In [38]:
```python
import pandas as pd
import numpy as np
import scipy
import h5py
import os
import matplotlib.pyplot as plt
import scipy
from PIL import Image
from scipy import ndimage
%matplotlib inline
import imageio
from skimage.transform import resize
import sklearn
```

In [39]:
```python
os.getcwd()
os.chdir('C:\\Users\\manjm\\OneDrive\\Desktop\\IASRI_Project')
```

Reading Train and Test Data

In [40]:
```python
train_file = "train_catvnoncat.h5"
train_data = h5py.File(train_file, 'r')
train_data.keys()

train_x=train_data.get("train_set_x")
train_x = np.array(train_x)
print(train_x.shape)
train_y=train_data.get("train_set_y")
train_y = np.array(train_y)
print(train_y.shape)

test_file = "test_catvnoncat.h5"
test_data = h5py.File(test_file, 'r')
test_data.keys()

test_x=test_data.get("test_set_x")
test_x = np.array(test_x)
print(test_x.shape)
test_y=test_data.get("test_set_y")
test_y = np.array(test_y)
print(test_y.shape)
```

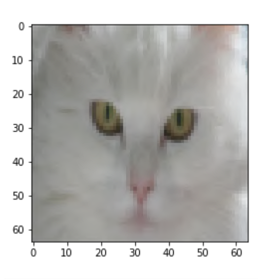
```
(209, 64, 64, 3)
(209,)
(50, 64, 64, 3)
(50,)
```

Function for class prediction

In [5]:
```python
def class_predict(n):
    if n==1:
        return "Cat"
    else:
        return "Not Cat"
```

In [6]:
```python
index= 50
plt.imshow(train_x[index])
image=train_y[index]
class_predict(image)
```

Out[6]:
```
'Cat'
```



In [7]:
```python
### START CODE HERE ### (≈ 3 lines of code)
m_train = train_y.shape[0]
m_test = test_y.shape[0]
num_px = train_x.shape[1]
### END CODE HERE ###

print ("Number of training examples: m_train = " + str(m_train))
print ("Number of testing examples: m_test = " + str(m_test))
print ("Height/Width of each image: num_px = " + str(num_px))
print ("Each image is of size: (" + str(num_px) + ", " + str(num_px) + ", 3)")
print ("train_set_x shape: " + str(train_x.shape))
print ("train_set_y shape: " + str(train_y.shape))
print ("test_set_x shape: " + str(test_x.shape))
print ("test_set_y shape: " + str(test_y.shape))
```

```
Number of training examples: m_train = 209
Number of testing examples: m_test = 50
Height/Width of each image: num_px = 64
Each image is of size: (64, 64, 3)
train_set_x shape: (209, 64, 64, 3)
train_set_y shape: (209,)
test_set_x shape: (50, 64, 64, 3)
test_set_y shape: (50,)
```

In [8]:
```python
# Reshape the training and test examples

### START CODE HERE ### (≈ 2 lines of code)
train_set_x_flatten = train_x.reshape(train_x.shape[0], -1).T
test_set_x_flatten = test_x.reshape(test_x.shape[0], -1).T
### END CODE HERE ###

print ("train_set_x_flatten shape: " + str(train_set_x_flatten.shape))
print ("train_set_y shape: " + str(train_y.shape))
print ("test_set_x_flatten shape: " + str(test_set_x_flatten.shape))
print ("test_set_y shape: " + str(test_y.shape))
print ("sanity check after reshaping: " + str(train_set_x_flatten[0:5,0]))
```

```
train_set_x_flatten shape: (12288, 209)
train_set_y shape: (209,)
test_set_x_flatten shape: (12288, 50)
test_set_y shape: (50,)
sanity check after reshaping: [17 31 56 22 33]
```

In [9]:
```python
train_set_x = train_set_x_flatten / 255
test_set_x = test_set_x_flatten / 255
```

In [10]:
```python
# SIGMOID FUNCTION

def sigmoid(z):
    """
    Compute the sigmoid of z

    Arguments:
    x -- A scalar or numpy array of any size.

    Return:
    s -- sigmoid(z)
    """

    ### START CODE HERE ### (≈ 1 line of code)
    s = 1 / (1 + np.exp(-z))
    ### END CODE HERE ###

    return s
```

In [11]:
```python
print ("sigmoid(0) = " + str(sigmoid(0)))
print ("sigmoid(100) = " + str(sigmoid(9.2)))
```

```
sigmoid(0) = 0.5
sigmoid(100) = 0.9998989708060922
```

In [12]:
```python
#initialize_with_zeros

def initialize_with_zeros(dim):
    """
    This function creates a vector of zeros of shape (dim, 1) for w and initializes b to 0.

    Argument:
    dim -- size of the w vector we want (or number of parameters in this case)

    Returns:
    w -- initialized vector of shape (dim, 1)
    b -- initialized scalar (corresponds to the bias)
    """

    ### START CODE HERE ### (≈ 1 line of code)
    w = np.zeros(shape=(dim, 1))
    b = 0
    ### END CODE HERE ###

    assert(w.shape == (dim, 1))
    assert(isinstance(b, float) or isinstance(b, int))

    return w, b
```

In [13]:
```python
dim = 3
w, b = initialize_with_zeros(dim)
print ("w = " + str(w))
print ("b = " + str(b))
```

```
w = [[0.]
 [0.]
 [0.]]
b = 0
```

In [30]:
```python
# FUNCTION: propagate

def propagate(w, b, X, Y):
    """
    Implement the cost function and its gradient for the propagation explained above

    Arguments:
    w -- weights, a numpy array of size (num_px * num_px * 3, 1)
    b -- bias, a scalar
    X -- data of size (num_px * num_px * 3, number of examples)
    Y -- true "label" vector (containing 0 if non-cat, 1 if cat) of size (1, number of examples)

    Return:
    cost -- negative log-likelihood cost for logistic regression
    dw -- gradient of the loss with respect to w, thus same shape as w
    db -- gradient of the loss with respect to b, thus same shape as b

    Tips:
    - Write your code step by step for the propagation
    """

    m = X.shape[1]

    # FORWARD PROPAGATION (FROM X TO COST)
    ### START CODE HERE ### (≈ 2 lines of code)
    A = sigmoid(np.dot(w.T, X) + b)  # compute activation
    cost = (- 1 / m) * np.sum(Y * np.log(A) + (1 - Y) * (np.log(1 - A)))  # compute cost
    ### END CODE HERE ###

    # BACKWARD PROPAGATION (TO FIND GRAD)
    ### START CODE HERE ### (≈ 2 lines of code)
    dw = (1 / m) * np.dot(X, (A - Y).T)
    db = (1 / m) * np.sum(A - Y)
    ### END CODE HERE ###

    assert(dw.shape == w.shape)
    assert(db.dtype == float)
    cost = np.squeeze(cost)
    assert(cost.shape == ())

    grads = {"dw": dw,
             "db": db}

    return grads, cost
```

In [31]:
```python
w, b, X, Y = np.array([[1], [2]]), 2, np.array([[1,2], [3,4]]), np.array([[1, 0]])
grads, cost = propagate(w, b, X, Y)
print ("dw = " + str(grads["dw"]))
print ("db = " + str(grads["db"]))
print ("cost = " + str(cost))
```

```
dw = [[0.99993216]
 [1.99980262]]
db = 0.49993523062470574
cost = 6.000064773192205
```

In [16]:
```python
# FUNCTION: optimize

def optimize(w, b, X, Y, num_iterations, learning_rate, print_cost = False):
    """
    This function optimizes w and b by running a gradient descent algorithm

    Arguments:
    w -- weights, a numpy array of size (num_px * num_px * 3, 1)
    b -- bias, a scalar
    X -- data of shape (num_px * num_px * 3, number of examples)
    Y -- true "label" vector (containing 0 if non-cat, 1 if cat), of shape (1, number of examples)
    num_iterations -- number of iterations of the optimization loop
    learning_rate -- learning rate of the gradient descent update rule
    print_cost -- True to print the loss every 100 steps

    Returns:
    params -- dictionary containing the weights w and bias b
    grads -- dictionary containing the gradients of the weights and bias with respect to the cost function
    costs -- list of all the costs computed during the optimization, this will be used to plot the learning curve.

    Tips:
     Basically we need to write down two steps and iterate through them:
        1) Calculate the cost and the gradient for the current parameters. Use propagate().
        2) Update the parameters using gradient descent rule for w and b.
    """

    costs = []

    for i in range(num_iterations):


        # Cost and gradient calculation (≈ 1-4 lines of code)
        ### START CODE HERE ###
        grads, cost = propagate(w, b, X, Y)
        ### END CODE HERE ###

        # Retrieve derivatives from grads
        dw = grads["dw"]
        db = grads["db"]

        # update rule (≈ 2 lines of code)
        ### START CODE HERE ###
        w = w - learning_rate * dw  # need to broadcast
        b = b - learning_rate * db
        ### END CODE HERE ###

        # Record the costs
        if i % 100 == 0:
            costs.append(cost)

        # Print the cost every 100 training examples
        if print_cost and i % 100 == 0:
            print ("Cost after iteration %i: %f" % (i, cost))

    params = {"w": w,
              "b": b}

    grads = {"dw": dw,
             "db": db}

    return params, grads, costs
```

In [17]:
```python
params, grads, costs = optimize(w, b, X, Y, num_iterations= 100, learning_rate = 0.009, print_cost = False)

print ("w = " + str(params["w"]))
print ("b = " + str(params["b"]))
print ("dw = " + str(grads["dw"]))
print ("db = " + str(grads["db"]))
```

```
w = [[0.1124579 ]
 [0.23106775]]
b = 1.5593049248448891
dw = [[0.90158428]
 [1.76250842]]
db = 0.4304620716786828
```

In [18]:
```python
# FUNCTION: predict

def predict(w, b, X):
    '''
    Predict whether the label is 0 or 1 using learned logistic regression parameters (w, b)

    Arguments:
    w -- weights, a numpy array of size (num_px * num_px * 3, 1)
    b -- bias, a scalar
    X -- data of size (num_px * num_px * 3, number of examples)

    Returns:
    Y_prediction -- a numpy array (vector) containing all predictions (0/1) for the examples in X
    '''

    m = X.shape[1]
    Y_prediction = np.zeros((1, m))
    w = w.reshape(X.shape[0], 1)

    # Compute vector "A" predicting the probabilities of a cat being present in the picture
    ### START CODE HERE ### (≈ 1 line of code)
    A = sigmoid(np.dot(w.T, X) + b)
    ### END CODE HERE ###

    for i in range(A.shape[1]):
        # Convert probabilities a[0,i] to actual predictions p[0,i]
        ### START CODE HERE ### (≈ 4 lines of code)
        Y_prediction[0, i] = 1 if A[0, i] > 0.5 else 0
        ### END CODE HERE ###

    assert(Y_prediction.shape == (1, m))

    return Y_prediction
```

In [33]:
```python
print("predictions = " + str(predict(w, b, X)))
```

```
predictions = [[1. 1.]]
```

In [20]:
```python
# FUNCTION: model

def model(X_train, Y_train, X_test, Y_test, num_iterations=2000, learning_rate=0.5, print_cost=False):
    """
    Builds the logistic regression model by calling the function you've implemented previously

    Arguments:
    X_train -- training set represented by a numpy array of shape (num_px * num_px * 3, m_train)
    Y_train -- training labels represented by a numpy array (vector) of shape (1, m_train)
    X_test -- test set represented by a numpy array of shape (num_px * num_px * 3, m_test)
    Y_test -- test labels represented by a numpy array (vector) of shape (1, m_test)
    num_iterations -- hyperparameter representing the number of iterations to optimize the parameters
    learning_rate -- hyperparameter representing the learning rate used in the update rule of optimize()
    print_cost -- Set to true to print the cost every 100 iterations

    Returns:
    d -- dictionary containing information about the model.
    """

    ### START CODE HERE ###
    # initialize parameters with zeros (≈ 1 line of code)
    w, b = initialize_with_zeros(X_train.shape[0])

    # Gradient descent (≈ 1 line of code)
    parameters, grads, costs = optimize(w, b, X_train, Y_train, num_iterations, learning_rate, print_cost)

    # Retrieve parameters w and b from dictionary "parameters"
    w = parameters["w"]
    b = parameters["b"]

    # Predict test/train set examples (≈ 2 lines of code)
    Y_prediction_test = predict(w, b, X_test)
    Y_prediction_train = predict(w, b, X_train)

    ### END CODE HERE ###

    # Print train/test Errors
    print("train accuracy: {} %".format(100 - np.mean(np.abs(Y_prediction_train - Y_train)) * 100))
    print("test accuracy: {} %".format(100 - np.mean(np.abs(Y_prediction_test - Y_test)) * 100))


    d = {"costs": costs,
         "Y_prediction_test": Y_prediction_test,
         "Y_prediction_train" : Y_prediction_train,
         "w" : w,
         "b" : b,
         "learning_rate" : learning_rate,
         "num_iterations": num_iterations}

    return d
```

In [21]:
```python
d = model(train_set_x, train_y, test_set_x, test_y, num_iterations = 2000, learning_rate = 0.005, print_cost = True)
```

```
Cost after iteration 0: 0.693147
Cost after iteration 100: 0.584508
Cost after iteration 200: 0.466949
Cost after iteration 300: 0.376007
Cost after iteration 400: 0.331463
Cost after iteration 500: 0.303273
Cost after iteration 600: 0.279880
Cost after iteration 700: 0.260042
Cost after iteration 800: 0.242941
Cost after iteration 900: 0.228004
Cost after iteration 1000: 0.214820
Cost after iteration 1100: 0.203078
Cost after iteration 1200: 0.192544
Cost after iteration 1300: 0.183033
Cost after iteration 1400: 0.174399
Cost after iteration 1500: 0.166521
Cost after iteration 1600: 0.159305
Cost after iteration 1700: 0.152667
Cost after iteration 1800: 0.146542
Cost after iteration 1900: 0.140872
train accuracy: 99.04306220095694 %
test accuracy: 70.0 %
```

In [51]:
```python
d["Y_prediction_train"][0]
```

Out[51]:
```
array([0., 0., 1., 0., 0., 0., 0., 1., 0., 0., 0., 1., 0., 1., 1., 0., 0.,
       0., 0., 1., 0., 0., 0., 0., 1., 1., 0., 1., 0., 1., 0., 0., 0., 0.,
       0., 0., 0., 0., 1., 0., 0., 0., 1., 0., 0., 0., 0., 1., 0., 0., 1.,
       0., 0., 0., 1., 0., 1., 1., 0., 1., 1., 1., 0., 0., 0., 0., 0., 0.,
       1., 0., 0., 1., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 1., 1.,
       0., 0., 0., 1., 0., 0., 0., 1., 1., 1., 0., 0., 1., 0., 0., 0., 0.,
       1., 0., 1., 0., 1., 1., 1., 1., 1., 1., 0., 0., 0., 0., 0., 1., 0.,
       0., 0., 1., 0., 0., 1., 0., 1., 0., 1., 1., 0., 0., 0., 1., 1., 1.,
       1., 1., 0., 0., 0., 0., 1., 0., 1., 1., 1., 0., 1., 1., 0., 0., 0.,
       1., 0., 0., 1., 0., 0., 0., 0., 0., 1., 0., 1., 0., 1., 0., 0., 1.,
       1., 1., 0., 0., 1., 1., 0., 1., 0., 1., 0., 0., 0., 0., 0., 1., 0.,
       0., 1., 0., 0., 0., 1., 0., 0., 0., 0., 1., 0., 0., 1., 0., 0., 0.,
       0., 0., 0., 0., 0.])
```

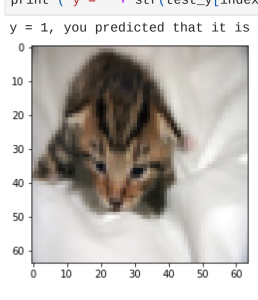
Metrics

In [56]:
```python
from sklearn.metrics import classification_report
print(sklearn.metrics.classification_report(train_y, d["Y_prediction_train"][0]))
print(sklearn.metrics.classification_report(test_y, d["Y_prediction_test"][0]))
```

```
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       137
           1       0.99      0.99      0.99        72

    accuracy                           0.99       209
   macro avg       0.99      0.99      0.99       209
weighted avg       0.99      0.99      0.99       209

              precision    recall  f1-score   support

           0       0.55      0.71      0.62        17
           1       0.82      0.70      0.75        33

    accuracy                           0.70        50
   macro avg       0.68      0.70      0.68        50
weighted avg       0.73      0.70      0.71        50
```

In [22]:
```python
# Example of a picture that was wrongly classified.
index = 1
plt.imshow(test_set_x[:,index].reshape((num_px, num_px, 3)))
print ("y = " + str(test_y[index]) + ", you predicted that it is a \"" + class_predict(d["Y_prediction_test"][0, index]) +  "\" picture.")
```

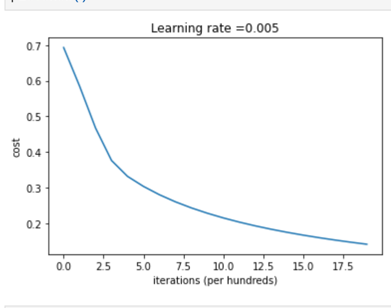
```
y = 1, you predicted that it is a "Cat" picture.
```



In [23]:
```python
d['Y_prediction_test'].shape
```

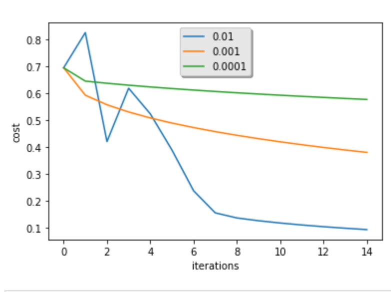
Out[23]:
```
(1, 50)
```

In [24]:
```python
# Plot learning curve (with costs)
costs = np.squeeze(d['costs'])
plt.plot(costs)
plt.ylabel('cost')
plt.xlabel('iterations (per hundreds)')
plt.title("Learning rate =" + str(d["learning_rate"]))
plt.show()
```



In [25]:
```python
learning_rates = [0.01, 0.001, 0.0001]
models = {}
for i in learning_rates:
    print ("learning rate is: " + str(i))
    models[str(i)] = model(train_set_x, train_y, test_set_x, test_y, num_iterations = 1500, learning_rate = i, print_cost = False)
    print ('\n' + "-------------------------------------------------------" + '\n')

for i in learning_rates:
    plt.plot(np.squeeze(models[str(i)]["costs"]), label= str(models[str(i)]["learning_rate"]))

plt.ylabel('cost')
plt.xlabel('iterations')

legend = plt.legend(loc='upper center', shadow=True)
frame = legend.get_frame()
frame.set_facecolor('0.90')
plt.show()
```

```
learning rate is: 0.01
train accuracy: 99.52153110047847 %
test accuracy: 68.0 %

-------------------------------------------------------

learning rate is: 0.001
train accuracy: 88.99521531100478 %
test accuracy: 64.0 %

-------------------------------------------------------

learning rate is: 0.0001
train accuracy: 68.42105263157895 %
test accuracy: 36.0 %

-------------------------------------------------------
```



In [26]:
```python
class_predict(1.000)
```

Out[26]:
```
'Cat'
```

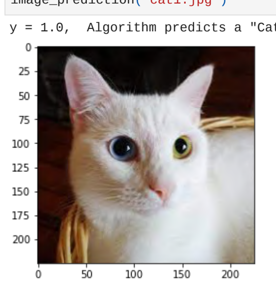
In [27]:
```python
## Image Prediction from model
def image_prediction(my_image):
    #my_image = "cat1.jpg"   # change this to the name of your image file
    ## END CODE HERE ##

    # We preprocess the image to fit your algorithm.
    fname = "images/" + my_image
    image = np.array(imageio.imread(fname))
    my_image=resize(image, (num_px, num_px)).reshape((1, num_px * num_px * 3)).T

    my_predicted_image = predict(d["w"], d["b"], my_image)

    plt.imshow(image)
    print("y = " + str(np.squeeze(my_predicted_image)) + ",  Algorithm predicts a \"" + class_predict(my_predicted_image[0][0]))
```

In [62]:
```python
image_prediction("nssta.jpg")
```

```
y = 0.0,  Algorithm predicts a "Not Cat
```

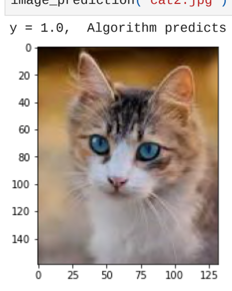
In [63]:
```python
image_prediction("cat1.jpg")
```

```
y = 1.0,  Algorithm predicts a "Cat
```



In [64]:
```python
image_prediction("cat2.jpg")
```

```
y = 1.0,  Algorithm predicts a "Cat
```



In [65]:
```python
image_prediction("Raghvendra_Image.jpg")
```

```
y = 0.0,  Algorithm predicts a "Not Cat
```