```
In [91]:
          import os
          %matplotlib inline
          # Prevent CUDA from using GPU as it does not work well on my pc
          os.environ["CUDA_VISIBLE_DEVICES"] = "-1"
          # Set Constants of the model
          BATCH SIZE = 64
          SHUFFLE BUFFER SIZE = 100
 In [2]:
          # Helper functions
          import numpy as np
          # Breaks down a list of integer values into a one-hot like format
          def one_hot_training(np_array):
              transformed list = []
              for arr in np array:
                  new_arr = np.zeros(10)
                  new_arr[int(arr)] = 1
                  transformed_list.append(new_arr)
              return np.array(transformed list)
          # This translates the highest value from the one-hot encoding into the correct sign nam
          def one_hot_translator(np_array):
              labels names = ['Stop','Yield','Red Light','Green Light','Roundabout','Right Turn 0
                           'Do Not Enter', 'Crosswalk', 'Handicap Parking', 'No Parking']
              return labels names[np.argmax(np array)]
          # This translates an entire array of one-hot encoded sign predictions
          def translate all(np array):
              translated_values = []
              for i in np_array:
                  translated_values.append(one_hot_translator(i))
              return np.array(translated values)
 In [3]:
          # First import the data
          import tensorflow as tf
          data_train = np.load('data_train.npy').transpose()
          labels train = np.load('labels train.npy')
          data train = np.array([i.reshape(300,300,3) for i in data train])
          data train = np.array(tf.cast(tf.image.resize(data train,(150,150)), np.uint8))
 In [4]:
          # Process the data so that it is in the expected form for the InceptionV3 model
          import tensorflow as tf
          processed = tf.keras.applications.inception v3.preprocess input(data train, data format
          # Break down data into training and test sets
          from sklearn.model selection import train test split
          x train, x test, t train, t test = train test split(processed, one hot training(labels
 In [5]:
          # Augment data to reduce overfitting
          from tensorflow.keras.preprocessing.image import ImageDataGenerator
          train datagen = ImageDataGenerator(horizontal flip=True,
```

```
brightness_range=(.75, 1))
       train generator = train datagen.flow(
           x_train,
           y = t train,
           batch_size=BATCH_SIZE)
In [6]:
       # Import the InceptionV3 Model
       from tensorflow.keras.applications.inception_v3 import InceptionV3
       inception = InceptionV3(input shape=(150,150,3),
                           include_top=False,
                           weights='imagenet')
       # Set layers to false to prevent overwriting the existing model
       for layer in inception.layers:
           layer.trainable = False
       # Create output layers that will be trained
       from tensorflow.keras.optimizers import SGD
       x = tf.keras.layers.Flatten()(inception.output)
       x = tf.keras.layers.Dense(1024, activation="relu")(x)
       x = tf.keras.layers.Dropout(0.15)(x)
       x = tf.keras.layers.Dense(10, activation='softmax')(x)
       # Create Optimizer
       Adam = tf.keras.optimizers.Adam(learning rate=0.001, beta 1=0.9, beta 2=0.999, epsilon=
       Nadam = tf.keras.optimizers.Nadam(learning rate=0.001, beta 1=0.9, beta 2=0.999, epsilo
       SGD = SGD(learning rate=0.01, nesterov=True)
       optimizer = SGD
       # Finalize and compile the model
       model = tf.keras.Model(inception.input, outputs = x)
       model.compile(optimizer = optimizer,
                  loss = 'categorical crossentropy',
                  metrics = ['categorical_accuracy', 'acc', 'mean_squared_error'])
In [7]:
       # Fit the model to the dataset
       es = tf.keras.callbacks.EarlyStopping(monitor='acc', mode='max', verbose=1, patience=10
       callbacks = tf.keras.callbacks.Callback()
       history = model.fit(train generator, epochs=140, batch size=BATCH SIZE, callbacks=[es])
       model.save("140_epoch.h5")
       Epoch 1/140
       uracy: 0.6959 - acc: 0.6959 - mean_squared_error: 0.0451
       Epoch 2/140
       uracy: 0.8565 - acc: 0.8565 - mean squared error: 0.0206
       uracy: 0.8931 - acc: 0.8931 - mean squared error: 0.0164
       Epoch 4/140
       uracy: 0.9036 - acc: 0.9036 - mean squared error: 0.0144
```

vertical\_flip=True,
rotation range=90,

```
Epoch 5/140
uracy: 0.9118 - acc: 0.9118 - mean_squared_error: 0.0132
Epoch 6/140
uracy: 0.9151 - acc: 0.9151 - mean squared error: 0.0127
Epoch 7/140
uracy: 0.9221 - acc: 0.9221 - mean_squared_error: 0.0118
Epoch 8/140
uracy: 0.9249 - acc: 0.9249 - mean_squared_error: 0.0116
Epoch 9/140
uracy: 0.9326 - acc: 0.9326 - mean_squared_error: 0.0104
Epoch 10/140
uracy: 0.9334 - acc: 0.9334 - mean_squared_error: 0.0104
Epoch 11/140
uracy: 0.9383 - acc: 0.9383 - mean_squared_error: 0.0095
Epoch 12/140
uracy: 0.9411 - acc: 0.9411 - mean_squared_error: 0.0092
Epoch 13/140
uracy: 0.9407 - acc: 0.9407 - mean_squared_error: 0.0090
Epoch 14/140
uracy: 0.9403 - acc: 0.9403 - mean_squared_error: 0.0092
Epoch 15/140
uracy: 0.9459 - acc: 0.9459 - mean squared error: 0.0085
Epoch 16/140
uracy: 0.9465 - acc: 0.9465 - mean_squared_error: 0.0084
Epoch 17/140
uracy: 0.9473 - acc: 0.9473 - mean squared error: 0.0082
Epoch 18/140
uracy: 0.9447 - acc: 0.9447 - mean squared error: 0.0085
Epoch 19/140
uracy: 0.9508 - acc: 0.9508 - mean_squared_error: 0.0076
Epoch 20/140
uracy: 0.9483 - acc: 0.9483 - mean_squared_error: 0.0080
Epoch 21/140
uracy: 0.9467 - acc: 0.9467 - mean squared error: 0.0082
Epoch 22/140
78/78 [============ ] - 37s 468ms/step - loss: 0.1691 - categorical_acc
uracy: 0.9548 - acc: 0.9548 - mean_squared_error: 0.0072
Epoch 23/140
uracy: 0.9580 - acc: 0.9580 - mean_squared_error: 0.0067
Epoch 24/140
uracy: 0.9518 - acc: 0.9518 - mean_squared_error: 0.0074
```

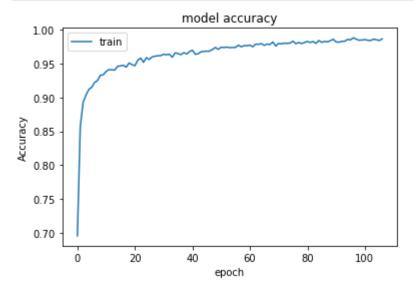
```
Epoch 25/140
uracy: 0.9586 - acc: 0.9586 - mean_squared_error: 0.0066
Epoch 26/140
uracy: 0.9560 - acc: 0.9560 - mean squared error: 0.0067
Epoch 27/140
uracy: 0.9598 - acc: 0.9598 - mean_squared_error: 0.0065
Epoch 28/140
uracy: 0.9607 - acc: 0.9607 - mean_squared_error: 0.0062
Epoch 29/140
uracy: 0.9615 - acc: 0.9615 - mean_squared_error: 0.0064
Epoch 30/140
uracy: 0.9617 - acc: 0.9617 - mean_squared_error: 0.0060
Epoch 31/140
uracy: 0.9637 - acc: 0.9637 - mean_squared_error: 0.0058
Epoch 32/140
uracy: 0.9629 - acc: 0.9629 - mean_squared_error: 0.0058
Epoch 33/140
uracy: 0.9637 - acc: 0.9637 - mean_squared_error: 0.0059
Epoch 34/140
uracy: 0.9592 - acc: 0.9592 - mean_squared_error: 0.0060
Epoch 35/140
uracy: 0.9657 - acc: 0.9657 - mean squared error: 0.0055
Epoch 36/140
uracy: 0.9647 - acc: 0.9647 - mean_squared_error: 0.0058
Epoch 37/140
uracy: 0.9631 - acc: 0.9631 - mean squared error: 0.0058
Epoch 38/140
uracy: 0.9659 - acc: 0.9659 - mean squared error: 0.0054
Epoch 39/140
uracy: 0.9641 - acc: 0.9641 - mean_squared_error: 0.0057
Epoch 40/140
uracy: 0.9675 - acc: 0.9675 - mean_squared_error: 0.0050
Epoch 41/140
uracy: 0.9695 - acc: 0.9695 - mean squared error: 0.0049
Epoch 42/140
78/78 [============] - 37s 467ms/step - loss: 0.1214 - categorical_acc
uracy: 0.9637 - acc: 0.9637 - mean_squared_error: 0.0057
Epoch 43/140
uracy: 0.9643 - acc: 0.9643 - mean_squared_error: 0.0050
Epoch 44/140
uracy: 0.9673 - acc: 0.9673 - mean_squared_error: 0.0049
```

```
Epoch 45/140
uracy: 0.9679 - acc: 0.9679 - mean_squared_error: 0.0049
Epoch 46/140
uracy: 0.9681 - acc: 0.9681 - mean squared error: 0.0048
Epoch 47/140
uracy: 0.9683 - acc: 0.9683 - mean_squared_error: 0.0048
Epoch 48/140
uracy: 0.9707 - acc: 0.9707 - mean_squared_error: 0.0048
Epoch 49/140
uracy: 0.9736 - acc: 0.9736 - mean_squared_error: 0.0042
Epoch 50/140
uracy: 0.9709 - acc: 0.9709 - mean_squared_error: 0.0046
Epoch 51/140
uracy: 0.9740 - acc: 0.9740 - mean_squared_error: 0.0044
Epoch 52/140
uracy: 0.9736 - acc: 0.9736 - mean_squared_error: 0.0044
Epoch 53/140
uracy: 0.9742 - acc: 0.9742 - mean_squared_error: 0.0041
Epoch 54/140
uracy: 0.9734 - acc: 0.9734 - mean_squared_error: 0.0044
Epoch 55/140
uracy: 0.9736 - acc: 0.9736 - mean squared error: 0.0042
Epoch 56/140
uracy: 0.9738 - acc: 0.9738 - mean_squared_error: 0.0041
Epoch 57/140
uracy: 0.9770 - acc: 0.9770 - mean squared error: 0.0038
Epoch 58/140
uracy: 0.9746 - acc: 0.9746 - mean squared error: 0.0039
Epoch 59/140
uracy: 0.9764 - acc: 0.9764 - mean_squared_error: 0.0039
Epoch 60/140
uracy: 0.9762 - acc: 0.9762 - mean_squared_error: 0.0040
Epoch 61/140
uracy: 0.9770 - acc: 0.9770 - mean squared error: 0.0037
Epoch 62/140
78/78 [============ ] - 39s 500ms/step - loss: 0.0819 - categorical_acc
uracy: 0.9748 - acc: 0.9748 - mean_squared_error: 0.0038
Epoch 63/140
uracy: 0.9784 - acc: 0.9784 - mean squared error: 0.0034
Epoch 64/140
uracy: 0.9784 - acc: 0.9784 - mean squared error: 0.0034
```

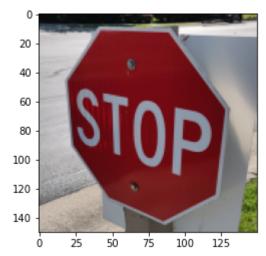
```
Epoch 65/140
uracy: 0.9792 - acc: 0.9792 - mean_squared_error: 0.0034
Epoch 66/140
uracy: 0.9768 - acc: 0.9768 - mean_squared_error: 0.0036
Epoch 67/140
uracy: 0.9786 - acc: 0.9786 - mean_squared_error: 0.0033
Epoch 68/140
uracy: 0.9780 - acc: 0.9780 - mean_squared_error: 0.0033
Epoch 69/140
uracy: 0.9816 - acc: 0.9816 - mean_squared_error: 0.0030
Epoch 70/140
uracy: 0.9758 - acc: 0.9758 - mean_squared_error: 0.0036
Epoch 71/140
uracy: 0.9796 - acc: 0.9796 - mean_squared_error: 0.0032
Epoch 72/140
uracy: 0.9790 - acc: 0.9790 - mean_squared_error: 0.0031
Epoch 73/140
uracy: 0.9800 - acc: 0.9800 - mean_squared_error: 0.0031
Epoch 74/140
uracy: 0.9796 - acc: 0.9796 - mean_squared_error: 0.0033
Epoch 75/140
uracy: 0.9802 - acc: 0.9802 - mean squared error: 0.0032
Epoch 76/140
uracy: 0.9828 - acc: 0.9828 - mean_squared_error: 0.0029
Epoch 77/140
uracy: 0.9792 - acc: 0.9792 - mean squared error: 0.0033
Epoch 78/140
uracy: 0.9810 - acc: 0.9810 - mean squared error: 0.0030
Epoch 79/140
uracy: 0.9794 - acc: 0.9794 - mean_squared_error: 0.0033
Epoch 80/140
uracy: 0.9810 - acc: 0.9810 - mean_squared_error: 0.0031
Epoch 81/140
uracy: 0.9824 - acc: 0.9824 - mean squared error: 0.0029
Epoch 82/140
78/78 [===========] - 38s 480ms/step - loss: 0.0614 - categorical_acc
uracy: 0.9810 - acc: 0.9810 - mean_squared_error: 0.0030
Epoch 83/140
uracy: 0.9824 - acc: 0.9824 - mean squared error: 0.0029
Epoch 84/140
uracy: 0.9796 - acc: 0.9796 - mean_squared_error: 0.0033
```

```
Epoch 85/140
uracy: 0.9839 - acc: 0.9839 - mean_squared_error: 0.0026
Epoch 86/140
uracy: 0.9812 - acc: 0.9812 - mean squared error: 0.0029
Epoch 87/140
uracy: 0.9826 - acc: 0.9826 - mean_squared_error: 0.0029
Epoch 88/140
uracy: 0.9818 - acc: 0.9818 - mean_squared_error: 0.0028
Epoch 89/140
uracy: 0.9837 - acc: 0.9837 - mean_squared_error: 0.0027
Epoch 90/140
uracy: 0.9857 - acc: 0.9857 - mean_squared_error: 0.0024
Epoch 91/140
uracy: 0.9818 - acc: 0.9818 - mean_squared_error: 0.0028
Epoch 92/140
uracy: 0.9814 - acc: 0.9814 - mean_squared_error: 0.0030
Epoch 93/140
uracy: 0.9826 - acc: 0.9826 - mean_squared_error: 0.0027
Epoch 94/140
78/78 [===========] - 36s 465ms/step - loss: 0.0555 - categorical_acc
uracy: 0.9828 - acc: 0.9828 - mean_squared_error: 0.0026
Epoch 95/140
uracy: 0.9855 - acc: 0.9855 - mean squared error: 0.0025
Epoch 96/140
uracy: 0.9849 - acc: 0.9849 - mean_squared_error: 0.0023
Epoch 97/140
uracy: 0.9879 - acc: 0.9879 - mean squared error: 0.0020
Epoch 98/140
uracy: 0.9859 - acc: 0.9859 - mean squared error: 0.0024
Epoch 99/140
uracy: 0.9843 - acc: 0.9843 - mean_squared_error: 0.0024
Epoch 100/140
uracy: 0.9847 - acc: 0.9847 - mean_squared_error: 0.0024
Epoch 101/140
uracy: 0.9853 - acc: 0.9853 - mean squared error: 0.0023
Epoch 102/140
uracy: 0.9843 - acc: 0.9843 - mean_squared_error: 0.0025
Epoch 103/140
uracy: 0.9839 - acc: 0.9839 - mean_squared_error: 0.0026
Epoch 104/140
uracy: 0.9859 - acc: 0.9859 - mean_squared_error: 0.0022
```

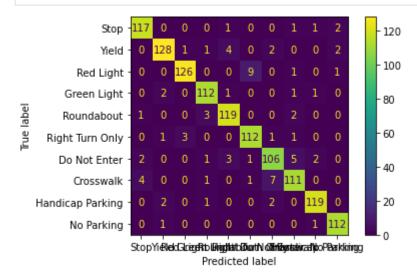
```
In [17]:  # Plot the progression of the acccuracy through the epochs
  import matplotlib.pyplot as plt
  plt.plot(history.history['acc'])
  plt.title('model accuracy')
  plt.ylabel('Accuracy')
  plt.xlabel('epoch')
  plt.legend(['train', 'test'], loc='upper left')
  plt.show()
```



Stop
Out[179... <matplotlib.image.AxesImage at 0x248214161c0>



In [21]: # Create a Confusion Matrix to show the weakness in the model
 predicted\_values = translate\_all(predictions)
 real\_values = translate\_all(t\_test)
 from sklearn.metrics import confusion\_matrix
 from sklearn.metrics import confusion\_matrix, ConfusionMatrixDisplay
 cfm = confusion\_matrix(real\_values, predicted\_values)
 disp = ConfusionMatrixDisplay(confusion\_matrix=cfm, display\_labels=['Stop','Yield','Red disp.plot()
 plt.show()

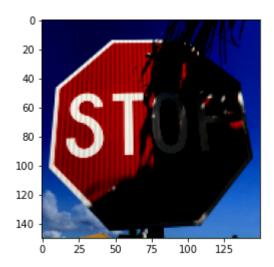


In [97]:

```
# This method is used to show an example of the post processed test data
from random import randint
import matplotlib.pyplot as plt
test_image = randint(0,len(x_train))
plt.imshow(x_train[test_image])
```

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

Out[97]:



<matplotlib.image.AxesImage at 0x24821a2caf0>

In [16]:

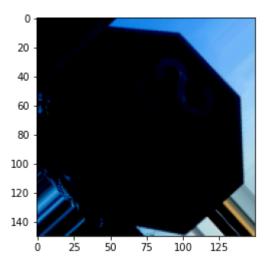
# Original 140 Epoch run was done with .25-.75 brightness range

In [37]:

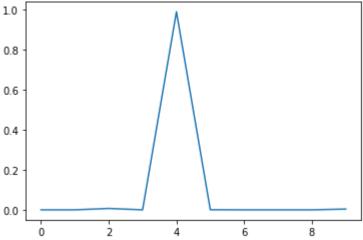
```
# This method is used to show an example of the post processed data
from random import randint
x,y = next(train_generator)

plt.imshow(x[randint(0,63)])
plt.show()
```

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).







```
In [250...

def calculate_std(np_array):
    translated_values = []
    for i in np_array:
        translated_values.append((np.argmax(i))/sum(i))
    return np.array(translated_values)

In [251...

x = calculate_std(predictions)
    print(x)
    print(np.argmax(x))

[2.00000003 7.00000062 6.99999951 ... 2.00000004 5.999999922 6.99999949]
422

In []:
```