

Classify Images of Road Traffic Signs

By

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Machine Learning

Machine learning is a broad domain with applications in information technology, statistics, probability, artificial intelligence, psychology, neurobiology, and several other fields. Machine learning can fix problems by simply building a model that is a great representation of a given dataset. Machine learning has evolved from teaching computer systems to mimic the human brain to a broad discipline that generates fundamental statistical computational concepts of learning processes. The goal of machine learning is to develop algorithms that help computers to learn. Learning is a method of discovering statistical regularities or other data patterns. Machine learning algorithms are designed to mimic the human learning approach for certain tasks (Nasteski, 2017). Adaptive programming is extremely popular. It can be used in machine learning applications that can identify patterns, learn from experience, abstract new discoveries from data, or improve the accuracy and efficiency of its processing and outcome.

Machine learning techniques are also used to work with multi - dimensional data, which is present in a wide range of application domains. As a result, machine learning algorithms are classified into the following groups based on the desired outcome of the algorithm (Nasteski, 2017).

1. Supervised learning
2. Unsupervised learning
3. Semi-supervised learning
4. Reinforcement learning

Supervised learning

It is distinguished by the uses labeled datasets to train model that accurately classify data or predict outcomes. As input data is fed into the model, the weights are adjusted until the model is properly fitted, which occurs as part of the cross-validation methodology. Supervised learning assists organizations in solving a wide range of real-world problems on a large scale, such as image classification.

There are two types of problems in supervised learning: classification and regression

Classification

An algorithm is used in classification to precisely assign test data to specific classes. It detects specific entities in the dataset and attempts to draw a conclusion about how those entities must be labeled or defined. Linear classifiers, support vector machines (SVM), decision trees, k-nearest neighbor, and random forest are examples of common classification algorithms.

Regression

Regression models forecast a continuous variable, such as the amount of rain or the intensity of sunlight. They also can predict probabilities, such as possibility of a cat appearing in an image. Probability of predicting of regression model could be used as aspect of a classifier by imposing a decision rule, such as deciding it's a cat if the probability is 50% or higher.

Linear Regression

Linear regression is commonly used to predict future outcomes by identifying the relationship between the dependent variable and one or more independent variables. Simple linear regression is used when there is only one independent variable and one dependent variable. Multiple linear regression is used when the number of independent variables increases. It attempts to plot a line of best fit, which is calculated using the least squares method, for each type of linear regression. However, unlike all the other regression models, when plotted on a graph, this line is straight (Education, 2020).

A linear hypothesis function is produced by linear regression. However, in classification problems, our data appear in a grouped distribution rather than a linear distribution. This is because our label data for regression problems is numerical, whereas our label data for classification problems is categorical. As a result, approaching linear regression will result in errors and inconsistencies in our estimates. This road traffic sign classification problem is a kind of classification problem, we cannot use linear regression.

Logistic Regression

Linear regression is used when the dependent variable is continuous, logistical regression is used when the dependent variable is categorical, which means it has categorical outputs. Linear regression and logistical regression models attempt to understand relationships between data inputs; logistic regression is primarily used to handle classification problems (Education, 2020). Logistic regression algorithm can be used to approach road traffic sign classification.

Deciphering features from pixels in an image is far too simple. Complex relationships are difficult to obtain using logistic regression. Image features are highly hierarchical and complicated, making it difficult to deduce them using a simple Linear layer. I'd highly suggest evaluating the performance of a Logistic Regression model to a similar Naive Bayes classifier or Support Vector Machine for "relatively" small dataset sizes. Even though, logistic regression is an excellent, strong model for simple classification tasks.

Most Deep Networks use Logistic Regression for classification. The final layer is almost a Logistic Regression layer. This algorithm is easily outperformed by much more powerful and compact algorithms, such as Neural Networks (Nasteski, 2017). In conclusion, for this problem, we have enough data to train our model. We can't solve our problem with a simple classification model like logistic regression. It only has a simple linear layer, which is insufficient to solve the image classification problem. It may solve the problem, but the model's performance low when compared to deep learning models. Relatively simple logistic regression models achieve acceptable results that are only marginally improved. When it comes to increased complexity, time, and computation power, more complex methods, such as Neural Networks are appropriate (Richard W. Issitt, 2022).

We recommend that a deep learning approach, such as CNN, is appropriate for this problem rather than logistic regression model. A logistic regression model could be used as the final layer of a deep learning model.

Random Forest

A decision tree is a basic tree-like structure made up of nodes and branches. At each node, data is split relying on any of the input features, resulting in two or more categories as output. This iterative process generates more branches and partitions the actual data. This process is repeated until a node is created in which all or nearly all of the data belongs to the same class and further splits or branches are no longer possible.

Decision tree aims to mimic the human decision-making process by binarizing every step of the process. To move forward, the algorithm can choose between True and False at each step. Decision tree algorithm is simple but extremely powerful, and it is widely used in machine learning techniques. However, one of the drawbacks of Decision Trees is their inability to generalize a problem. The algorithm learns so well how to make decisions about a given dataset that when we apply it to new data, it fails to provide the best answer.

To address this issue, a different type of Decision Tree algorithm was developed by gathering several Trees trained on different variants of the same dataset and combining them using average system to determine the best result for each data point (Santos, 2021). That is the Random Forest concept. When new data is added to the model, random forest can provide better predictions than decision tree. In this road traffic sign classification problem, random forest also outperforms decision tree.

CNN Algorithm

Neural networks, which are primarily used for deep learning algorithms, process training data by simulating the inter - connectivity of the human brain cells through layers of nodes. Every node has inputs, weights, a bias (or threshold), and an output. If the output value exceeds a certain threshold, the node "fires," or activates, sending data to another layer of the network. Through supervised learning, neural networks learn this mapping function, adjusting based on the loss function via gradient descent. When the cost function is close to zero, we can be confident that the model will produce the correct answer.

Convolutional Neural Networks are complicated feed forward neural networks used in machine learning. Because of their high accuracy, CNNs are used for image classification and recognition. The CNN uses a hierarchical model to build a network, similar to a funnel, and then outputs a completely-connected layer where all the neurons are joined to each other and the outcome is processed. We can solve the complex classification problem with high accuracy and better prediction using the CNN algorithm. CNN outperforms the previously mentioned algorithms in the classification of road traffic signs.

Best Algorithm for image classification problem

The most popular supervised learning algorithms are listed above, but SVM is not included because it is not discussed in our course module. As a result, I exclude SVM and compare other algorithms based on learning and resources. Based on the information discussed in each algorithm, we can come to a conclusion.

Linear regression is not a good approach in classification problem. If we used linear regression to detect road traffic signs, we would get errors and inconsistent results. For this problem, it is best to avoid linear regression. In contrast to linear regression, logistic regression can be used to classify road traffic signs. For small data sets, logistic regression performs better. When it comes to image classification, we need to train as many images as possible. Then only we can achieve better performance and prediction. However, we

cannot achieve better performance for large scale data sets using logistic regression. For this problem, we can avoid using the logistic regression algorithm.

Decision tree algorithm is widely used in machine learning techniques. The algorithms are learned well but when it comes to predict the result of the new data set it cannot perform well. So that we can choose Random Forest algorithm rather than choosing decision tree.

[Figure 1](#) illustrates the performance of each algorithm on particular articles (V, 2022). They used 50000 images for training and 10000 images for testing in image classification problem. We can conclude that the random forest algorithm gives better performance than decision tree. The Random Forest algorithm can be used to solve the problem of road traffic sign classification.

CNN refers to the various applications of a convolution operator in image processing. To efficiently classify images, the CNN architecture implicitly combines the benefits of standard neural model training with the convolution operation. CNN is scalable for large datasets, which is frequently the case when image classification is required. We can also use CNN to solve the problem of road traffic sign classification.

Based on the above discussion, we chose the random forest and CNN algorithms to solve the problem of road traffic sign classification.

Performance of trained model

To identify the shape of a road traffic sign, CNN and random forest methods are used. Then, compare the performance of each model and choose the best-performing algorithm to build a second model for identifying sign type.

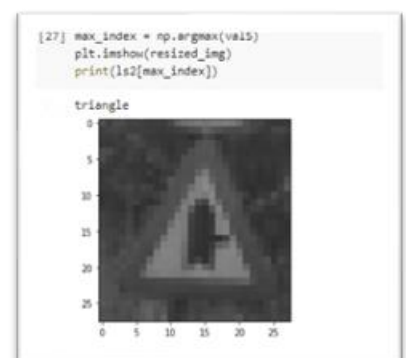
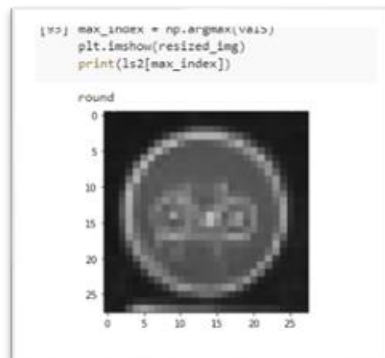
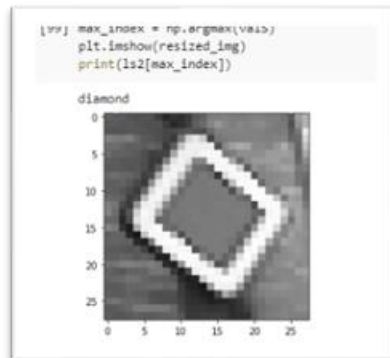
Before beginning to build a model, label the sign shape [\[Figure 2\]](#) and divide the data set into test and training data sets [\[Figure 3\]](#). Construct the Convolutional Neural Network by specifying the sequence of each layer. The Convolutional Layer uses eight filters at first, then sixteen filters, and finally 32 filters. The image dimensions have been sufficiently reduced, and added one more hidden layer in the model with a total of 10 neurons before the model completes in the output layer with the five neurons for the five different classes [\[Figure 4\]](#). The ReLU function does not simultaneously activate all neurons. This means that neurons will only be deactivated if the linear transformation output is less than 0. For multi-class classification problems, the Softmax function is used in the output layer. This is why it is used in the output layer. The model then went through 15 epochs of the entire training set while going through the algorithm's training or learning process [\[Figure 5\]](#).

When tested with the testing data set [\[Figure 9\]](#), the model had an accuracy of 0.9891 [\[Figure 6\]](#). We used a random forest algorithm to identify the sign type, and it gave a 0.96 accuracy [\[Figure 7\]](#). As a result, CNN outperformed random forest in terms of accuracy. Build the next model to predict the sign type [\[Figure 10\]](#) with CNN algorithm, because of the better accuracy than random forest. The accuracy of the CNN model for the second model was 0.955 [\[Figure 8\]](#). Finally, we combine CNN model 1 and 2 to forecast sign shape and type. It forecasts the correct sign shape and type.

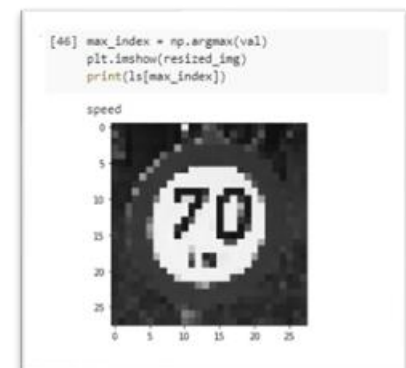
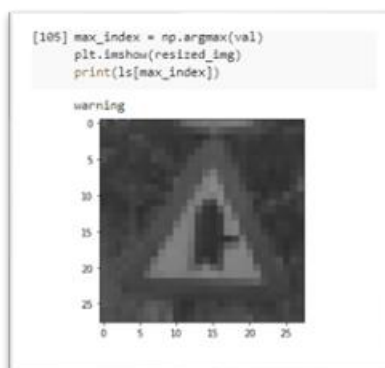
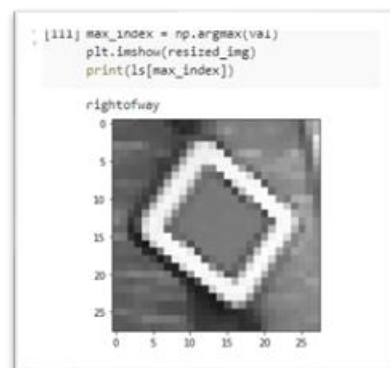
Conclusion

For large data sets, linear regression and logistic regression are not better solutions for image classification. When it comes to predicting new data sets, random forest outperforms decision tree. As a result, random forest and CNN were chosen to solve this image classification problem. When we compare the accuracy of random forest and CNN, CNN outperforms random forest. CNN is the better option for this road traffic sign classification problem.

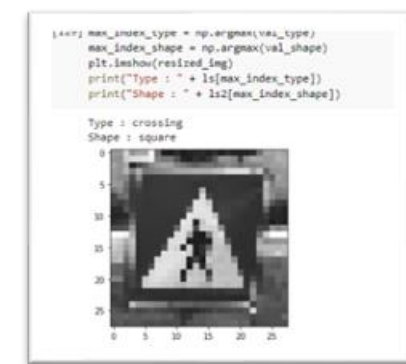
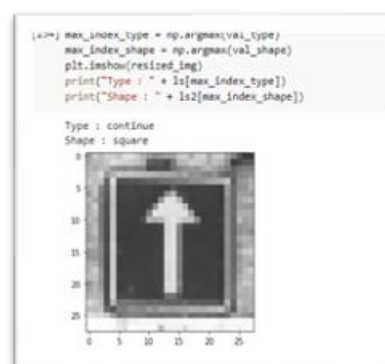
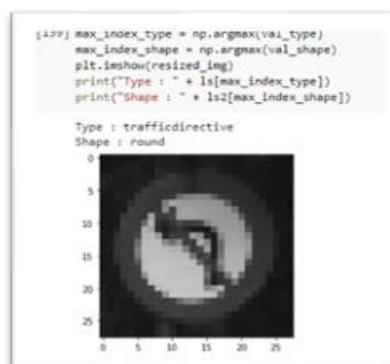
Model 1 Outcome (CNN algorithm)



Model 2 Outcome (CNN algorithm)



Combine Model Outcome (CNN algorithm)



References

Education, I. C. (2020, August 19). *IBM*. Retrieved from <https://www.ibm.com/cloud/learn/supervised-learning>

Nasteski, V. (2017, December). An overview of the supervised machine learning . p. 12.

Richard W. Issitt, M. C.-B. (2022, February 21). *Classification Performance of Neural Networks Versus Logistic Regression Models: Evidence From Healthcare Practice*. Retrieved from <https://www.cureus.com/articles/79255-classification-performance-of-neural-networks-versus-logistic-regression-models-evidence-from-healthcare-practice>

Santos, G. (2021, October 5). *Towards Data Science*. Retrieved from <https://towardsdatascience.com/understanding-random-forests-hyperparameters-with-images-9b53fce32cb3>

V, N. (2022, January 20). *Analytics Vidhya*. Retrieved from <https://www.analyticsvidhya.com/blog/2022/01/image-classification-using-machine-learning/>

Appendices

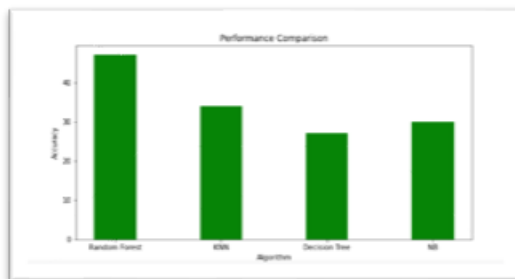


Figure 1

```
In [19]: shapes_dict = {
        'diamond': list(train_data_dir.glob('diamond/*.png')),
        'hex': list(train_data_dir.glob('hex/*.png')),
        'round': list(train_data_dir.glob('round/*.png')),
        'square': list(train_data_dir.glob('square/*.png')),
        'triangle': list(train_data_dir.glob('triangle/*.png'))
    }

In [20]: shapes_id_dict = {
        'diamond': 0,
        'hex': 1,
        'round': 2,
        'square': 3,
        'triangle': 4
    }
```

Figure 2

```
In [22]: Xs = np.array(Xs)
        ys = np.array(ys)

In [23]: from sklearn.model_selection import train_test_split
        Xs_train, Xs_test, ys_train, ys_test = train_test_split(Xs, ys, random_state=0)
```

Figure 3

```
[25]: model2 = keras.Sequential([
        # data augmentation
        keras.layers.Conv2D(8, 3, padding='same', activation='relu', input_shape=(28,28,1)),
        keras.layers.MaxPool2D(),
        #
        keras.layers.Conv2D(16, 3, padding='same', activation='relu'),
        keras.layers.MaxPool2D(),
        #
        keras.layers.Conv2D(32, 3, padding='same', activation='relu'),
        keras.layers.MaxPool2D(),
        keras.layers.Dropout(0.2),
        #
        keras.layers.Flatten(),
        #
        keras.layers.Dense(10, activation='relu'),
        #
        keras.layers.Dense(10, activation='softmax')
    ])
```

Figure 4

```
In [27]: model2.fit(Xs_train_scaled, ys_train, epochs=15)

Epoch 1/15: 100% [#####] - 2s 10ms/step - loss: 1.2054 - accuracy: 0.4870
Epoch 2/15: 100% [#####] - 2s 10ms/step - loss: 1.0987 - accuracy: 0.5084
Epoch 3/15: 100% [#####] - 2s 10ms/step - loss: 0.7388 - accuracy: 0.7380
Epoch 4/15: 100% [#####] - 2s 10ms/step - loss: 0.5799 - accuracy: 0.8038
Epoch 5/15: 100% [#####] - 2s 10ms/step - loss: 0.5404 - accuracy: 0.8301
Epoch 6/15: 100% [#####] - 2s 10ms/step - loss: 0.5192 - accuracy: 0.8490
Epoch 7/15: 100% [#####] - 2s 10ms/step - loss: 0.5203 - accuracy: 0.8618
Epoch 8/15: 100% [#####] - 2s 10ms/step - loss: 0.4989 - accuracy: 0.8749
Epoch 9/15: 100% [#####] - 2s 10ms/step - loss: 0.4913 - accuracy: 0.8723
Epoch 10/15: 100% [#####] - 2s 10ms/step - loss: 0.4778 - accuracy: 0.8771
Epoch 11/15: 100% [#####] - 2s 10ms/step - loss: 0.4639 - accuracy: 0.8811
Epoch 12/15: 100% [#####] - 2s 10ms/step - loss: 0.4593 - accuracy: 0.8825
Epoch 13/15: 100% [#####] - 2s 10ms/step - loss: 0.4477 - accuracy: 0.8851
Epoch 14/15: 100% [#####] - 2s 10ms/step - loss: 0.4401 - accuracy: 0.8888
Epoch 15/15: 100% [#####] - 2s 10ms/step - loss: 0.4304 - accuracy: 0.8906
```

Figure 5

```
Out[27]: <keras.callbacks.History at 0x7d037d15e10>

In [ ]: model2.evaluate(Xs_test_scaled, ys_test)

29/29 [#####] - 0s 9ms/step - loss: 0.4848 - accuracy: 0.9891
Out[28]: [0.48414476125839386, 0.989082992708738]
```

Figure 6

```
In [ ]: from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
accuracy_score(y_pred, y_test)
print(classification_report(y_pred, y_test))
```

	precision	recall	f1-score	support
0	0.88	1.00	0.94	61
1	0.50	1.00	0.67	7
2	0.99	0.95	0.97	465
3	0.94	0.97	0.96	147
4	0.97	0.97	0.97	236
accuracy			0.96	916
macro avg	0.86	0.98	0.90	916
weighted avg	0.97	0.96	0.96	916

You can see accuracy of Random Forests is 0.96 and accuracy CNN 0.98 so CNN model is better than Random Forest

Figure 7

```
In [19]: model.evaluate(X_test_scaled, y_test)
```

29/29 [=====] - 0s 8ms/step - loss: 0.2013 - accuracy: 0.9552

```
Out[19]: [0.2013154774904251, 0.9552401900291443]
```

Figure 8

```
In [ ]: max_index = np.argmax(vals)
plt.imshow(resized_img)
print(ls2[max_index])
```

diamond

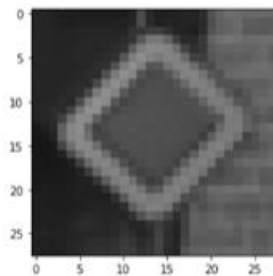


Figure 9

```
In [ ]: max_index = np.argmax(val)
plt.imshow(resized_img)
print(ls[max_index])
```

rightofway

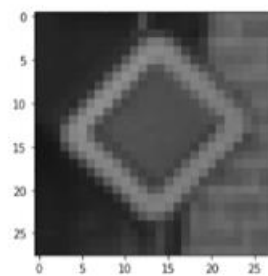


Figure 10