

# Traffic Sign Detection Using Machine Learning

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**Abstract:** Convolutional neural networks are currently the most popular deep learning methods for traffic signal classification [1], but because of the inherent limitations of the max pooling layer, they are unable to capture the position, view, and orientation of the images. The deep learning architecture known as capsule networks is used in this paper to provide a novel strategy for the detection of traffic signs that achieves exceptional performance on the German traffic sign dataset. A capsule network is made up of capsules, which are collections of neurons that use the dynamic routing and route by agreement algorithms to describe an object's position and orientation [2]. Our method reduces the manual labour and offers resistance to the spatial variations, in contrast to the earlier approaches of manual feature extraction and numerous deep neural networks with various parameters.

**Keywords:** CNN, Capsule Neural Networks, Pose, Traffic sign, Dataset, GTSRB

## I. INTRODUCTION

Traffic sign detection is a real-life task that involves many obstacles and complexities. Even a small misalignment of road markings can cause disaster and even lead to loss of life. It is applied to advanced driver assistance systems and autonomous vehicles. A camera on the car's dashboard then captures a real-time video stream that is encoded with images and then transmitted to an embedded deep learning model. Car dashboard. depth is strong and reliable at all times. Cameras can capture road signs in different ways and situations, but the algorithm must be able to recognize the correct signs [4] and the capsule system is a good deep learning method that is perfect for solving this problem.

In general, convolutional neural networks are used for deep neural network algorithms [5] in many image-related tasks. Convolution extracts the spatial information of the image using a kernel function in the convolution layer. CNN has input, output and hidden levels. The hidden layers in the front contain the transformation, aggregation, full integration and configuration. CNNs work well for image-related operations, but they have limitations and drawbacks. CNN fails[6] to capture space and orientation relationship. CNN can be easily confused by the structure of the image or by the change in position.

Declarative information can be the orientation, thickness, inclination, exact position of the object. Asking the biggest question is a big drawback of CNN because it can not spread the spatial classification between simple and complex objects, which leads to distortion and prevents them from mapping the connections between the pixels of that thing. reduces the data and reduces the information about the space of the data passing to the next layer. To overcome this drawback, the capsnet architecture is developed, which performs the highest on the MNIST dataset [2] and performs better than CNN on the Multi MNIST dataset.

## II. RELATED WORK

It is difficult to compare the research work done in the past in the field of traffic sign detection due to the large research efforts of researchers in this area and the use of different types of data. things to solve various problems including related research, classification. and tracking. Work.



### **A. Using computer vision feature extraction methods**

It was one of the first of many algorithms and techniques proposed by computer scientists before the advent of machine learning. Colour gradients are calculated using different histograms created and measured. In this method, colour image gradients are calculated using different histograms created in the scale. Scale Invariant Feature Transformation (SIFT) [8] is used for classification and sliding window techniques to perform classification and detection tasks simultaneously.

### **B. Using machine learning**

Many types of machine learning algorithms such as support vector machine, linear discriminant analysis [10], ensemble classifiers, random forest and kd-tree [11] have been used in the classification of road signs.

Linear Discriminant Analysis (LDA) [5] is based on the posterior estimation of a class. The class density is assumed to have a multivariate Gaussian matrix and a normal covariance matrix.

Random Forest is a classification system [1] that is based on the combination of unpruned decision trees. Each decision tree is constructed using randomly selected training data. based on majority voting considering decisions from all decision trees.

Support Vector Machines (SVM) is a classification algorithm that classifies data by dividing the data plane horizontally by surface for classification [9]. SVM can segment sparse data by transforming the segmentation plane into a higher dimension using a non-linear kernel function that uses a method called kernel manipulation for its implementation.

Machine learning techniques [12] have not been able to handle the different dimensions and image and feature measurements have to be manually processed which is time-consuming and an inconvenient process.

## **III. DATA SET**

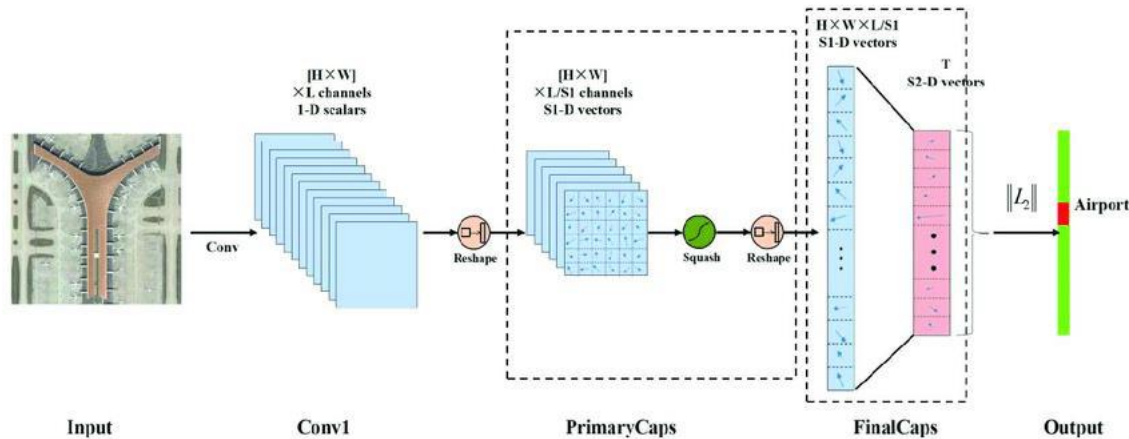
The German Traffic Sign Recognition Benchmark (GTSRB) is defined and presented visually. This is a publicly available dataset and was created from 10 hours of video of driving on various roads in Germany. The extraction of traffic signals is done using a software system based on the NISYS Advanced Development and Analysis Framework (ADAF) [16] module.

After cleaning and removing repeated frames, the dataset is reduced to 51,840 images from the 43 classes. All the images in the dataset are 32\*32 in size, and the total dataset is divided into training data and testing data. A total of 39,209 frames as training data and 12,630 frames as testing data.



**IV. CAPSULE NET ARCHITECTURE**

Capsule networks are capsules instead of neurons. Capsule [17] is an artificial neural network that performs complex calculations on their inputs and stores the results in a small vector. Each capsule holds the relative position of the object and if the position of the object is changed, the direction of the output vector [18] is changed and therefore, makes them the same.



**Fig. 2. 1 Capsule sign architecture for traffic sign detection**

Caps Net has many layers and the first layer is called core where each cap receives a small part of the host field as input and tries to detect the position of a particular pattern. The capsule output is a vector and a dynamic conversion method is used to ensure that the correct parents are sent to the layer which can be deduced from fig. 2.

**A. Computation of capsule vector inputs and outputs**

Capsule calculates the prediction vector [19] by multiplying the weight matrix ( $W_{ij}$ ) with its own output vector ( $u_i$ ). The correlation coefficient of the corresponding capsule production increases the dot product and prediction [20] for the capsule production.

$$u^j_i = W_{ij} u_i$$

where  $u^j_i$ =prediction vector,  $W_{ij}$ =weight matrix and  $u_i$ =output vector.

**B. Squash Function**

In capsule networks, an invisible activation function called crush function is used [21]. This function converts the length of the output vector to the probability that the capsule connects to this object. It reduces the long output vectors to slightly less than unit length and the small output vector is almost zero.

where  $s_j$ =Total Input,  $v_j$ =Vector Output of capsule  $j$ .

**C. Routing Algorithm**

CNN's scalar signal detector has been replaced with vector output capsules [18] and the maximum convergence and convergence method. The capsule segment increases with increasing levels due to the change from encoding (text in continuous space) to code number (text in) and the higher capsules represent the existing facilities. complex and have more degrees of freedom. The per-context method works better than the maximum package used in CNN.



## V. CONCLUSION

Traffic sign detection is a difficult task and capsule networks use their natural ability to detect pose and space transitions more efficiently compared to CNN and capsule networks increase reliability and accuracy by performing the task of processing and identifying images correctly, even if they are distorted, distorted and distorted. image. photo.

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