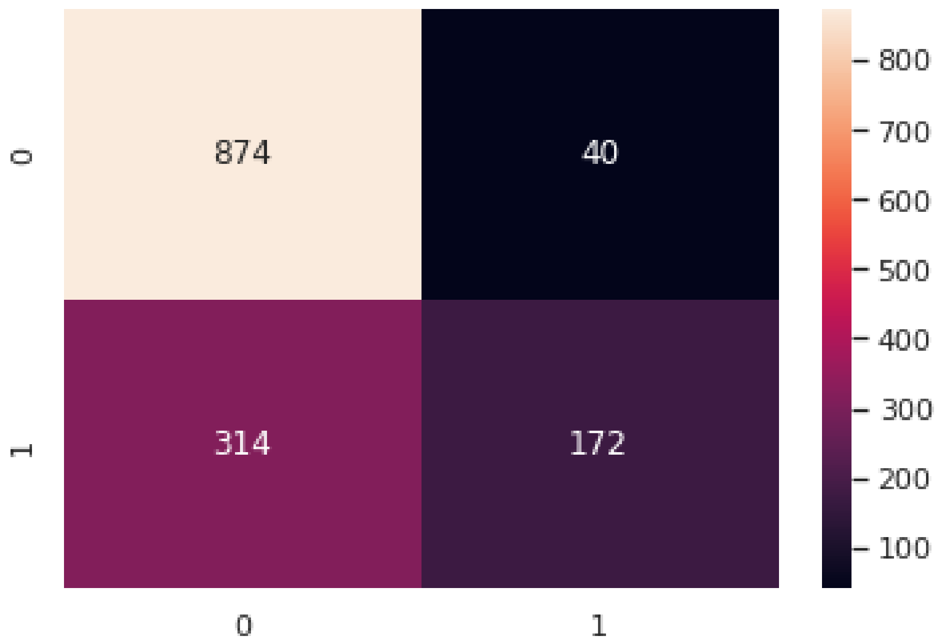
```
Test Accuracy
The accuracy is: 77.77777777777779%
Confusion Matrix:
```



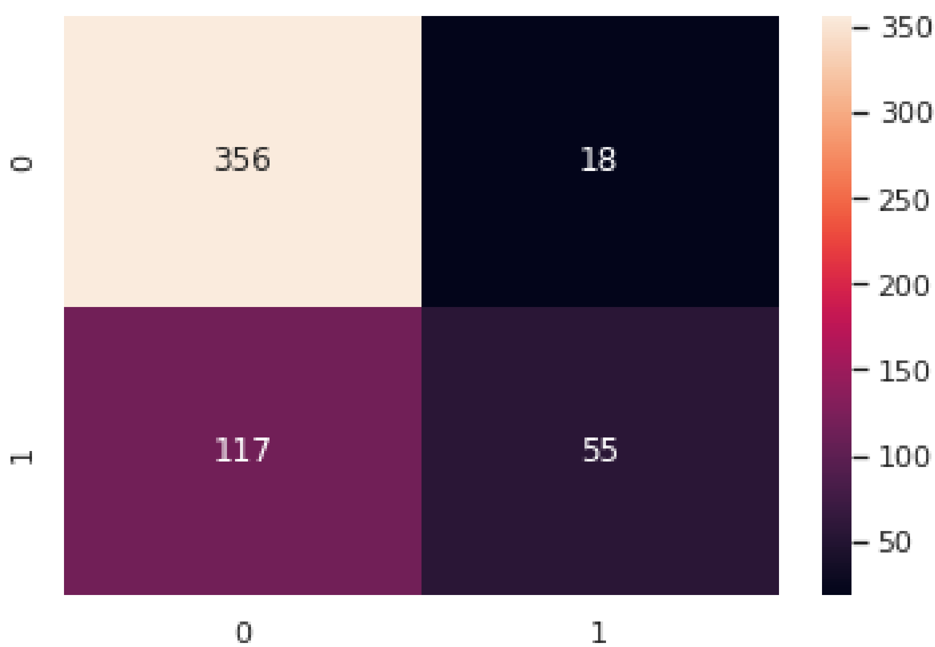

```
Regularization:0.1
```



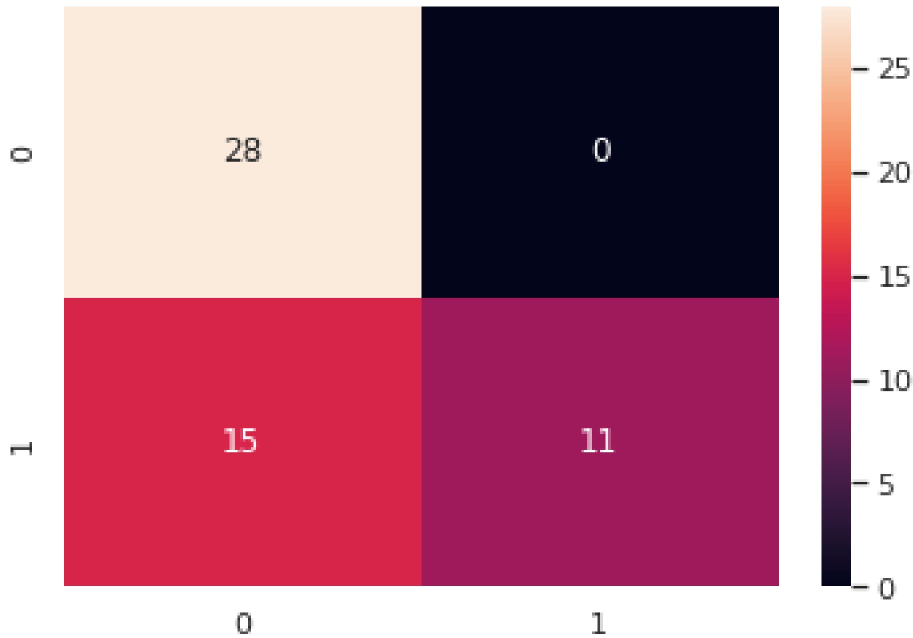

```
Number of epochs until convergence:499

Training Accuracy
The accuracy is: 74.71428571428571%
Confusion Matrix:
```



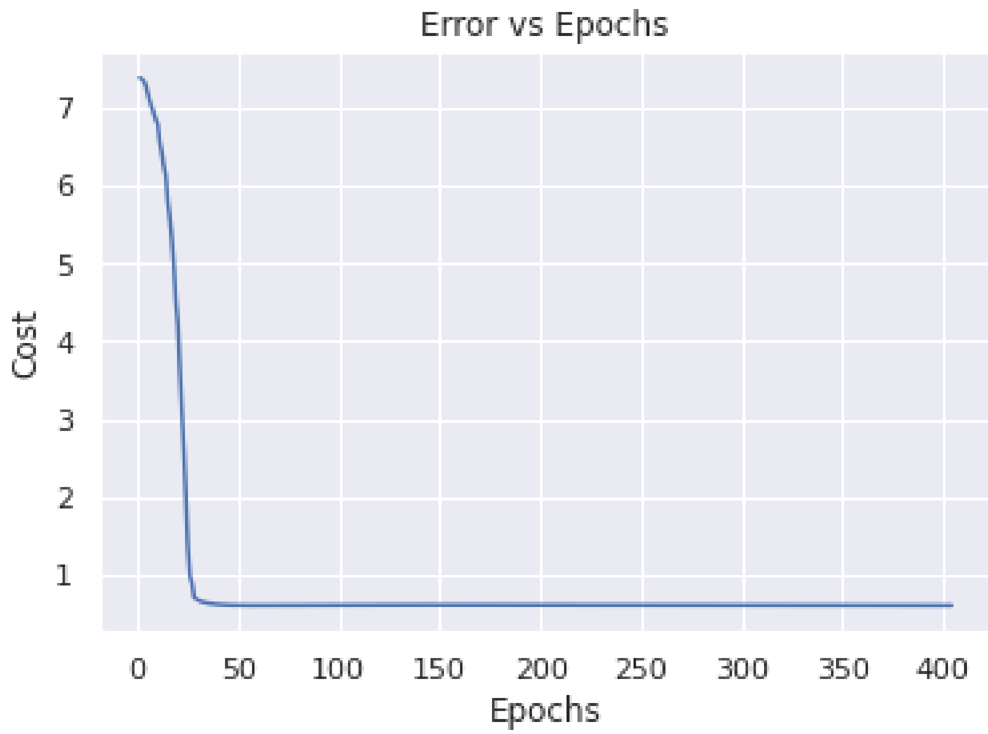

```
Validation Accuracy
The accuracy is: 75.27472527472527%
Confusion Matrix:
```



```
Test Accuracy
The accuracy is: 72.22222222222221%
Confusion Matrix:
```

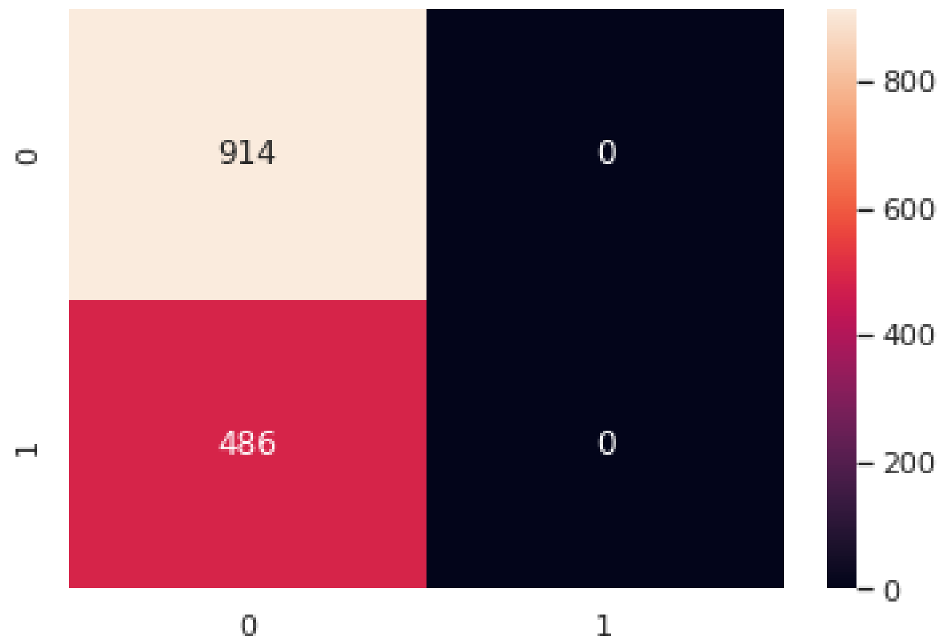



```
Regularization:0.2
```

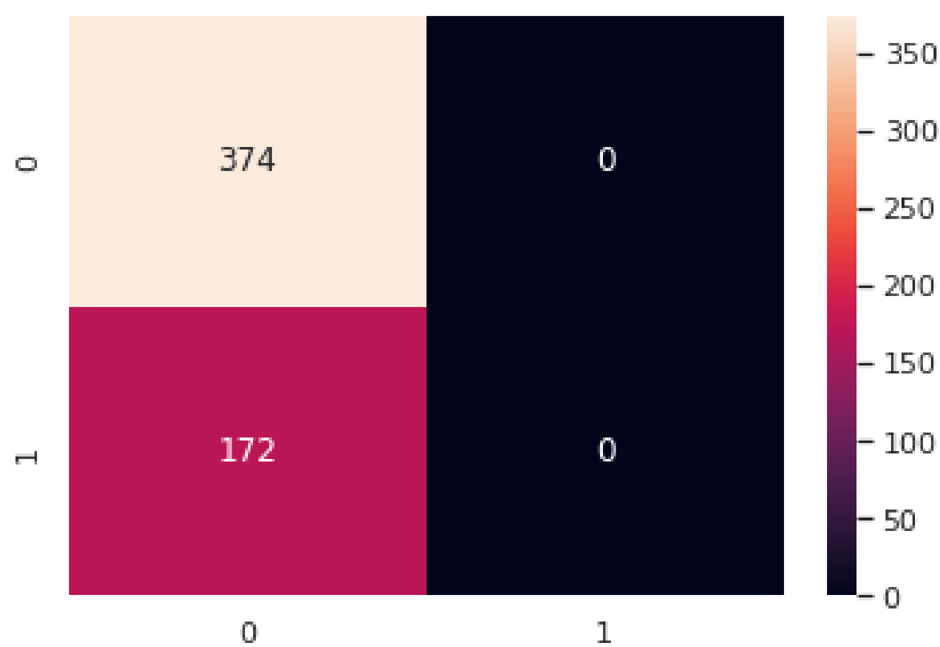


Number of epochs until convergence:404

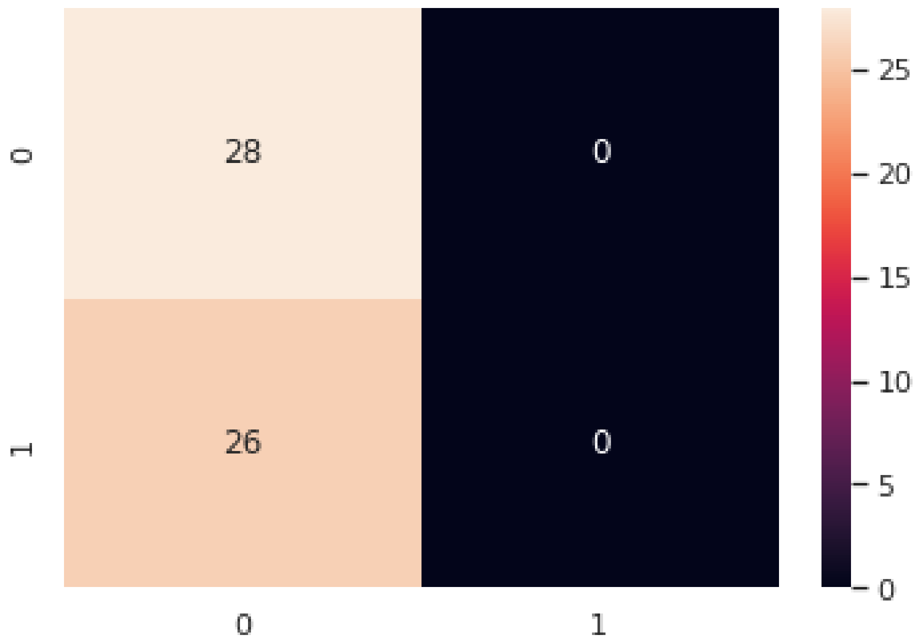
Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:



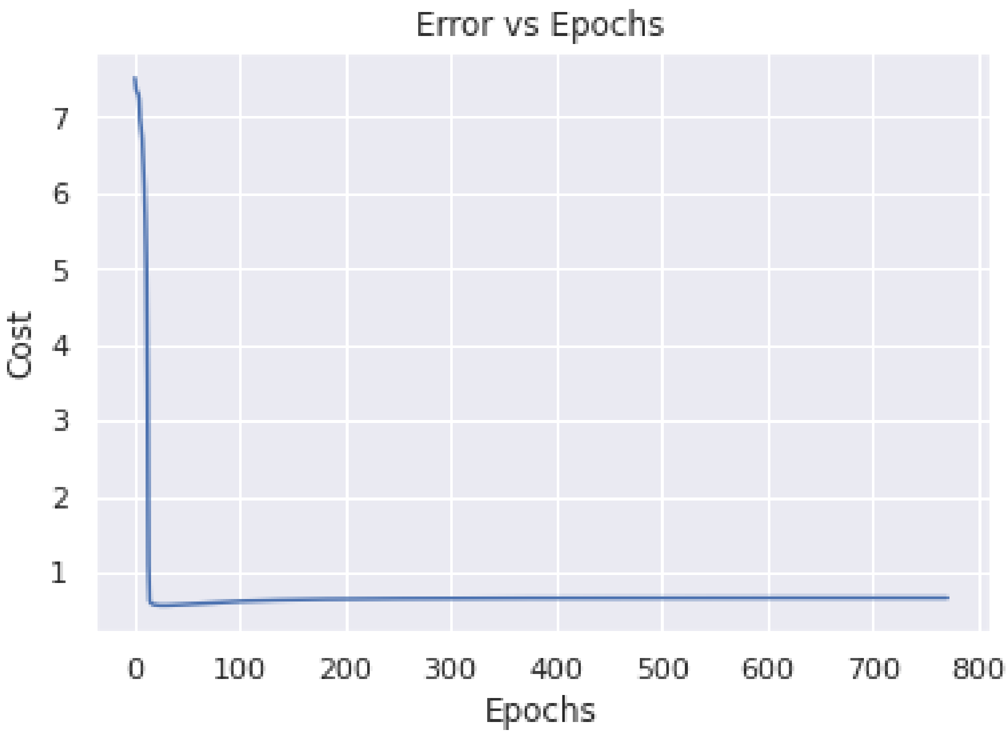

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



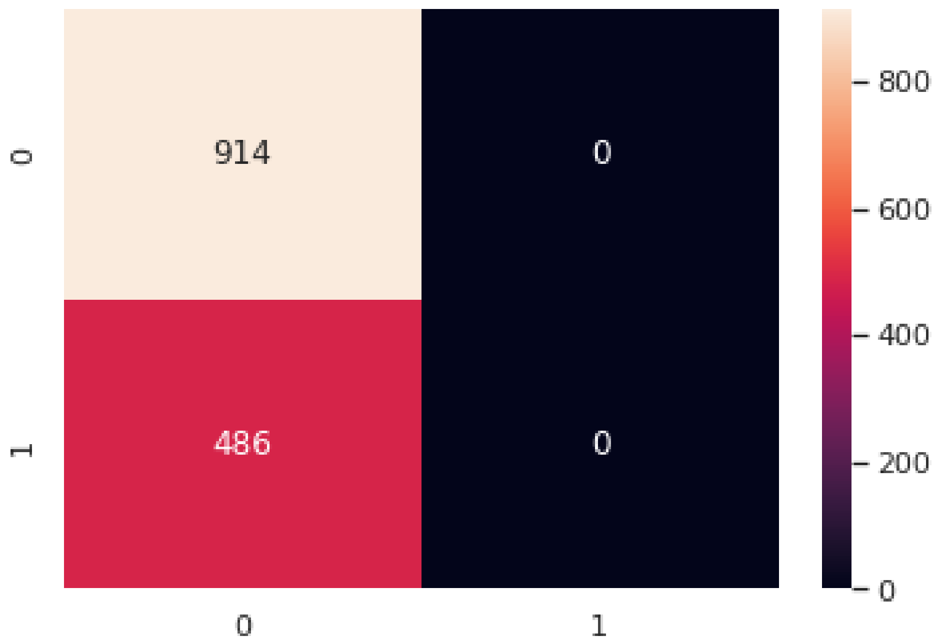
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



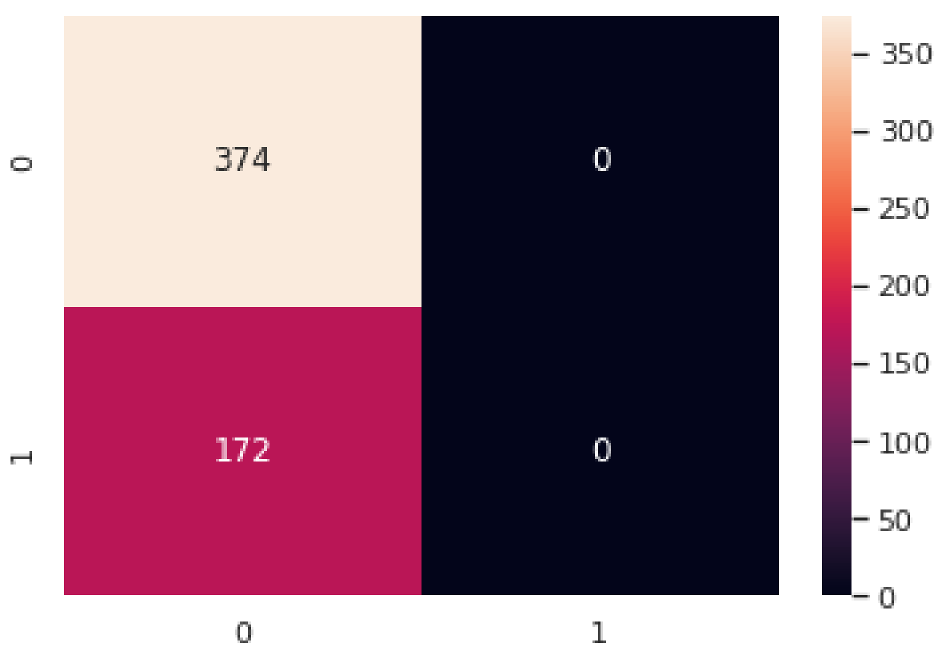

```
Regularization:0.30000000000000004
```



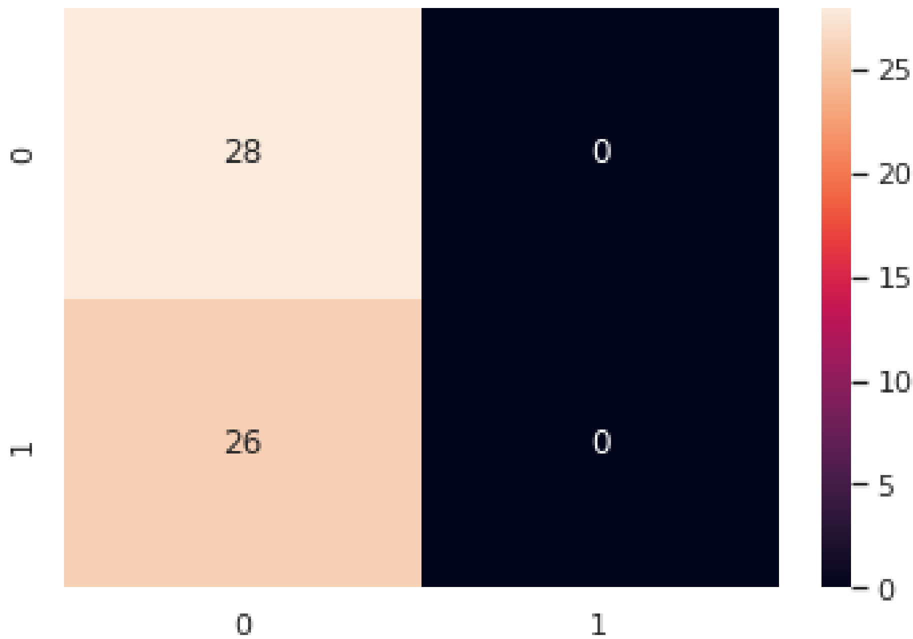

```
Number of epochs until convergence:771

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



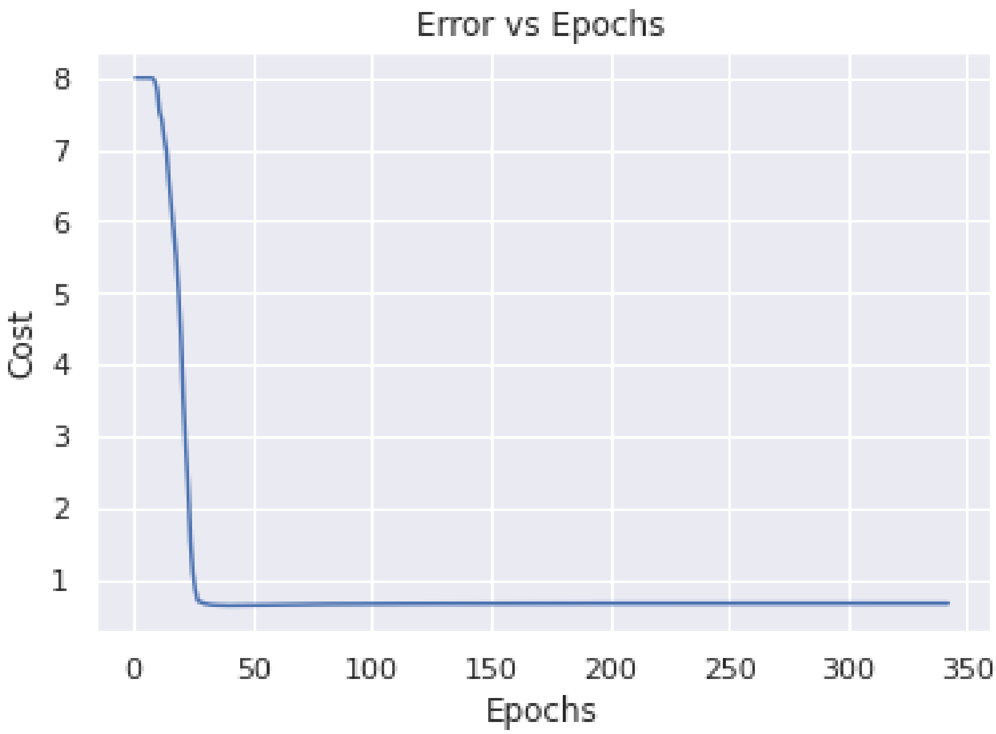

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



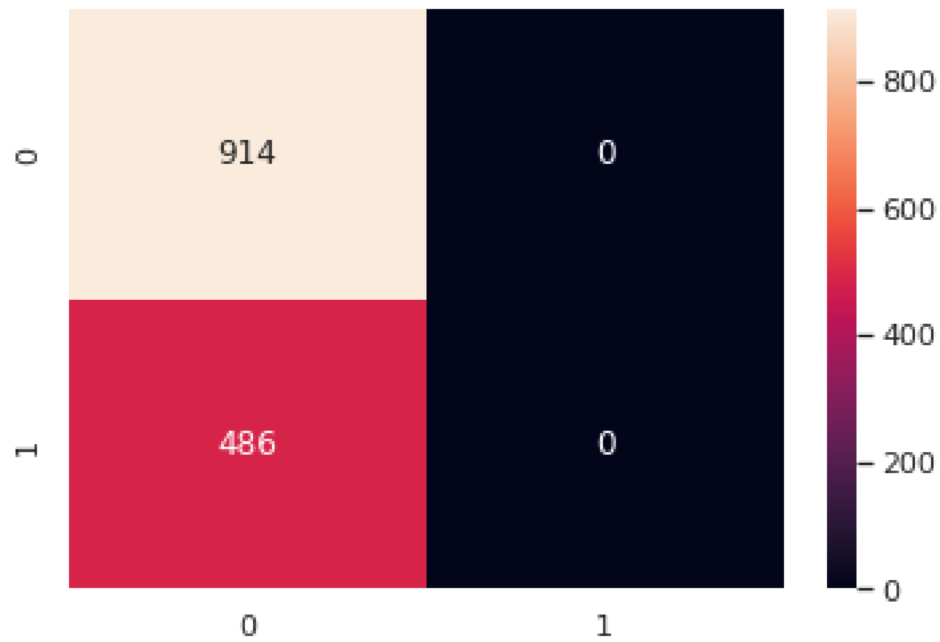
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



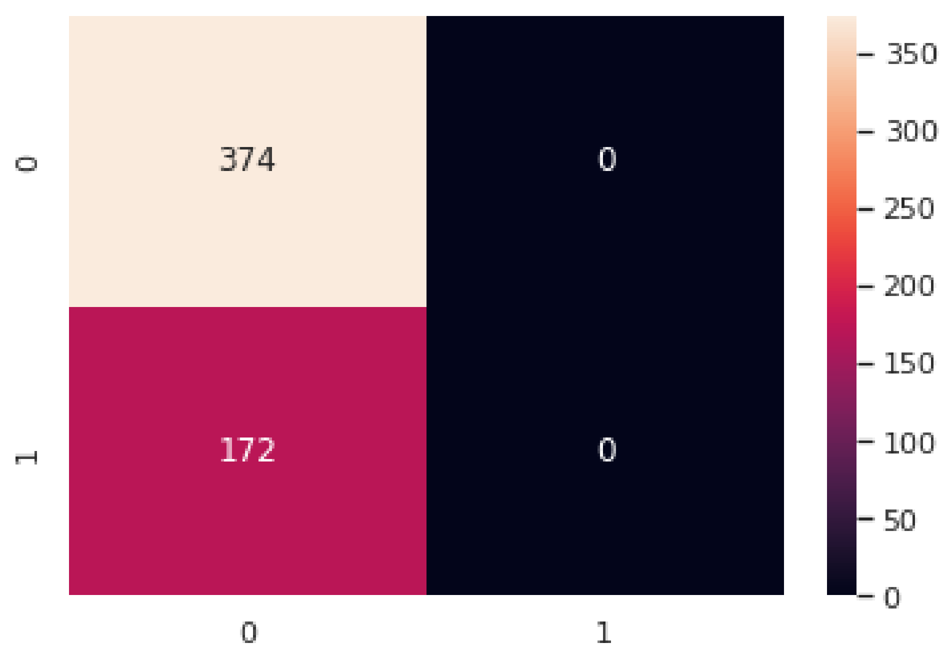

```
Regularization:0.4
```



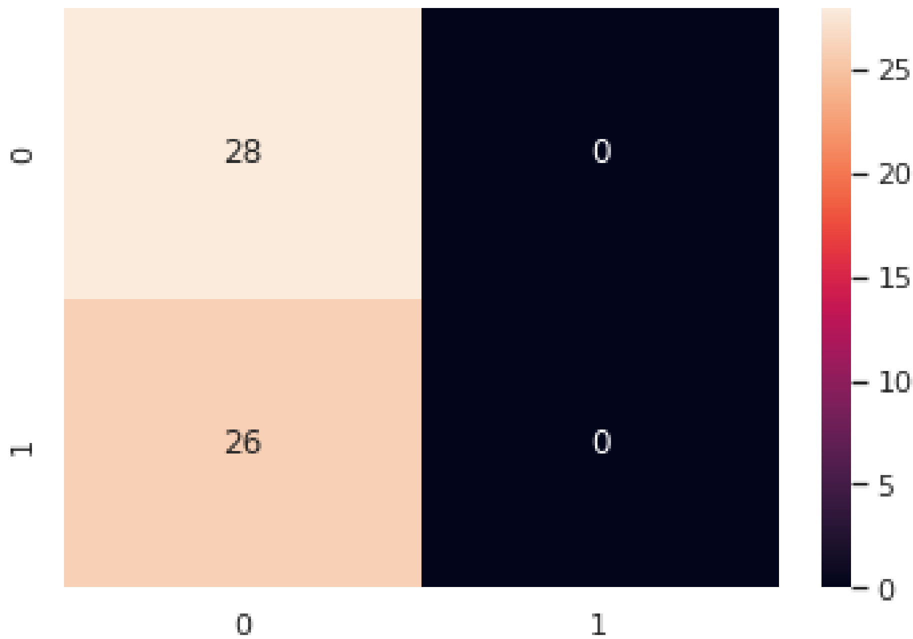

```
Number of epochs until convergence:342

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



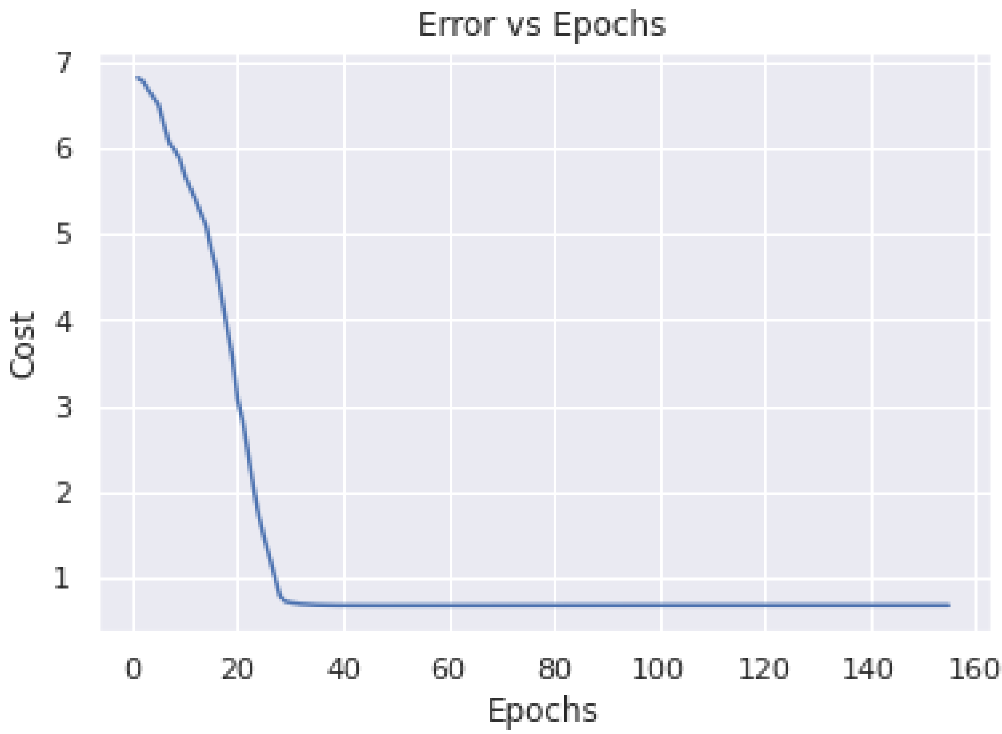

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



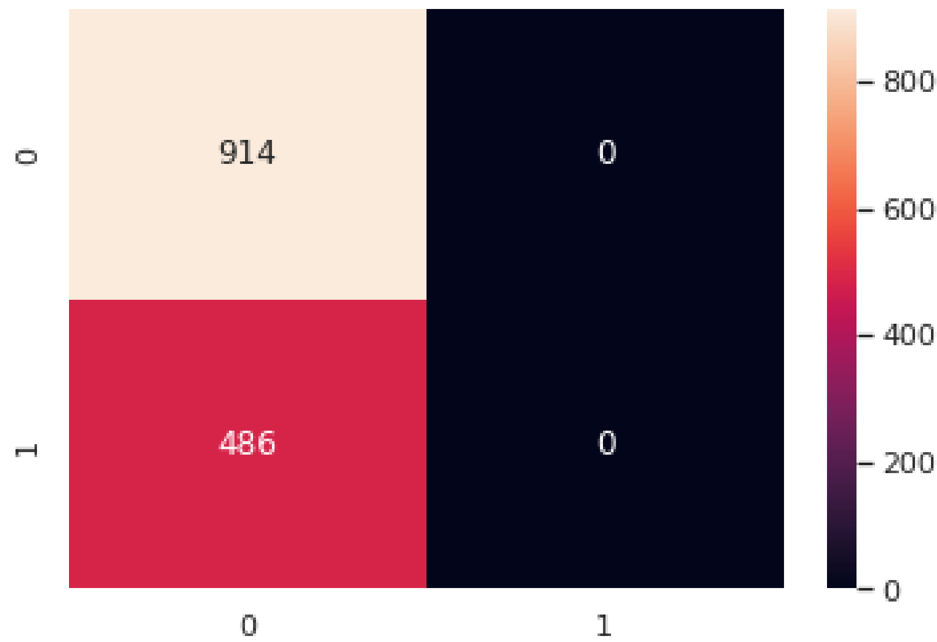
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



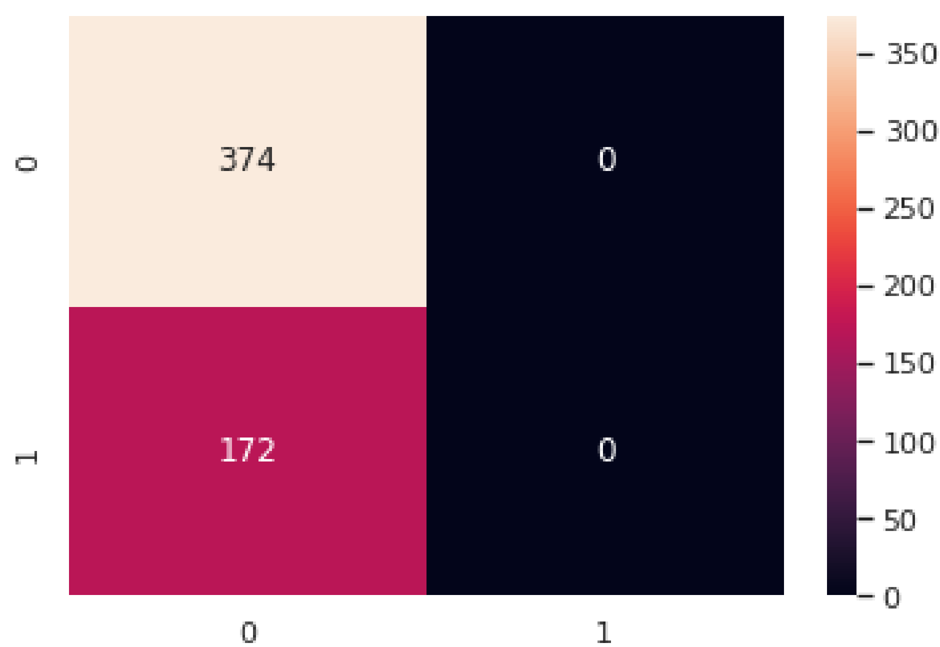

```
Regularization:0.5
```



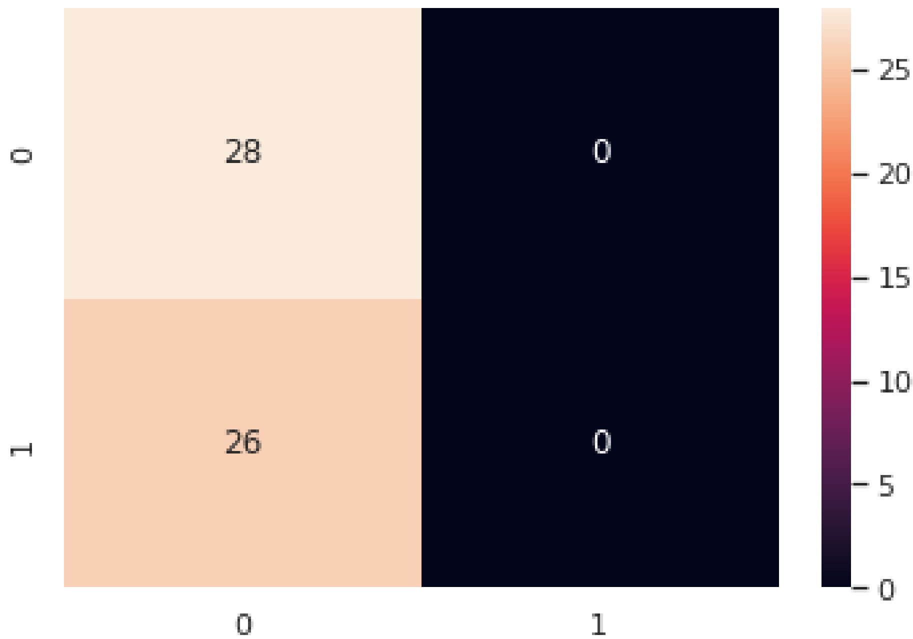

```
Number of epochs until convergence:155

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



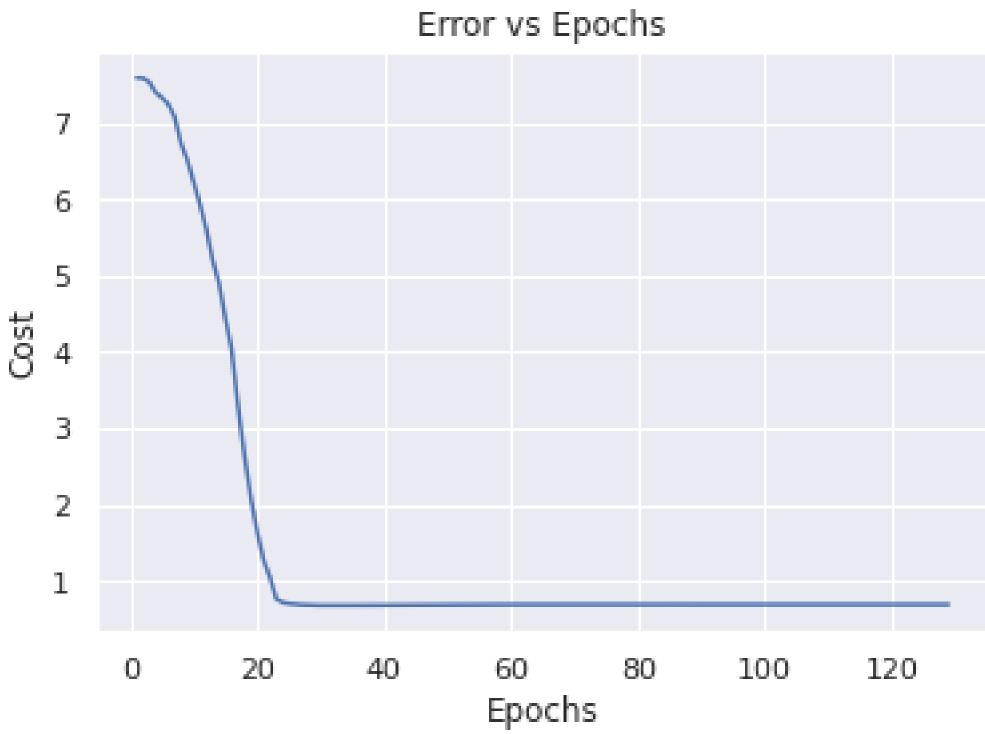

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



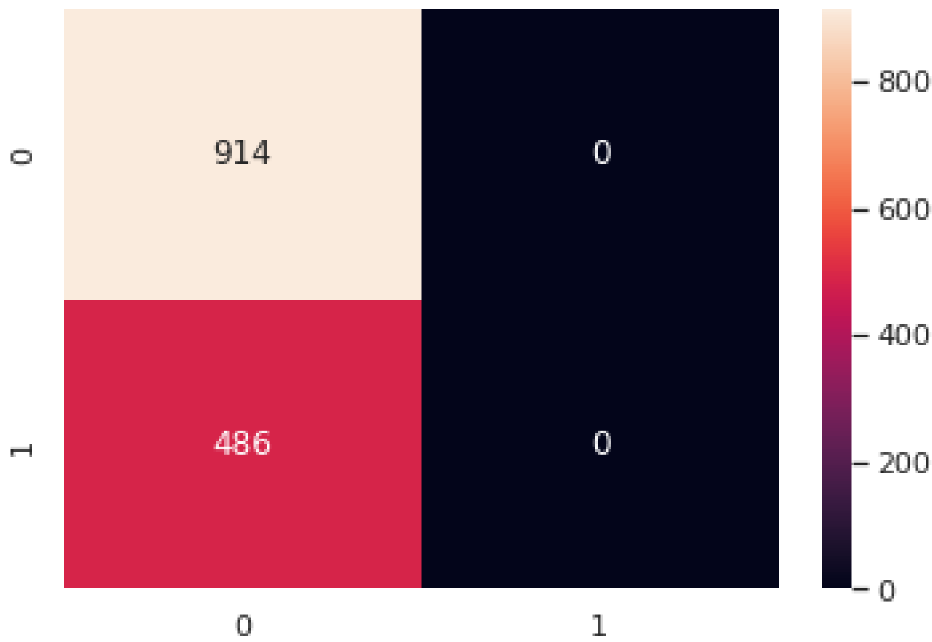
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



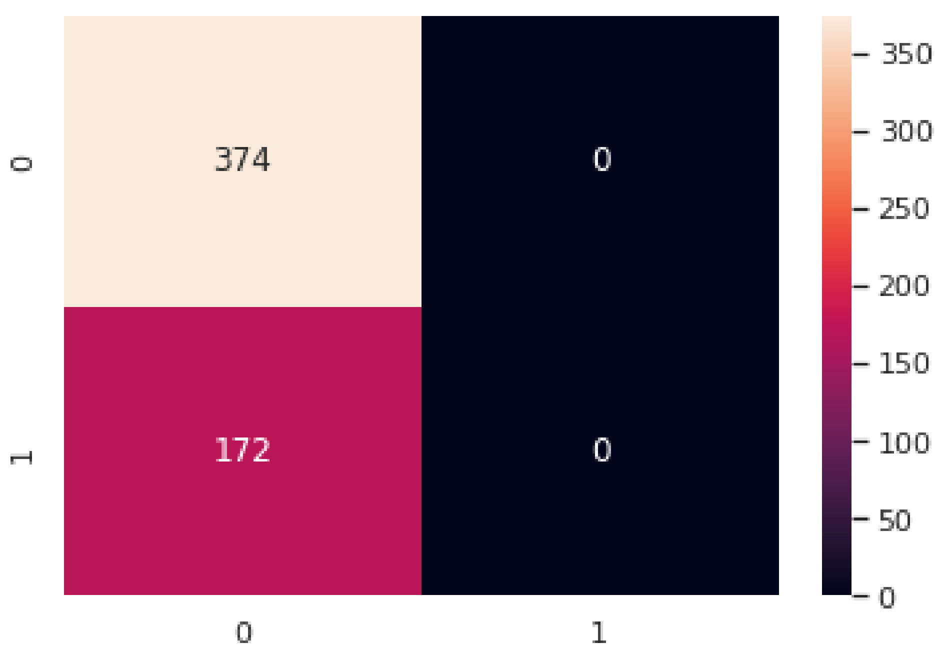

```
Regularization:0.6000000000000001
```



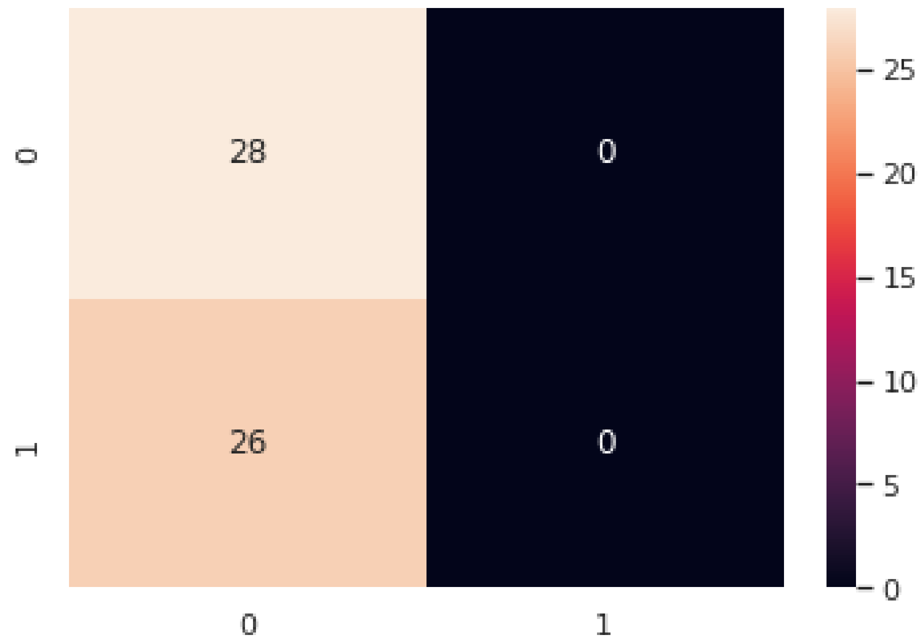

```
Number of epochs until convergence:129

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



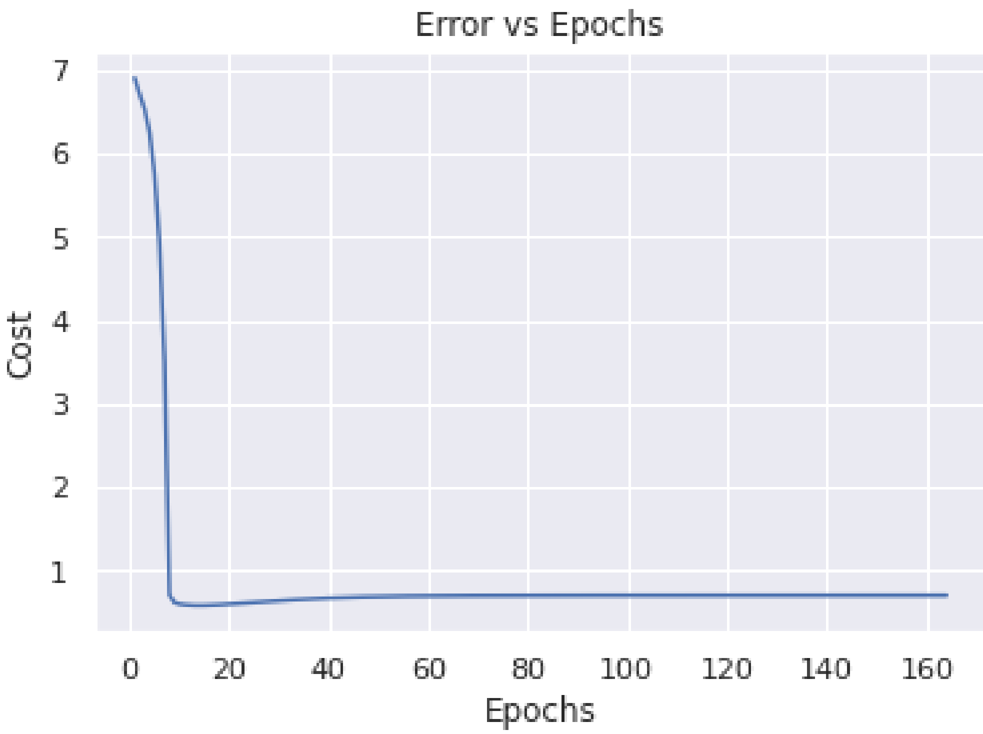

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



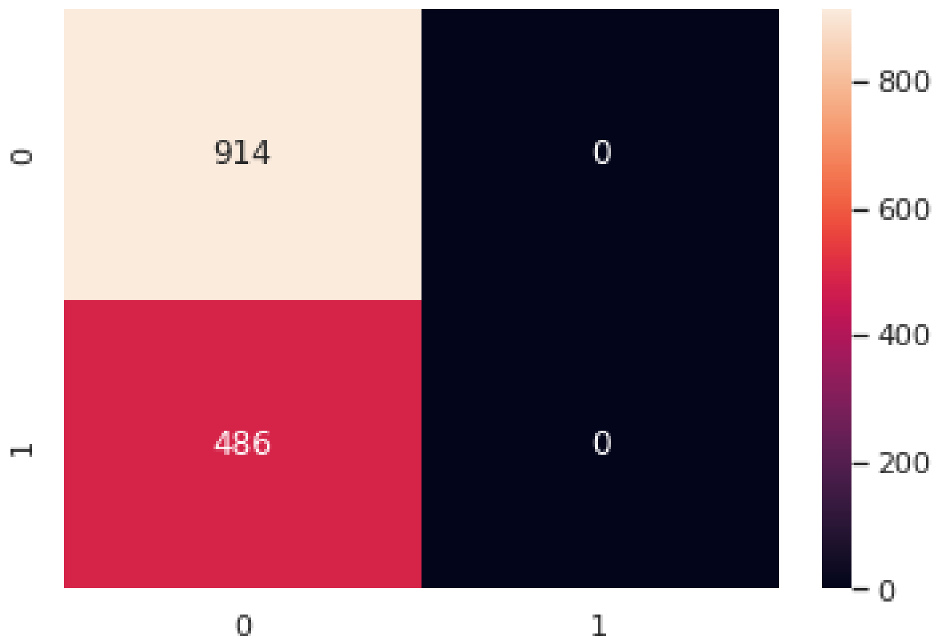
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



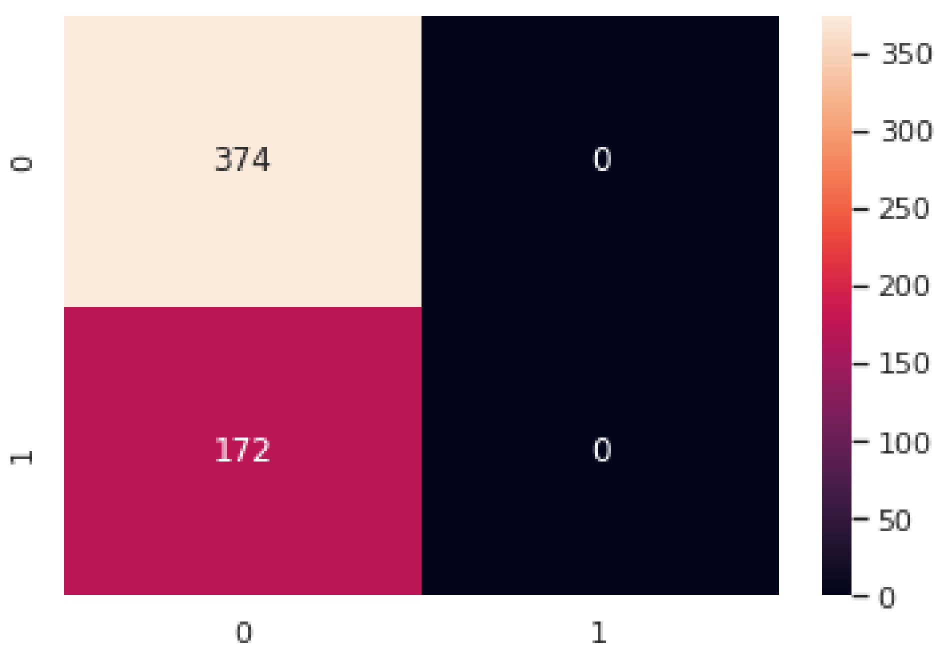

```
Regularization:0.7000000000000001
```



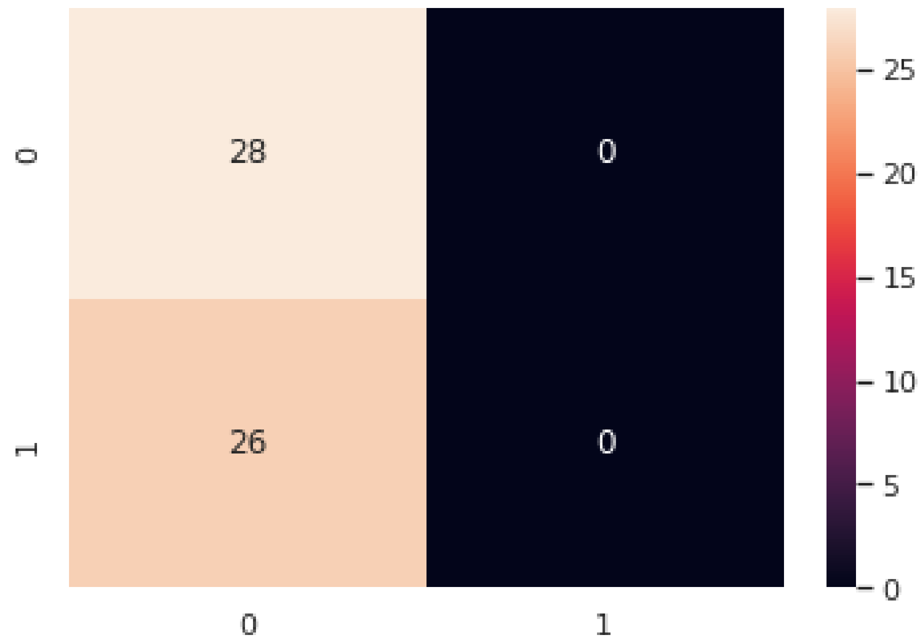

```
Number of epochs until convergence:164

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



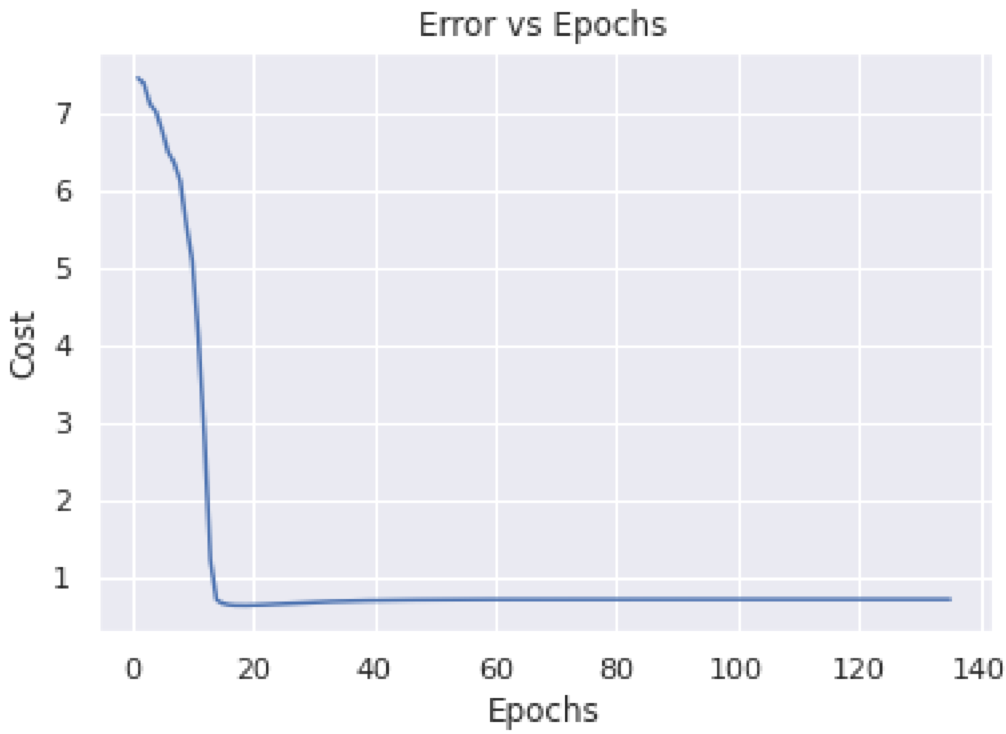

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



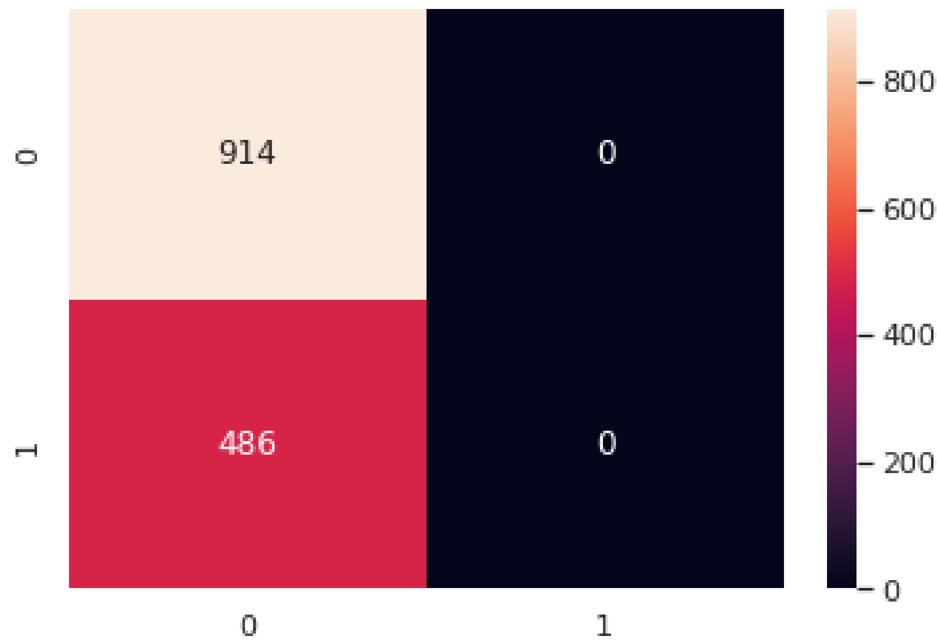
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



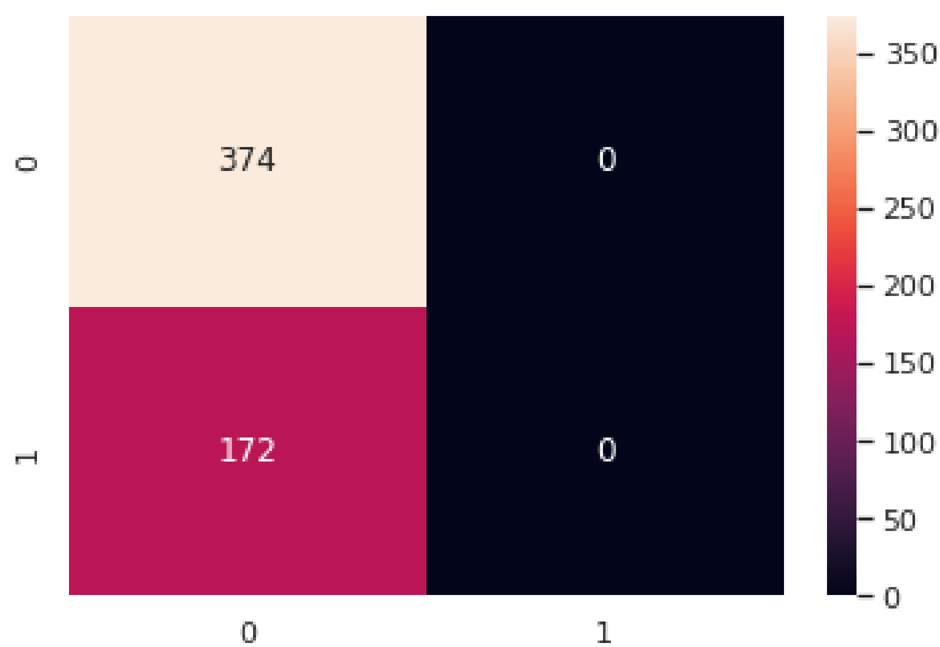

```
Regularization:0.8
```



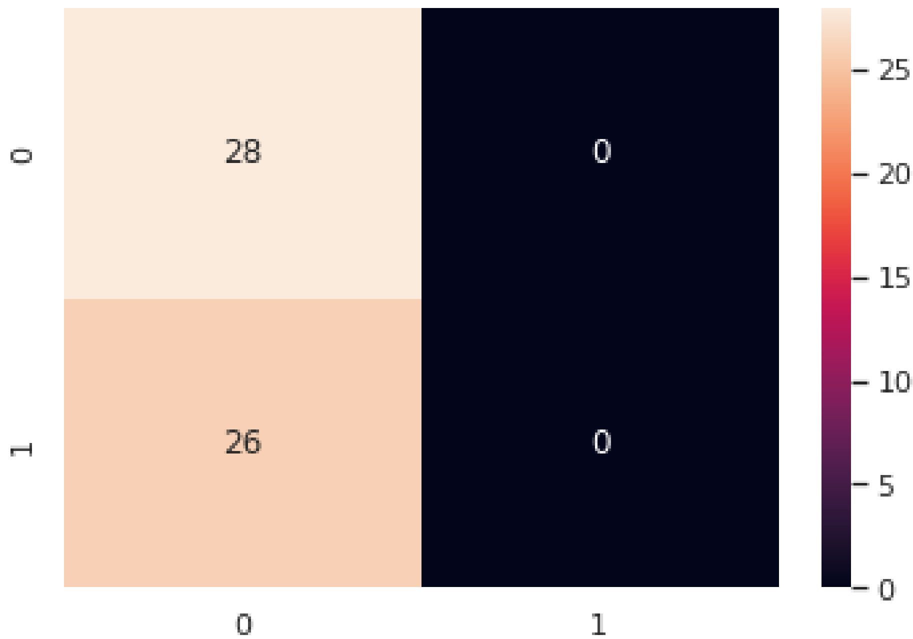

```
Number of epochs until convergence:135

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



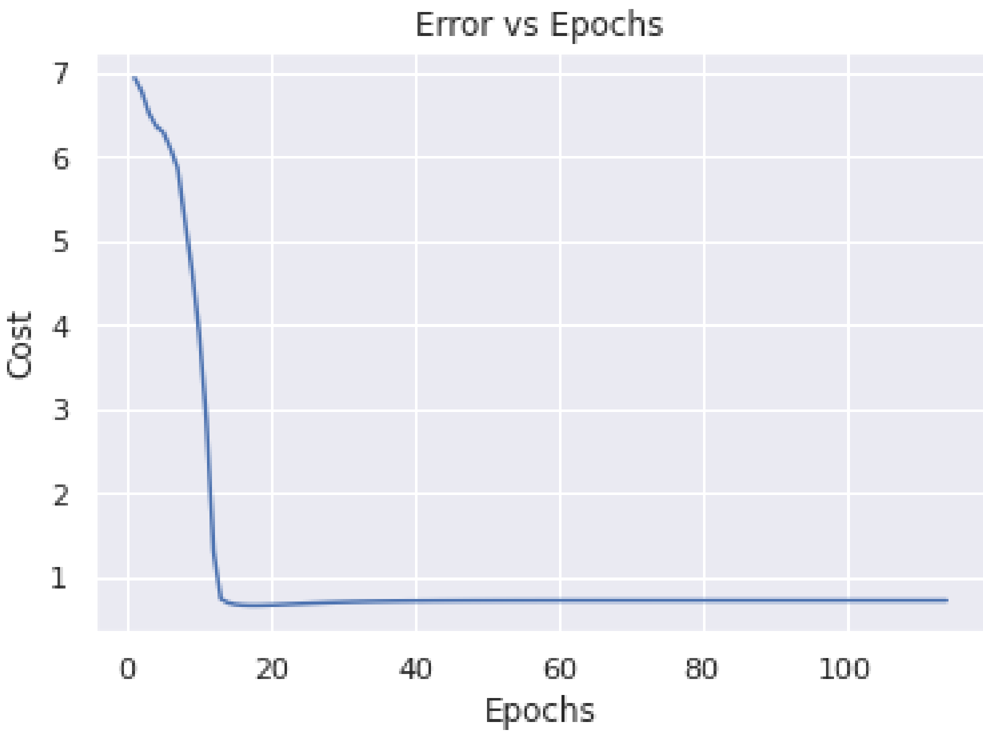

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



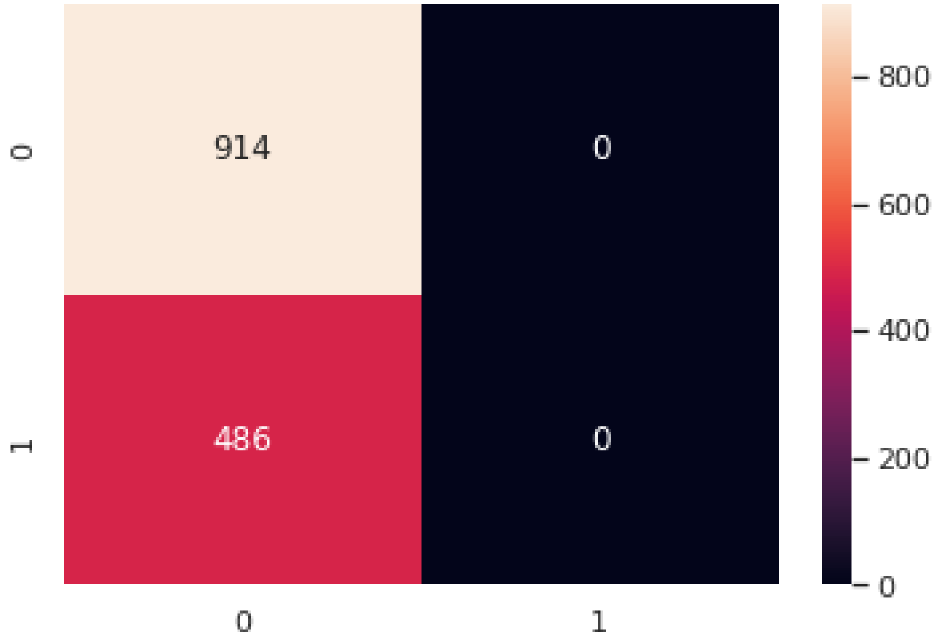
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



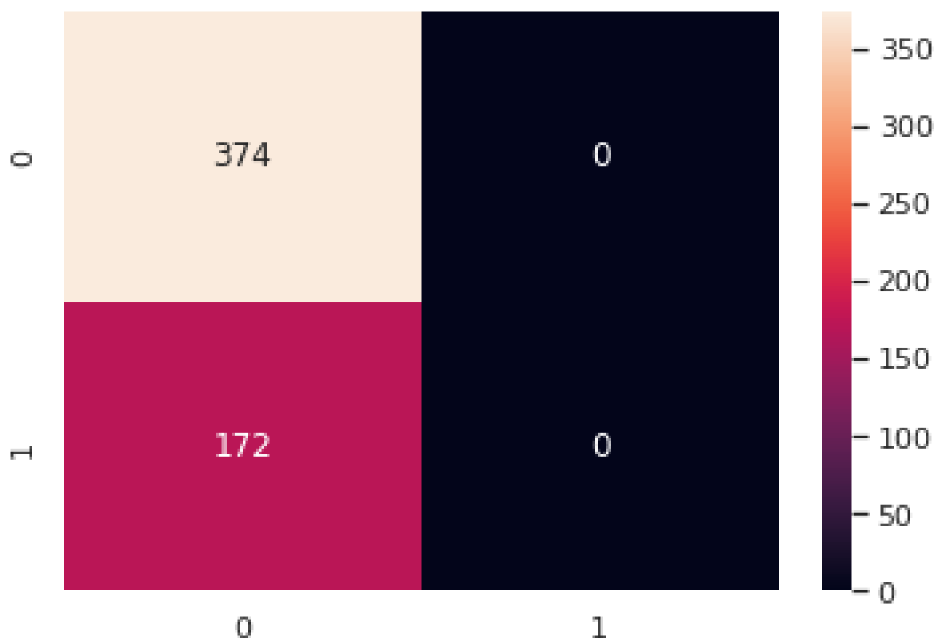

```
Regularization:0.9
```



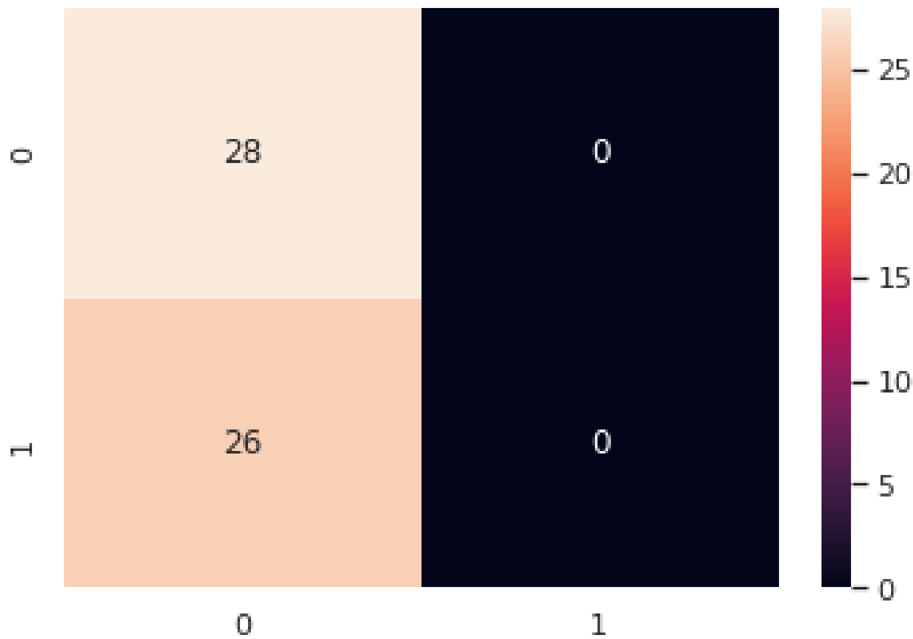

```
Number of epochs until convergence:114

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



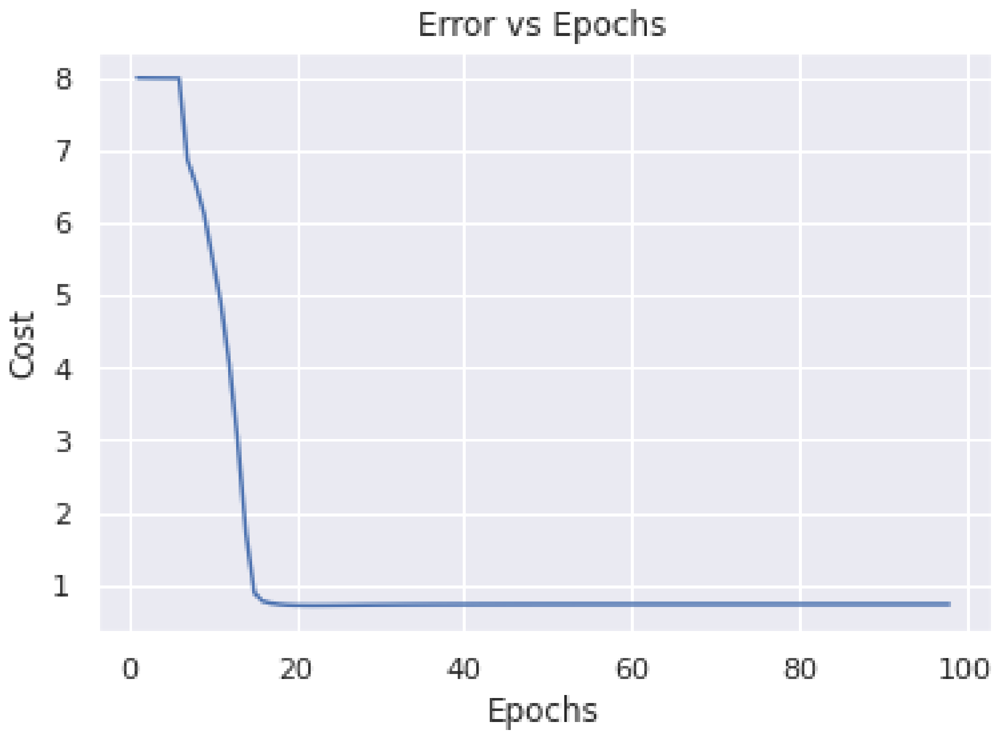

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



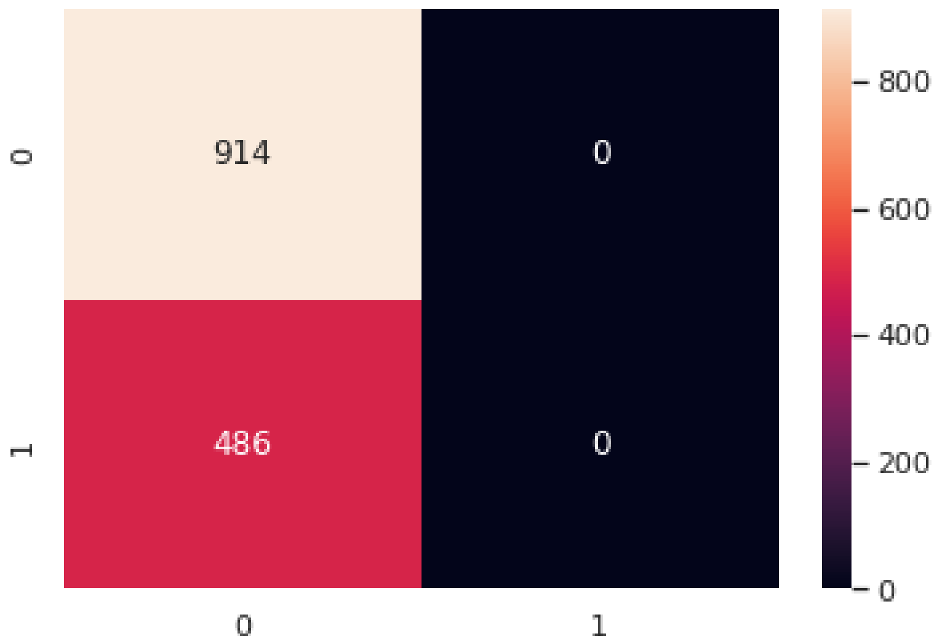
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



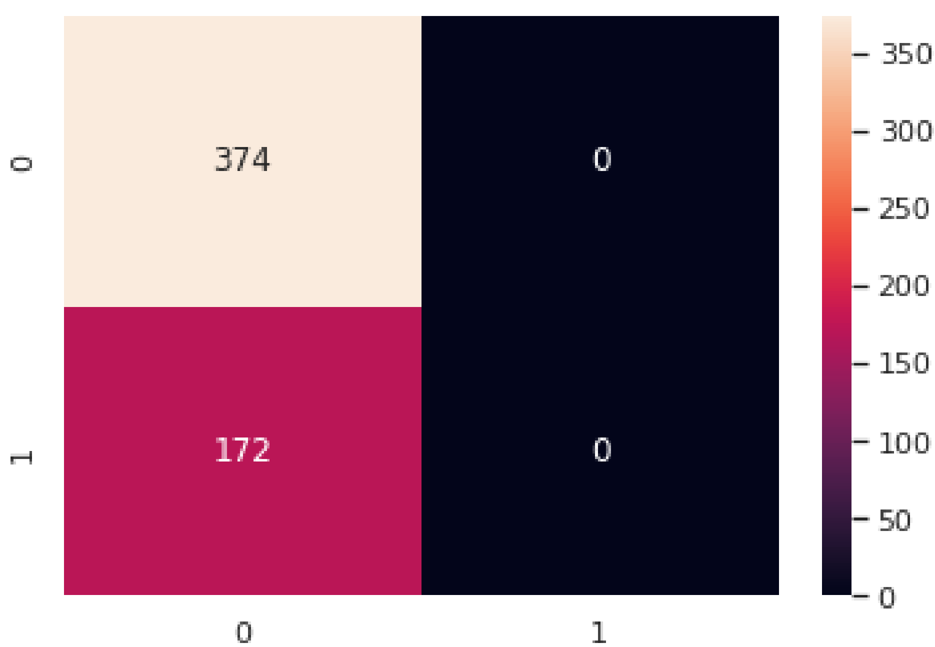

```
Regularization:1.0
```



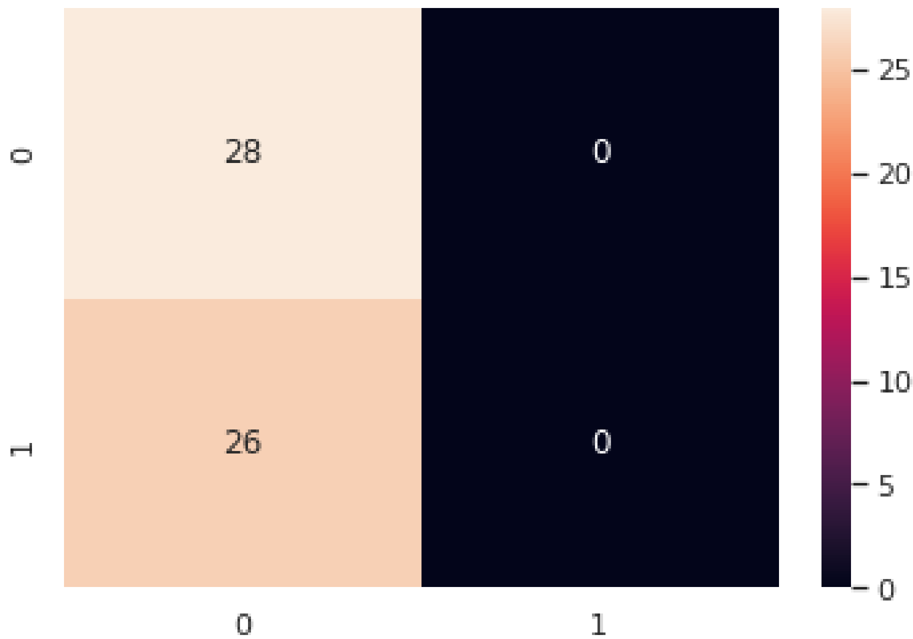

```
Number of epochs until convergence:98

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



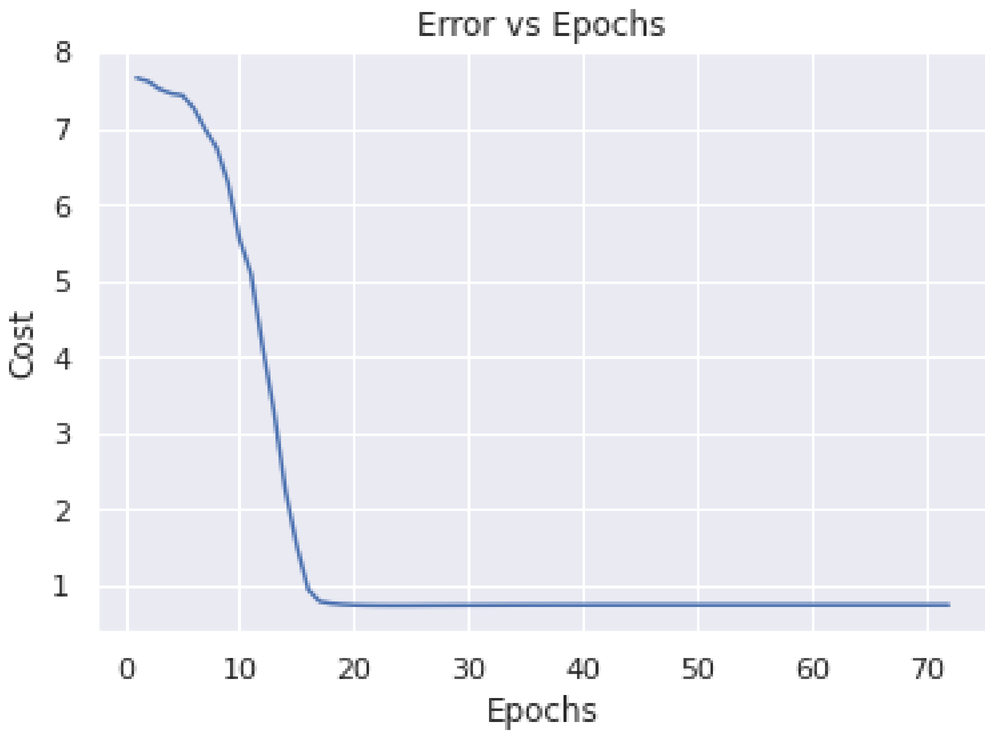

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



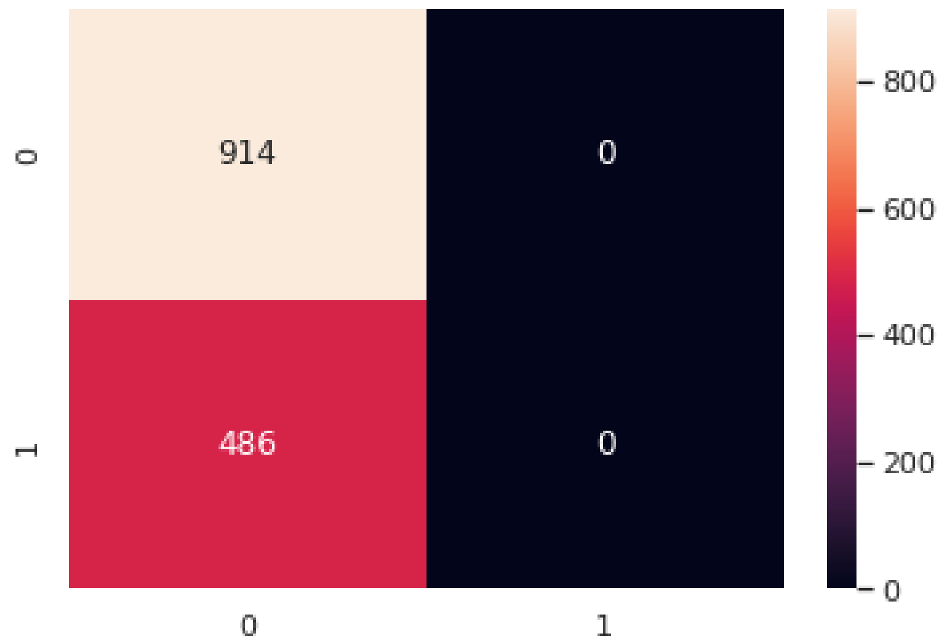
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



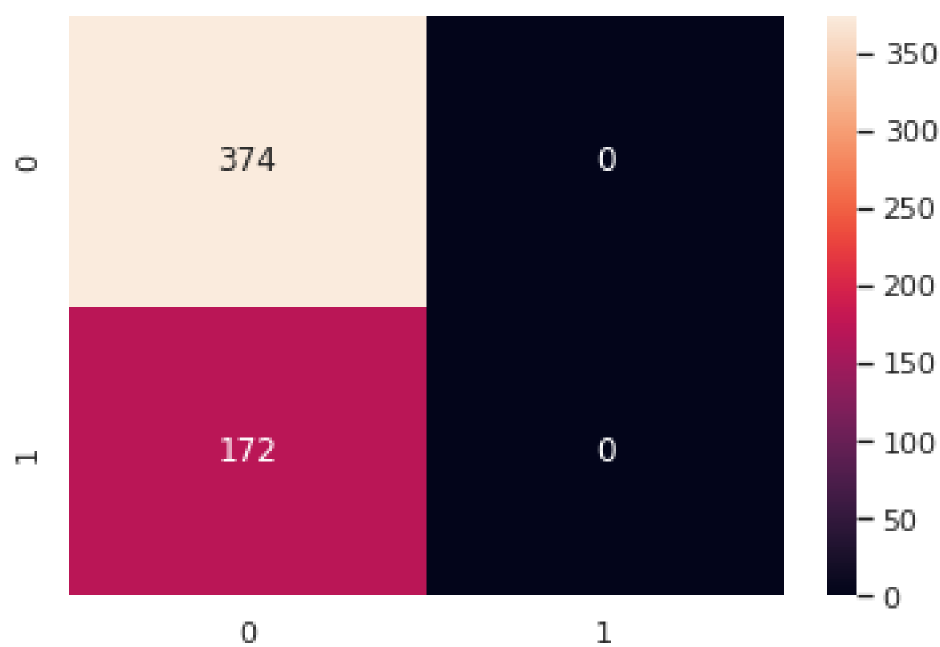

```
Regularization:1.1
```



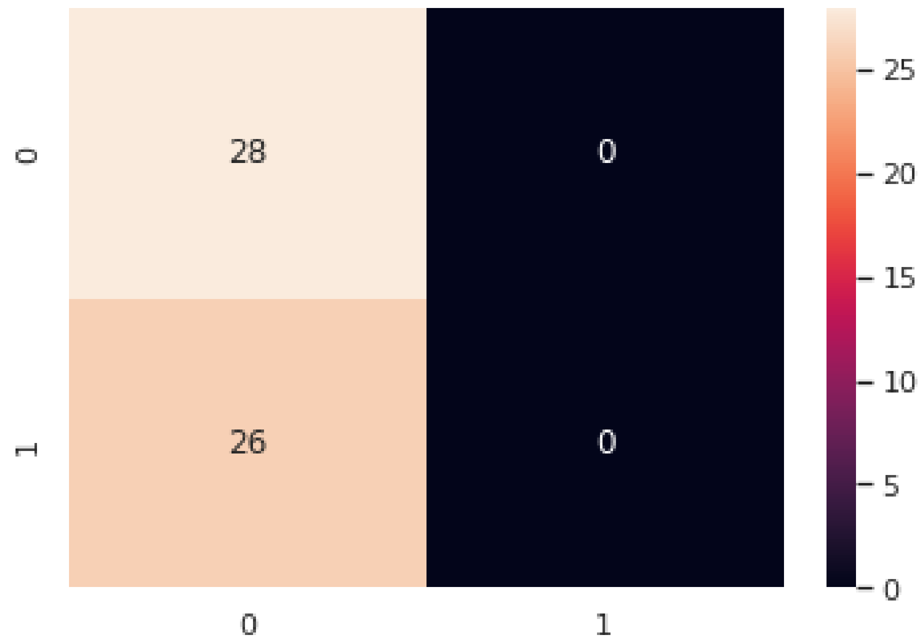

```
Number of epochs until convergence:72

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



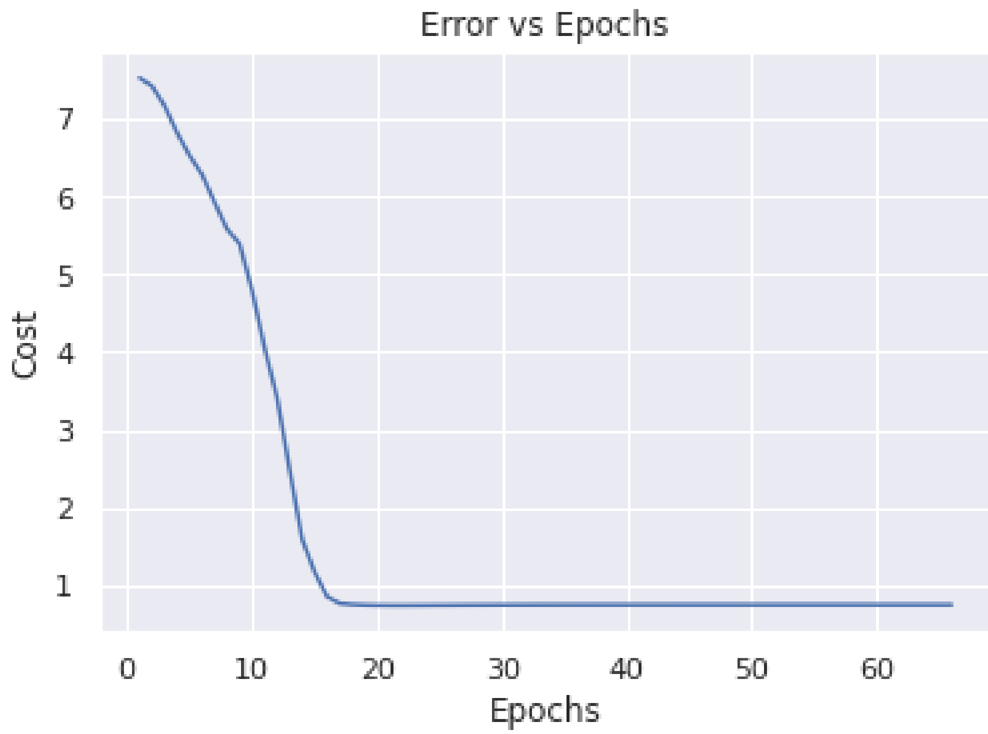
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:



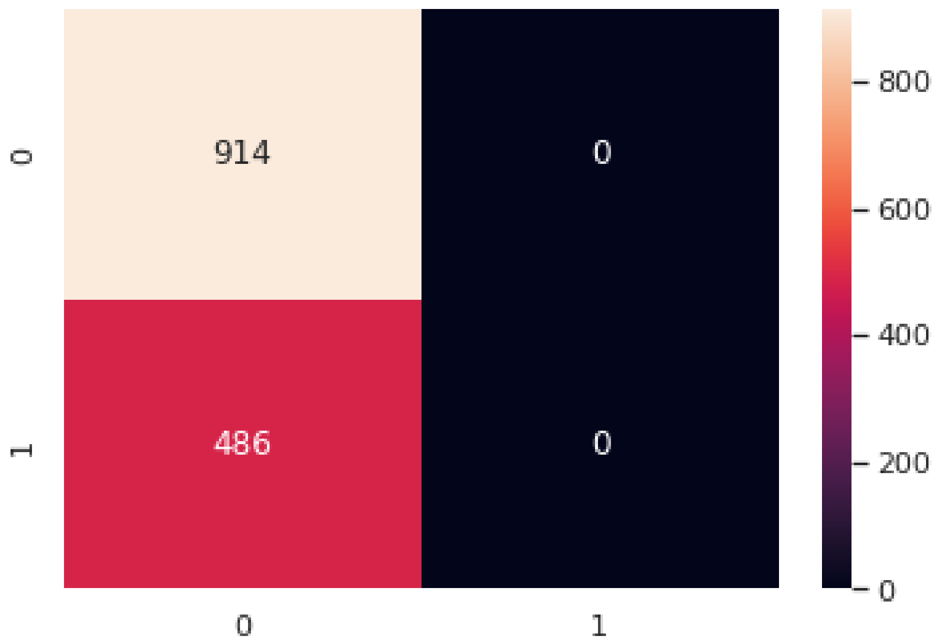
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



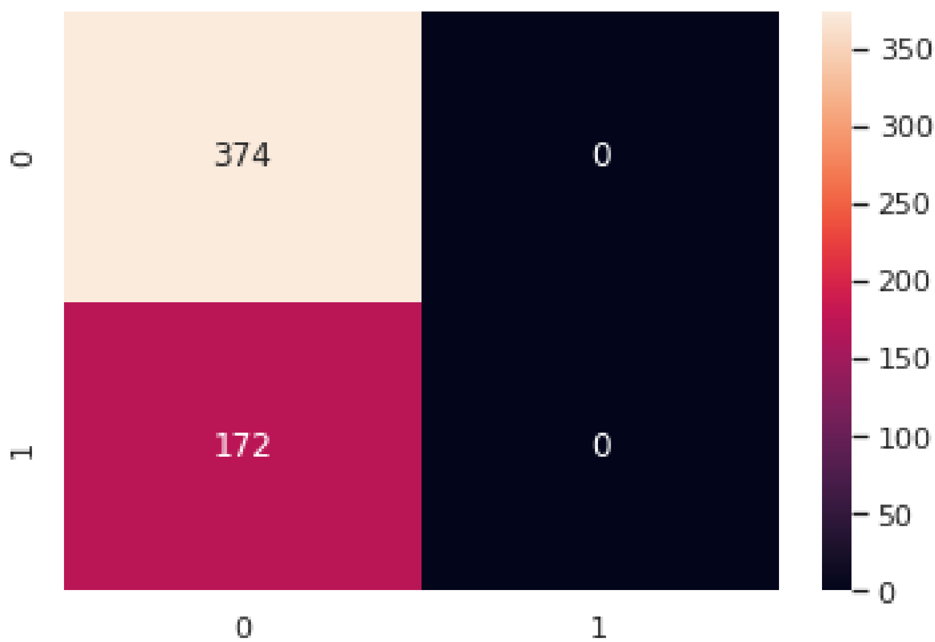

```
Regularization:1.2000000000000002
```



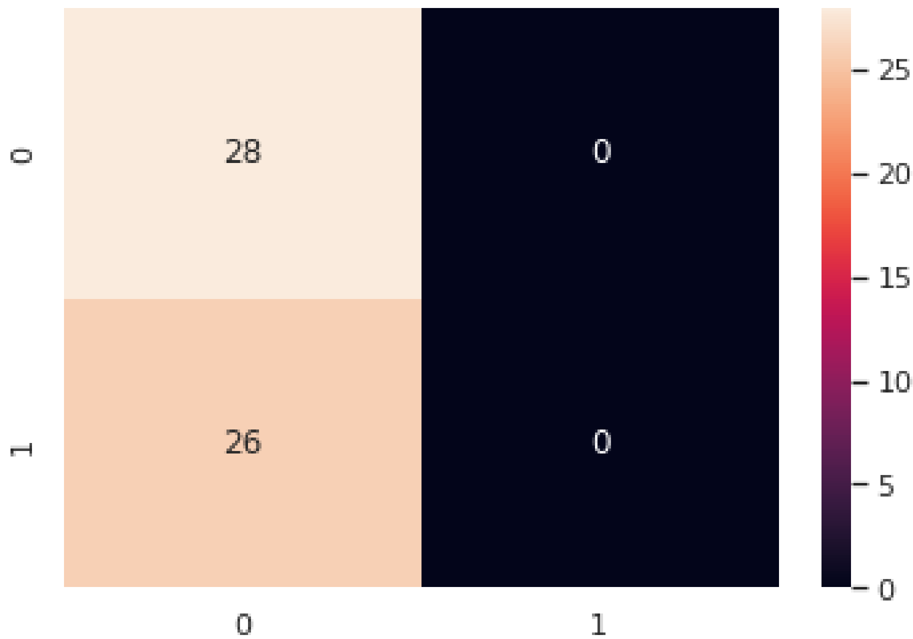

```
Number of epochs until convergence:66

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



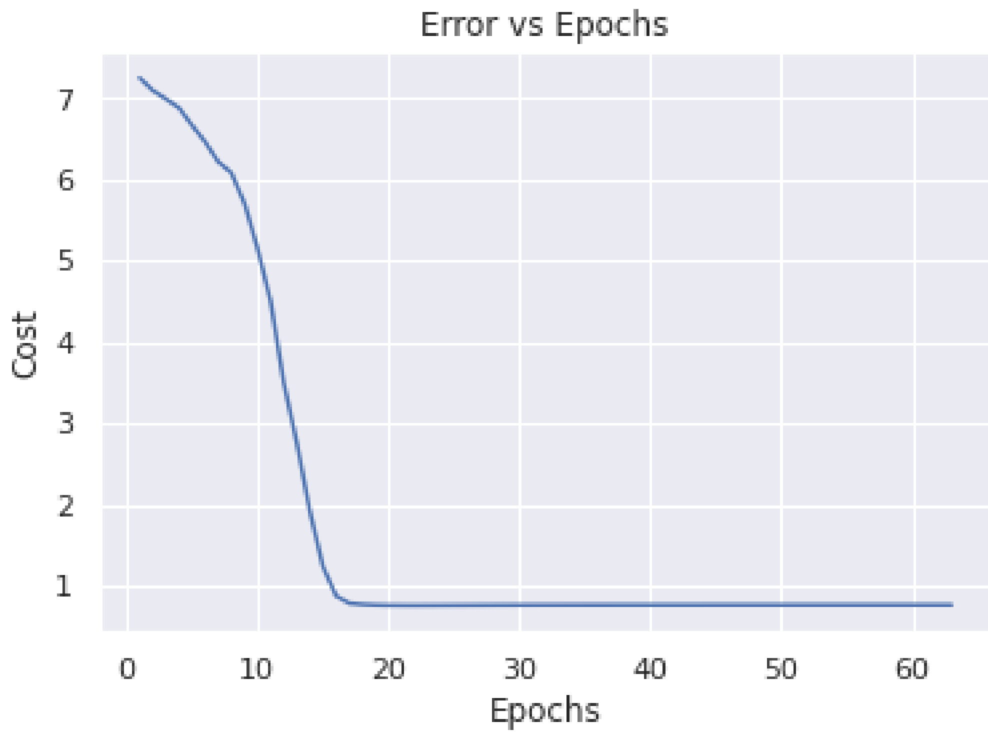

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



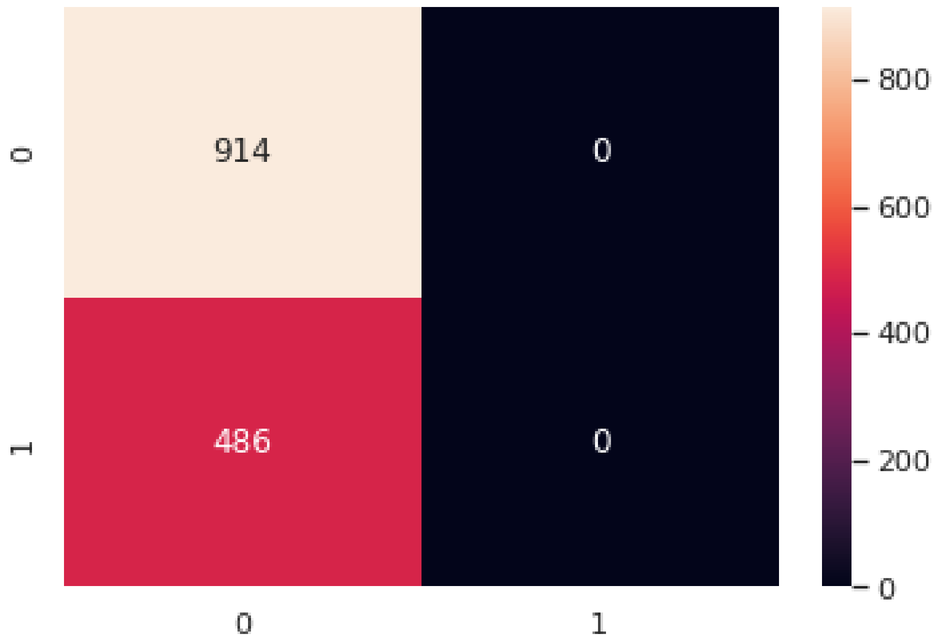
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



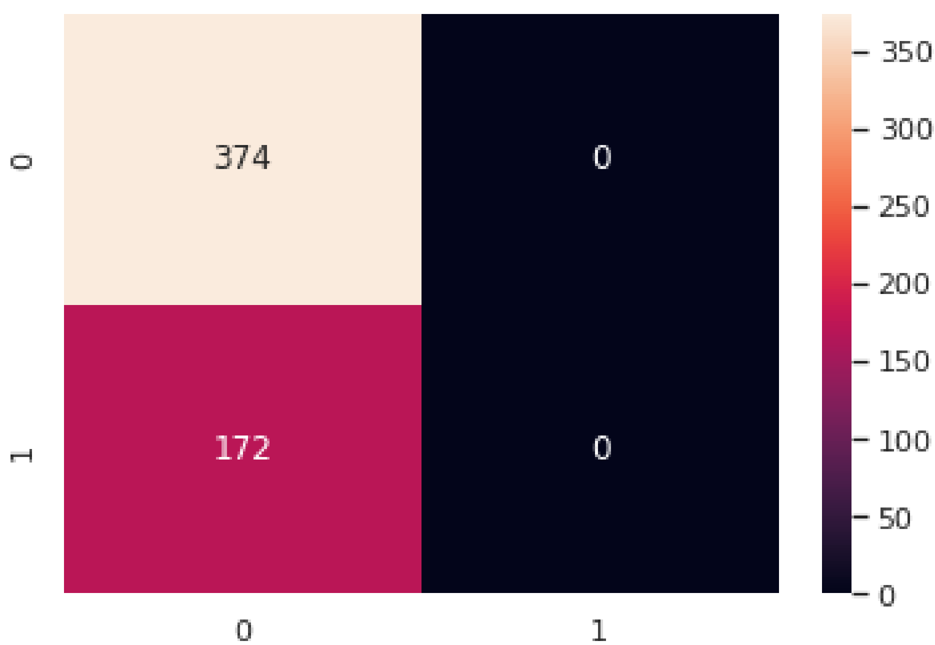

```
Regularization:1.3
```



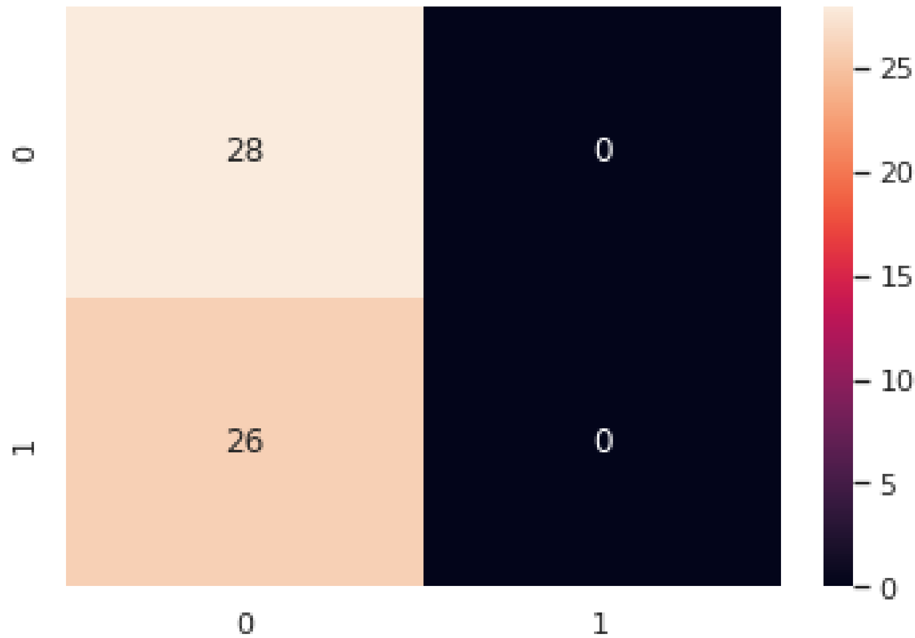

```
Number of epochs until convergence:63

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



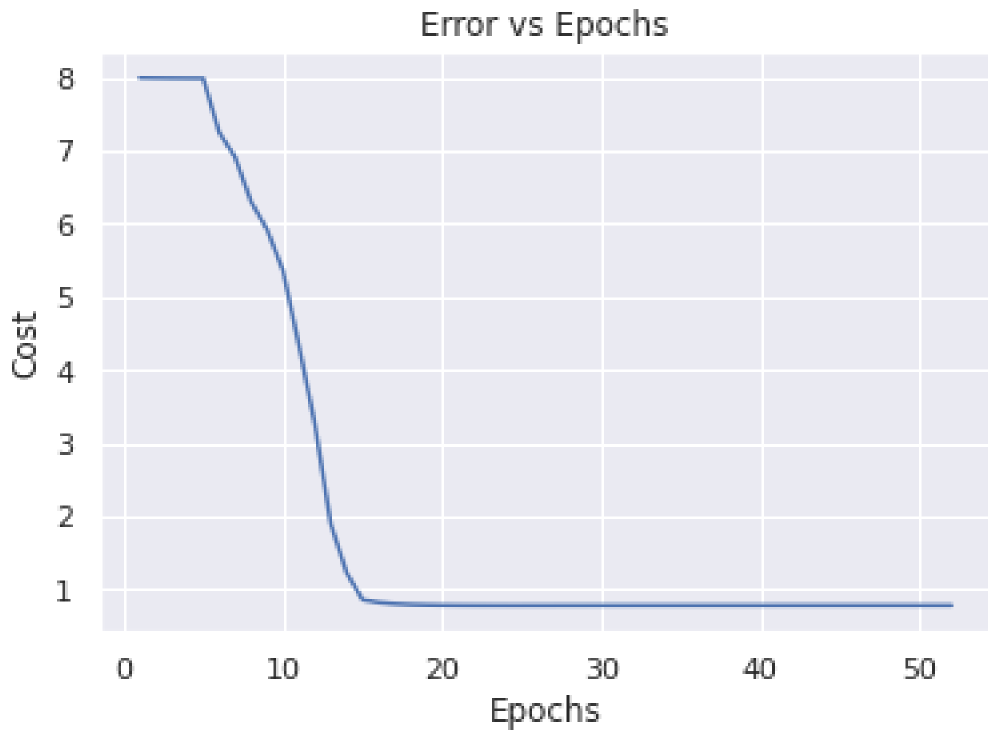
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:



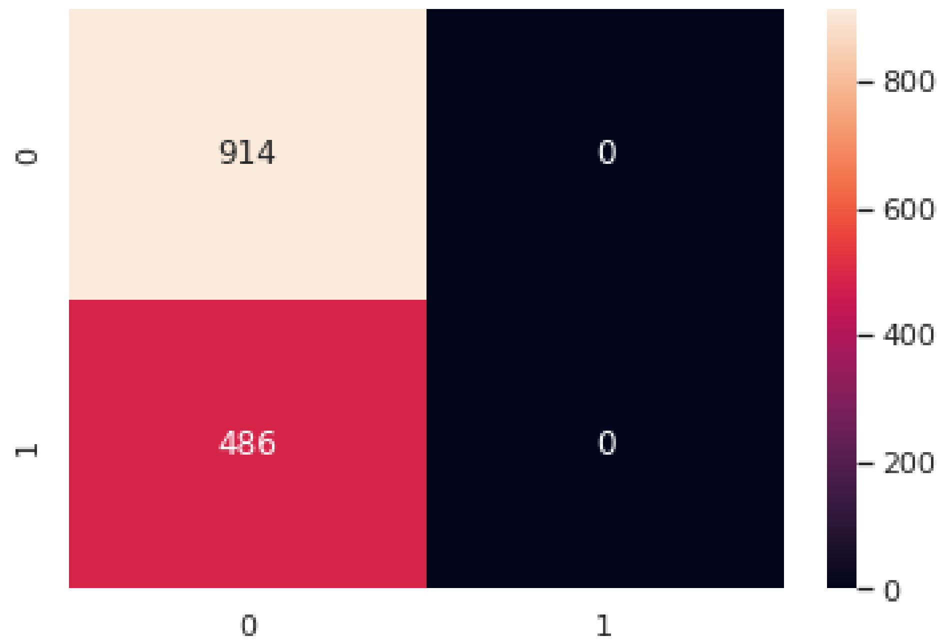
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



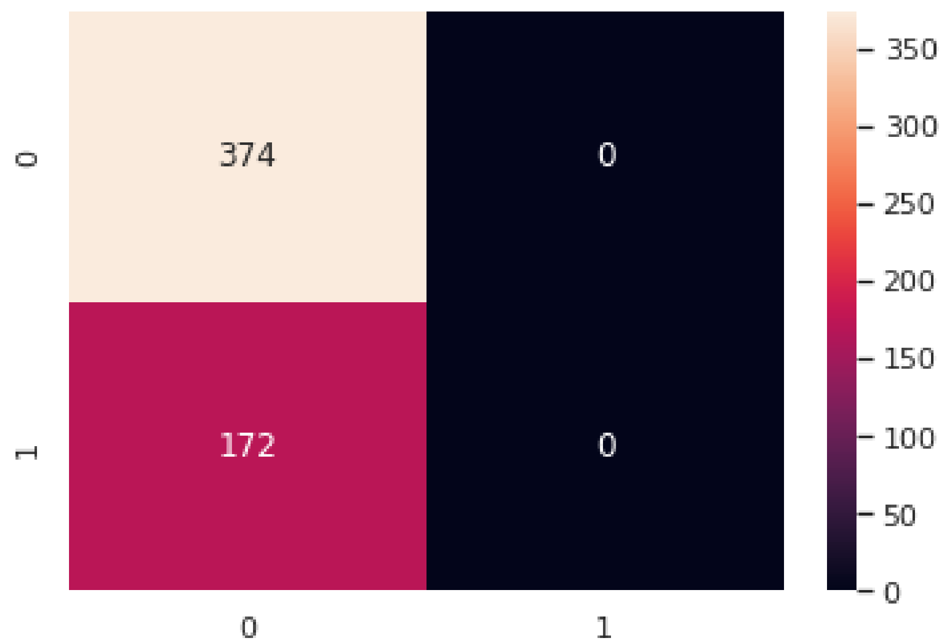

```
Regularization:1.4000000000000001
```



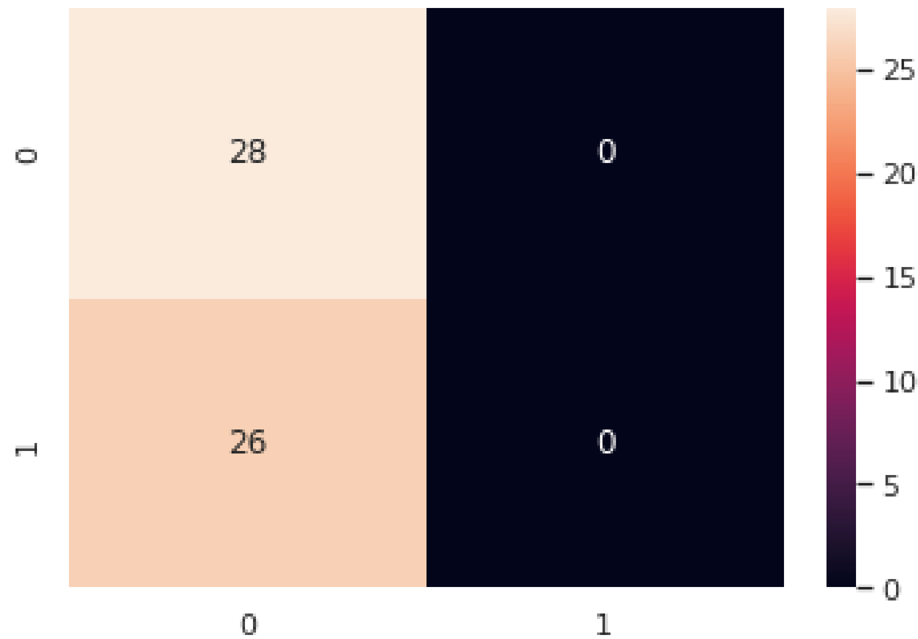

```
Number of epochs until convergence:52

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



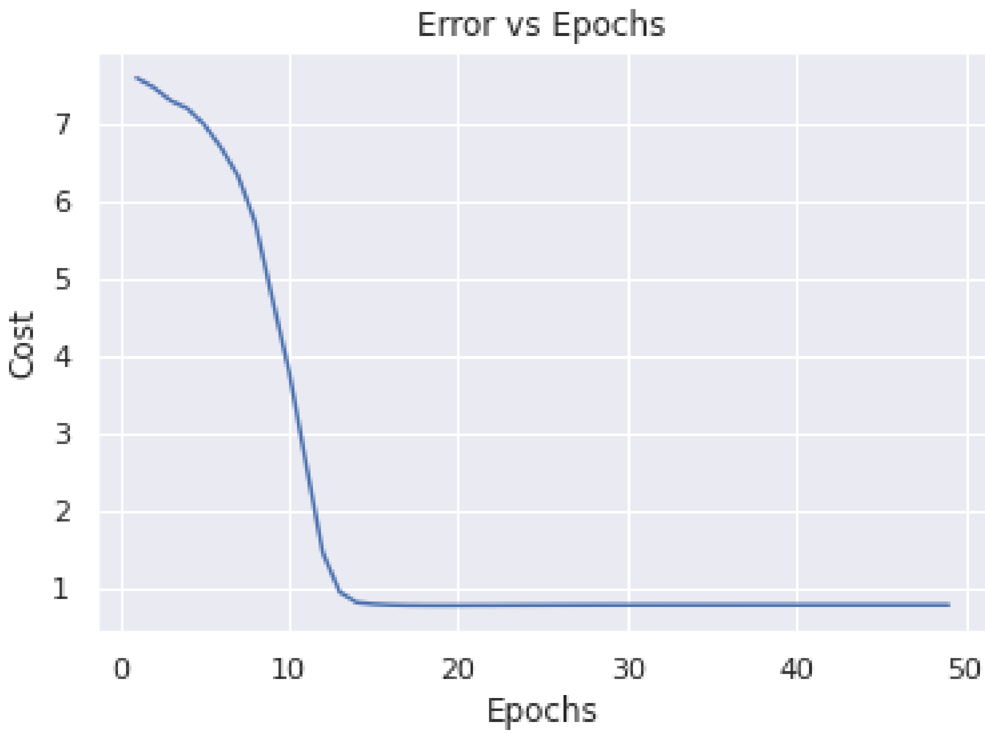

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



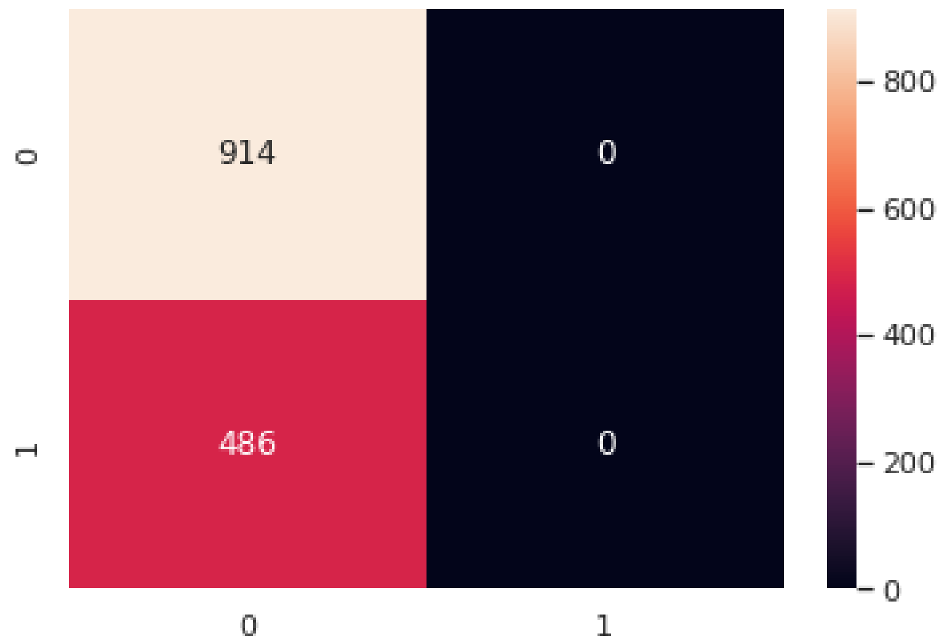
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



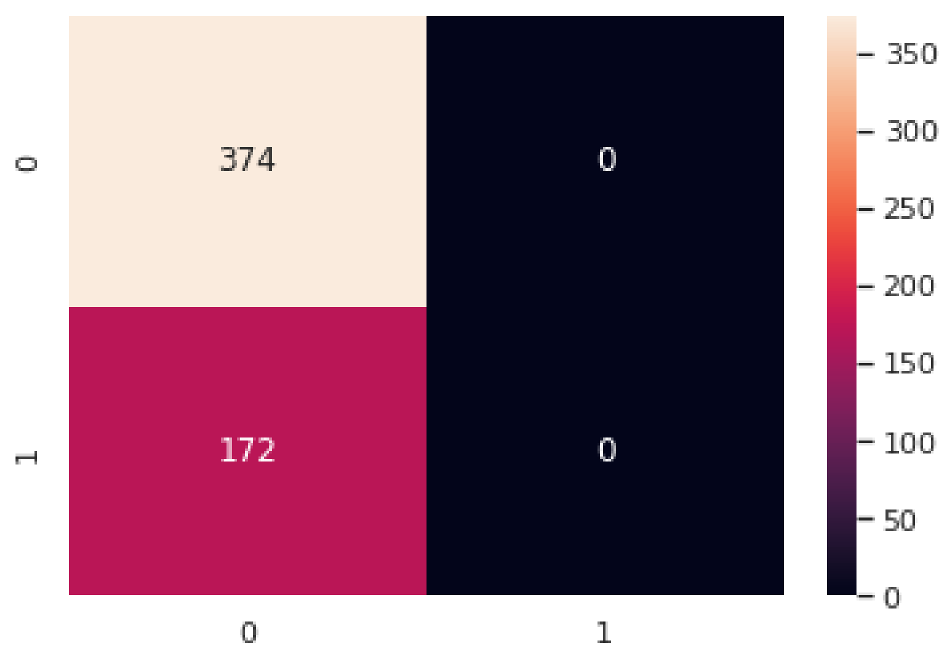

```
Regularization:1.5
```



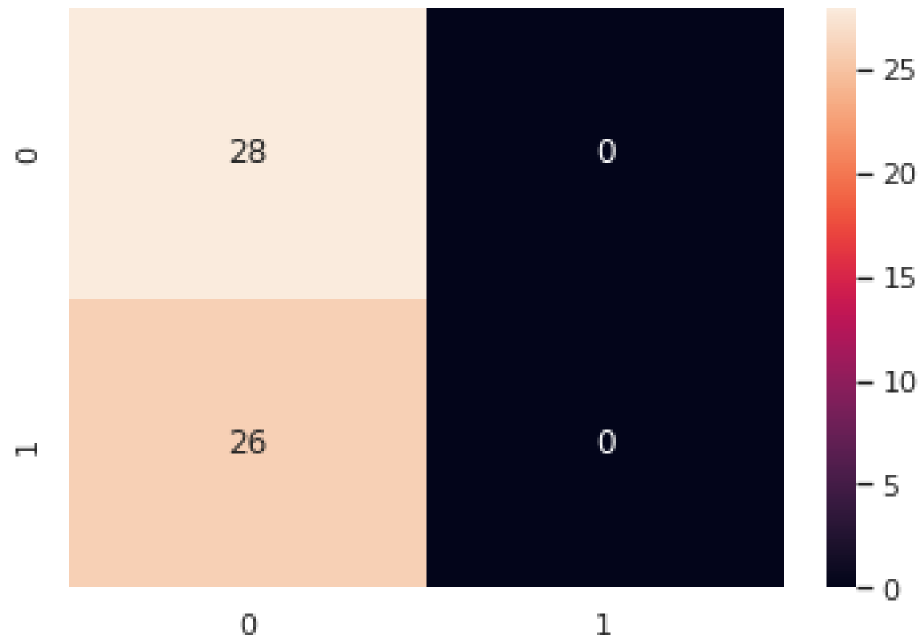

```
Number of epochs until convergence:49

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



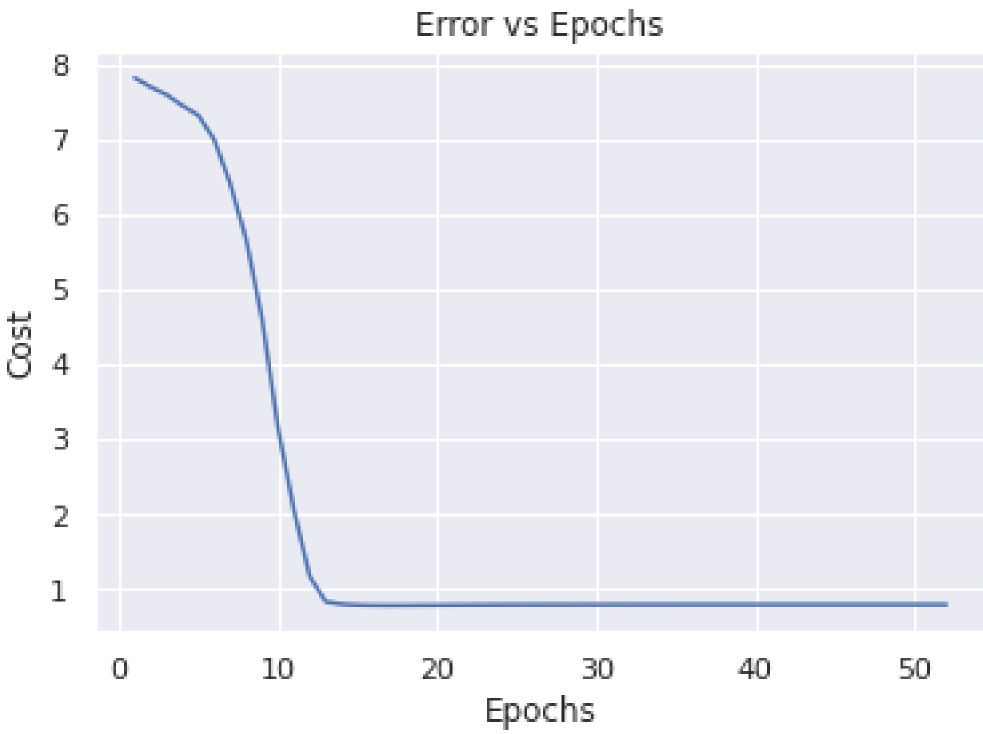

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



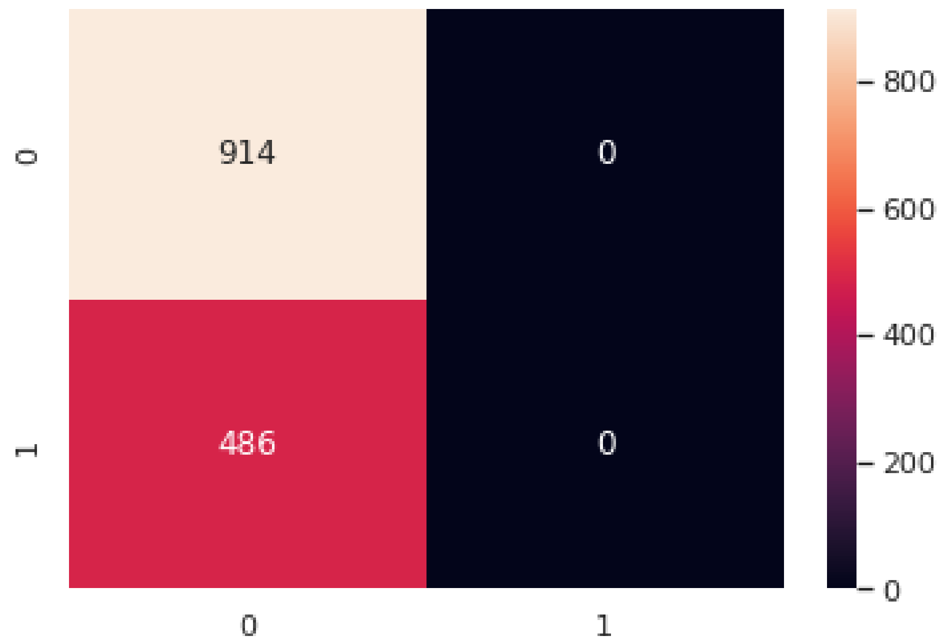
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



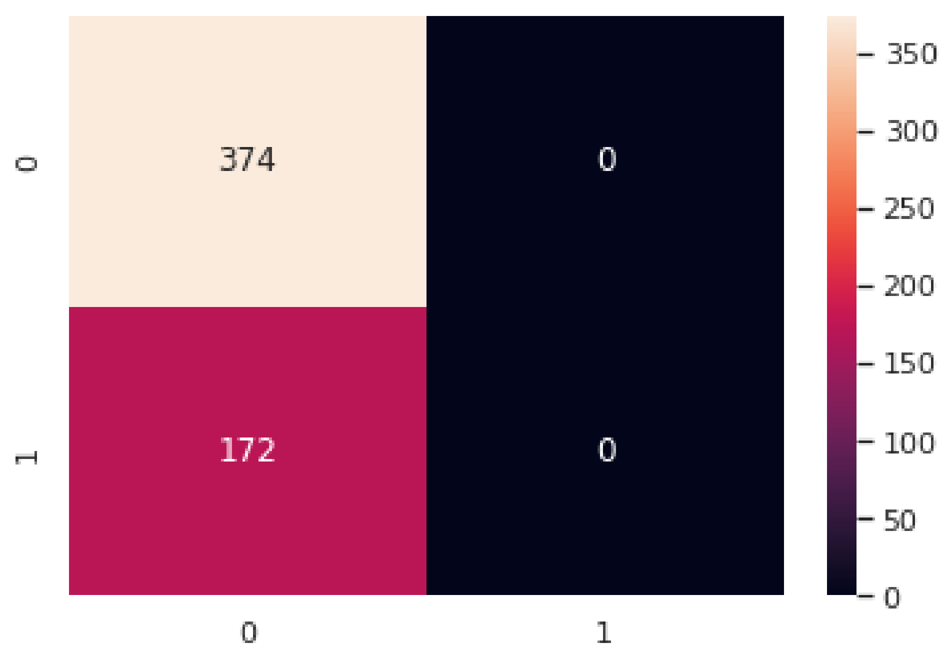

```
Regularization:1.6
```



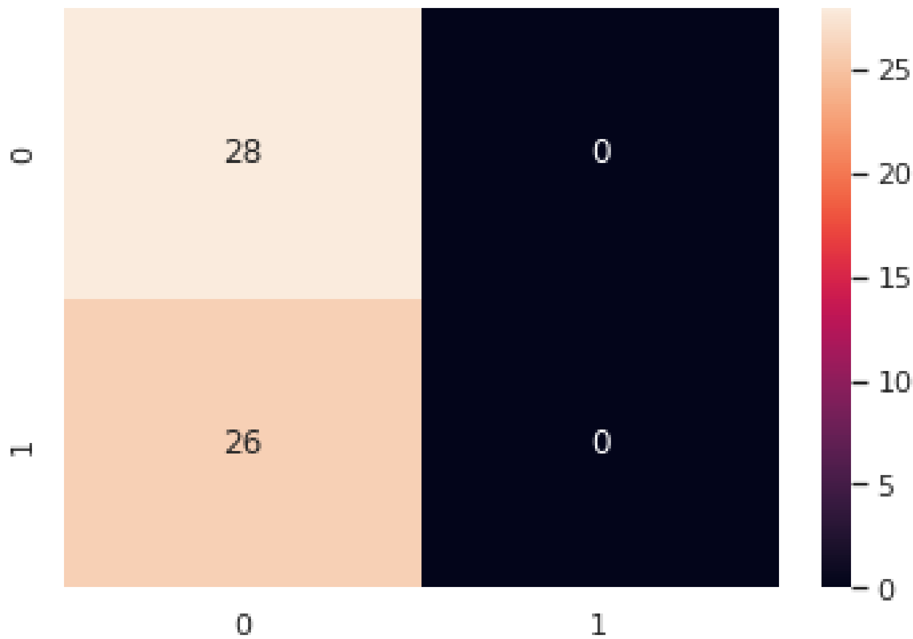

```
Number of epochs until convergence:52

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



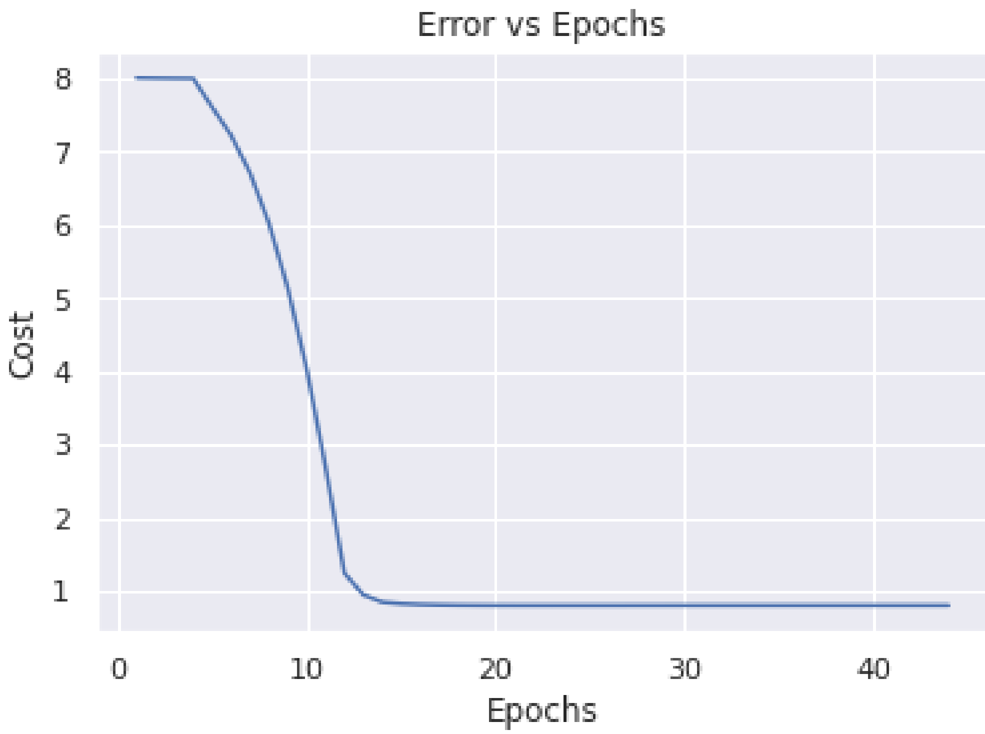
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:



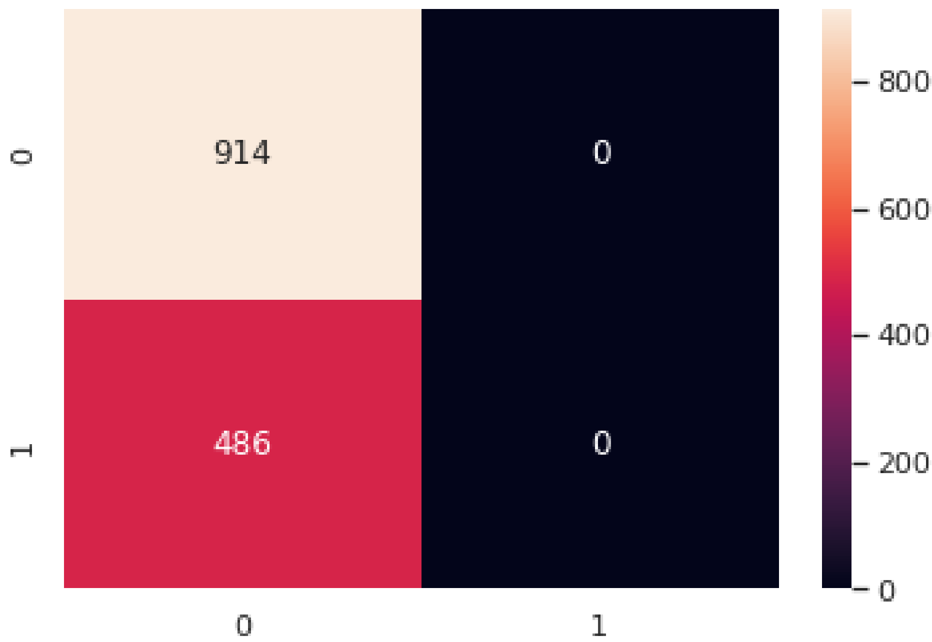
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



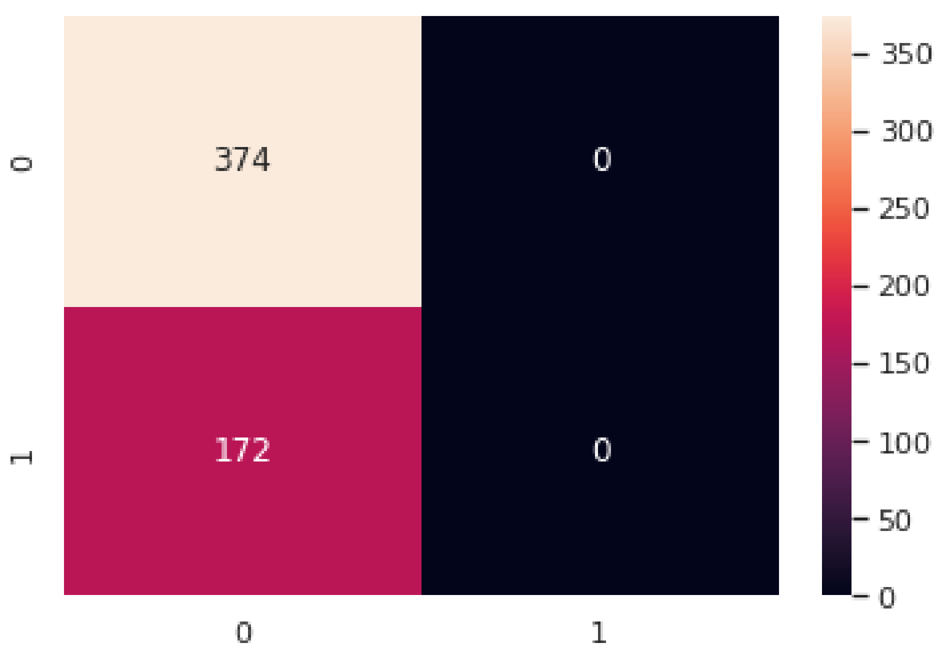

```
Regularization:1.7000000000000002
```



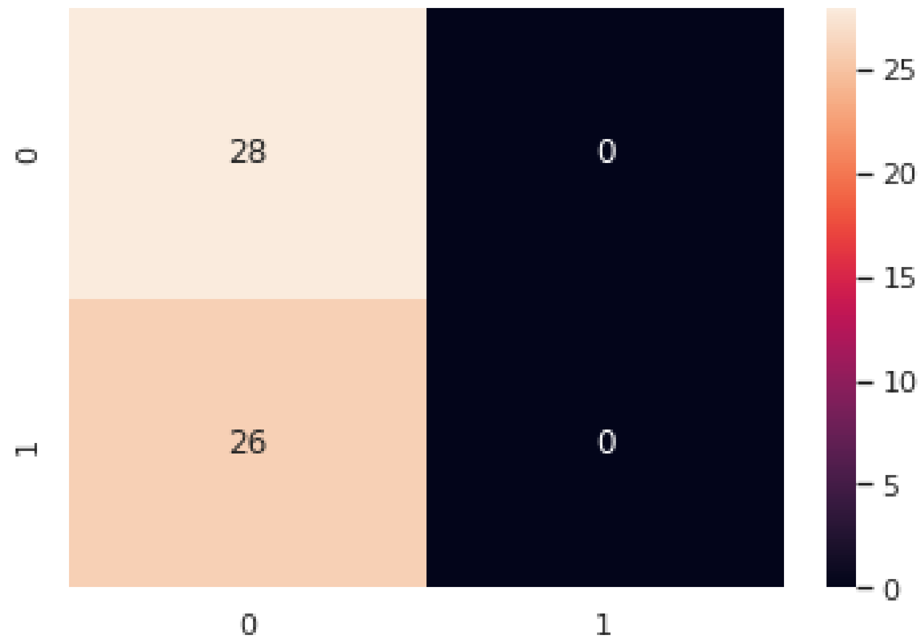

```
Number of epochs until convergence:44

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



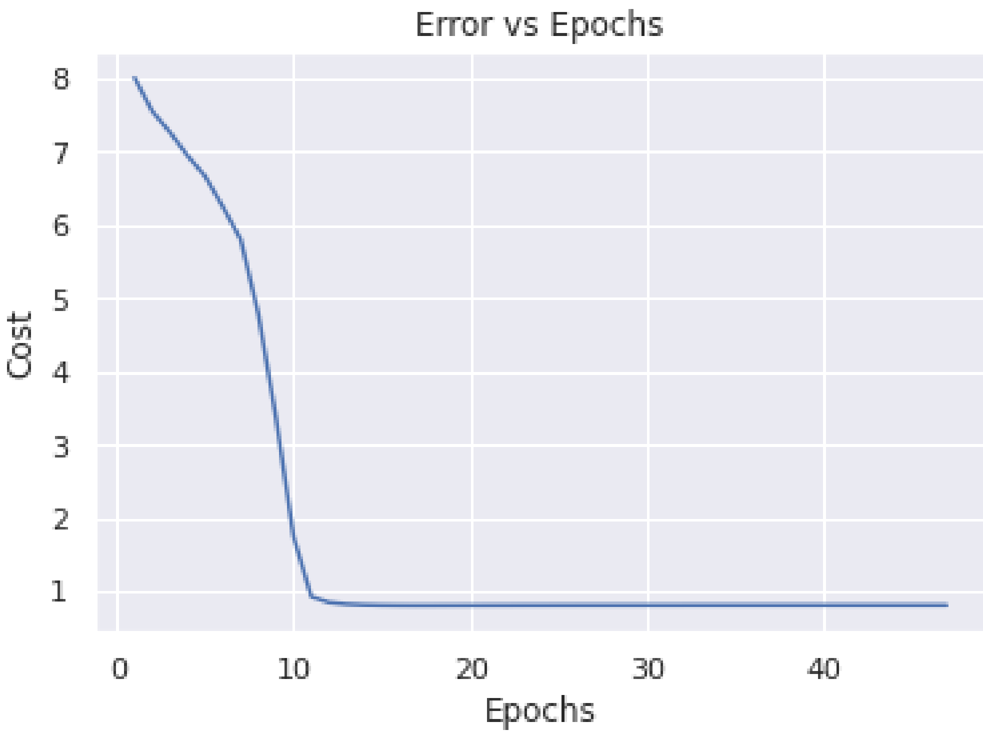

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



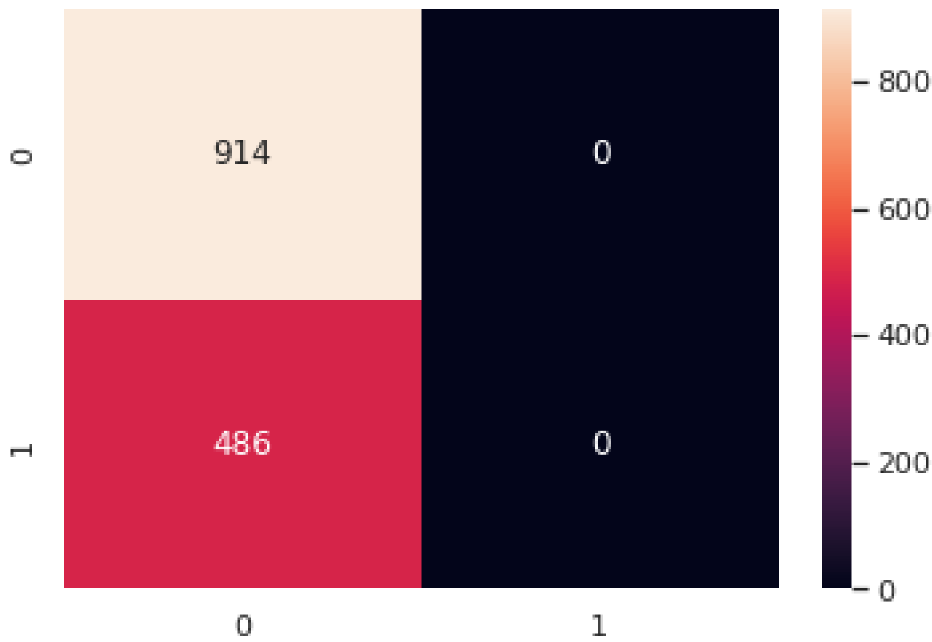
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



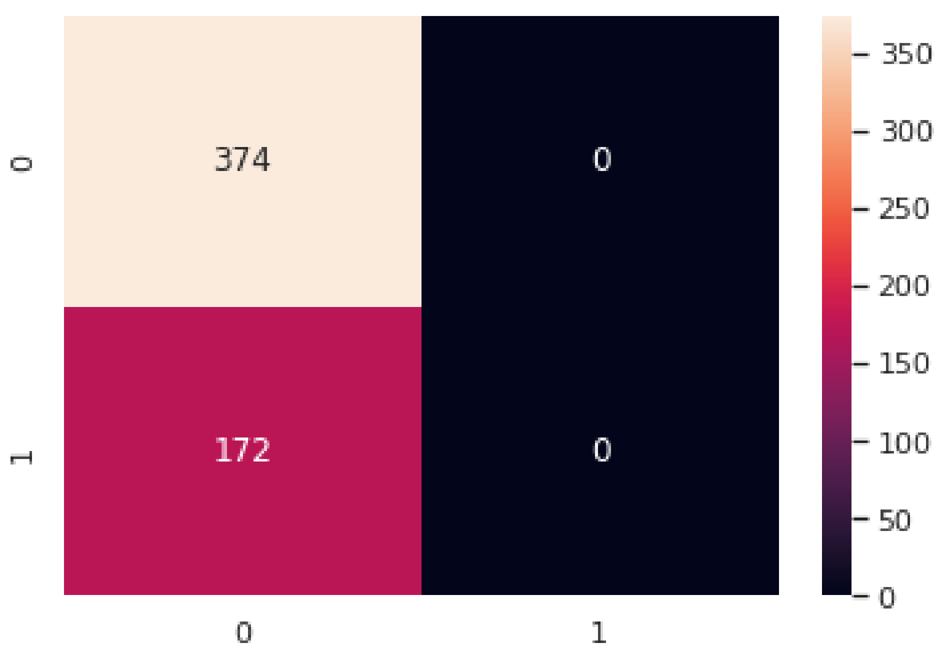

```
Regularization:1.8
```



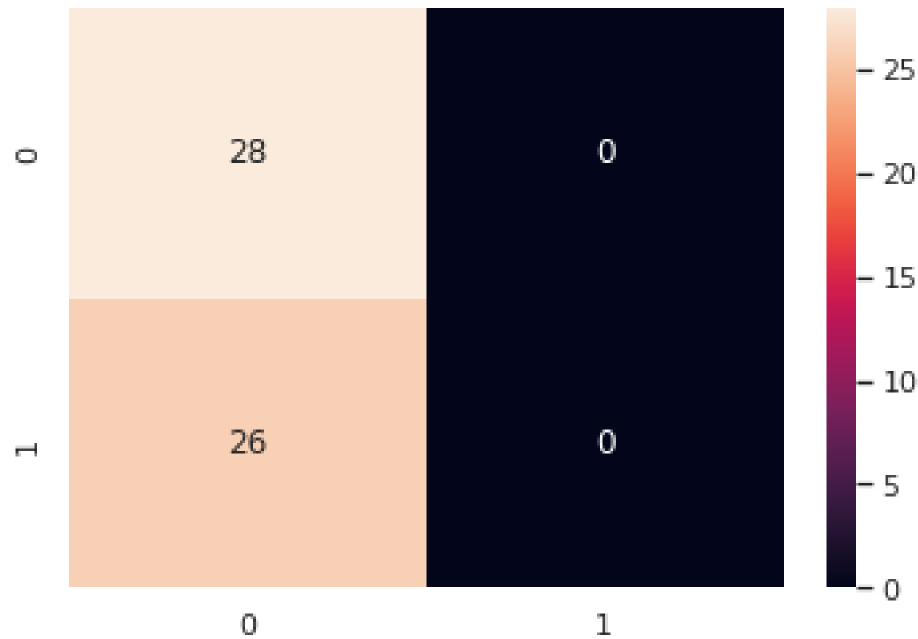

```
Number of epochs until convergence:47

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```



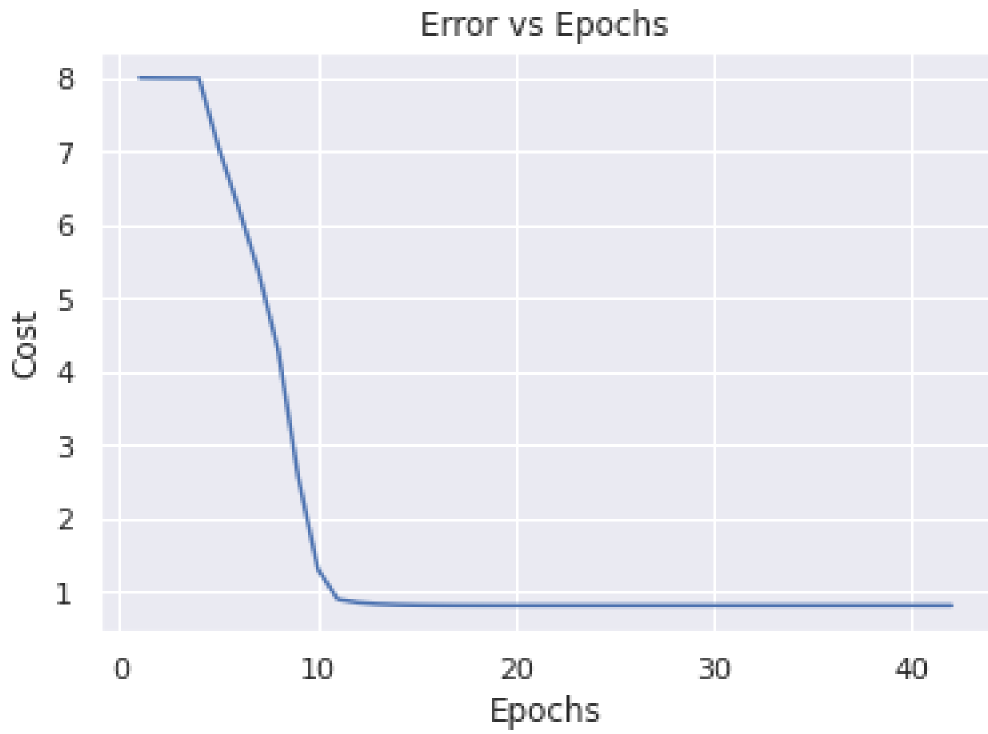

```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



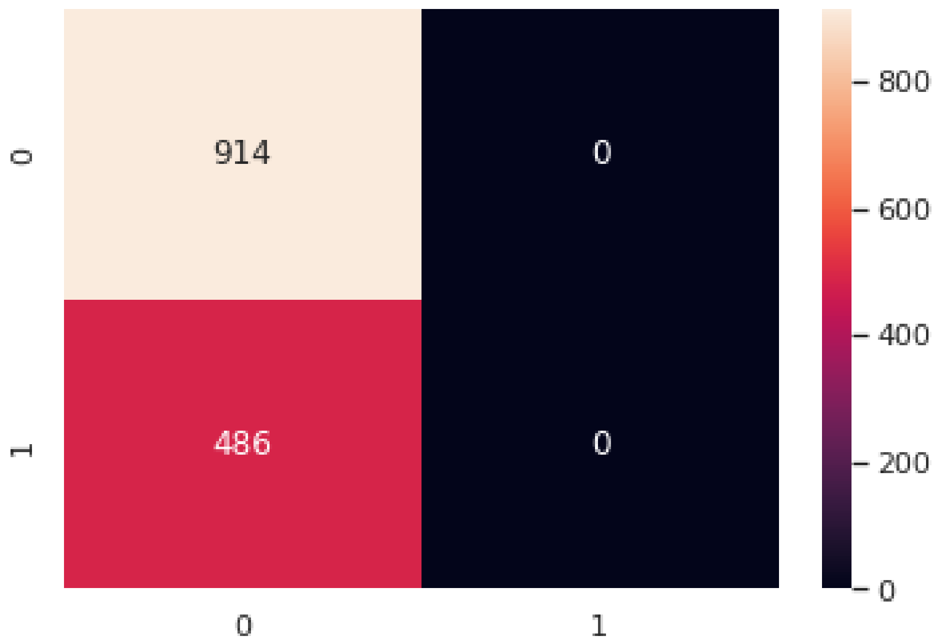
```
Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:
```



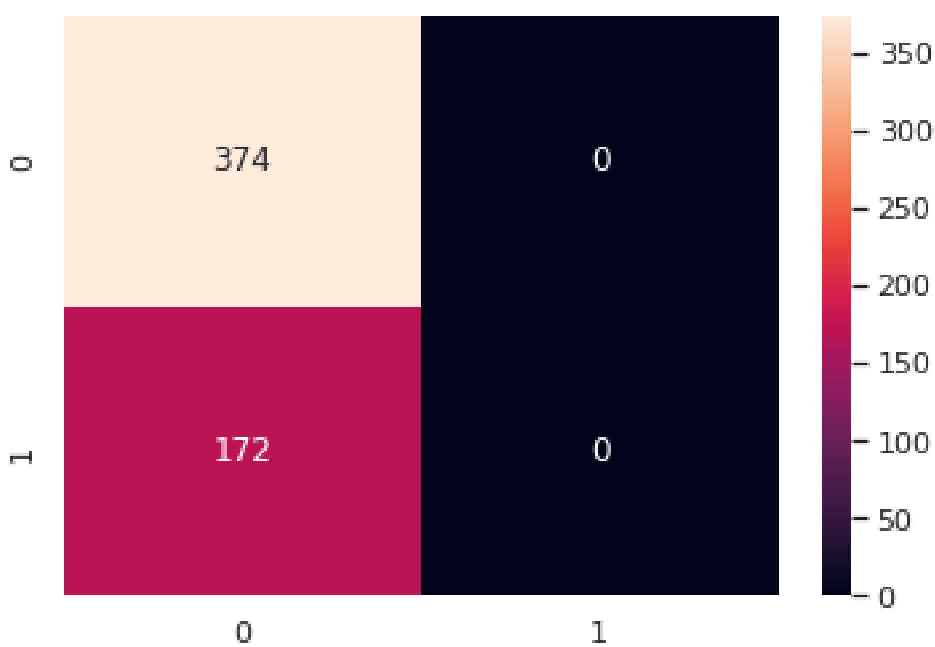

```
Regularization:1.9000000000000001
```



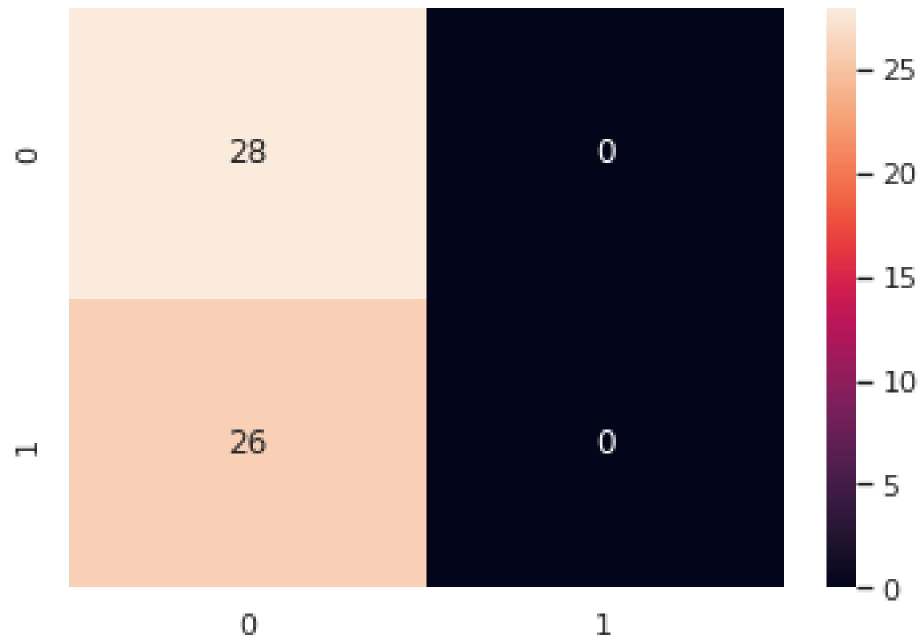

```
Number of epochs until convergence:42

Training Accuracy
The accuracy is: 65.28571428571428%
Confusion Matrix:
```




```
Validation Accuracy
The accuracy is: 68.4981684981685%
Confusion Matrix:
```



Test Accuracy
The accuracy is: 51.85185185185185%
Confusion Matrix:



Regularization	Epochs to train	Training Accuracy	Validation Accuracy	Testing Accuracy
0.0	1000	77.36	78.21	77.78
0.1	499	74.71	75.27	72.22
0.2	404	65.29	68.5	51.85
0.30000000000000004	771	65.29	68.5	51.85
0.4	342	65.29	68.5	51.85
0.5	155	65.29	68.5	51.85
0.6000000000000001	129	65.29	68.5	51.85
0.7000000000000001	164	65.29	68.5	51.85

0.8	135	65.29	68.5	51.85
0.9	114	65.29	68.5	51.85
1.0	98	65.29	68.5	51.85
1.1	72	65.29	68.5	51.85
1.2000000000000002	66	65.29	68.5	51.85
1.3	63	65.29	68.5	51.85
1.4000000000000001	52	65.29	68.5	51.85
1.5	49	65.29	68.5	51.85
1.6	52	65.29	68.5	51.85
1.7000000000000002	44	65.29	68.5	51.85
1.8	47	65.29	68.5	51.85
1.9000000000000001	42	65.29	68.5	51.85

The implementation of regularization seems to have had a negative effect on the accuracy of the network. When the regularization is set to 0, the network performs the best.