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Intelligent Road Traffic Control: Performance analysis of Support Vector Machines against Feedforward & Competitive Neural Networks

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Abstract— Road Traffic congestion solution is not yet a "won battle" and has received a relatively laudable attention especially in the last two decades in view of various engineering solutions that exists and commitments from management agencies in implementing emerging efficient and sophisticated control systems at traffic sections to alleviate ordeals of road users considering redundant waiting times, fuel economy and reduced environmental pollution due to emission from vehicles exhaust. Some responses to traffic congestion solutions include various implementations of technologies such as Radio Frequency Identification (RFID), inductive loop, magnetometer, infra-red based vehicle presence monitoring and the typical purely timer based controlled traffic lights. This research work builds on a more recent approach to road traffic control "*Road Traffic Control using Artificial Neural Networks*" in which a feedforward neural network was designed to classify congestion (road with denser traffic) levels using processed scene images captured at a traffic control section. The output of network was then used to drive traffic lights installed at the section and a recognition rate of 93% was achieved in the above mentioned work. This paper reviews the earlier mentioned research using vector support machines and competitive neural networks to realize the same task; and hence a comparative performance analysis made in consideration of achieved recognition rate, computational ease and manual input required (labelled data).
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Index Terms— Support Vector Machines, Artificial Neural Networks, Road traffic control, Congestion Solution, Image processing..

1 Introduction

Congestion is the impedance vehicles impose on each other, due to the speed-flow relationship, in conditions where the use of a transport system approaches capacity[1].
Highway traffic congestion is a major source of frustration for American travellers, causing an estimated 3.5 billion hours of delays per year in 75 of the largest metropolitan areas[2].
The typical road traffic control setup involves a signaling device (usually traffic lights), and a system that detects, measures or guesses amount of vehicles on the different roads at a traffic section.

The major considerations of technological innovations and ingenuity in this area have been designing more accurate, efficient, cost-effective and simple systems that can measure or quantify congestion levels reliably; the output of which is then used to control the traffic lights. Typical traffic lights are usually purely timer based driven with consequence that the congestion level of different roads at a traffic control section is not a consideration used in driving traffic, hence considered crude and unintelligent. This situation may give rise to circumstances where less congested or even empty roads are passed in place of more congested roads; leading to inefficient congestion control and therefore unnecessary delays at traffic sections. Hence, it becomes imperative to design more efficient congestion level quantifying systems to drive traffic lights. It is seen that by developing more effective signal timing systems to control traffic, the overall level of traffic congestion is reduced. e.g. by 5% for the United States[3].

There exists different systems to achieving this but this work focuses on an intelligent system approach to quantifying congestion levels of road traffic by processing scene images and then classifying them into which is denser (more congested) with vector support machine and competitive neural networks; and finally, a comparative study against an earlier work on feedforward neural network designed to achieve the same task is then presented.

2 Support Vector Machine (SVM)

Support vector machine (SVM) is an algorithm that belongs to a group of machine learning algorithm called maximum-margin classifiers. In the case of perceptrons based learning, training stops when error attains the minimum value (global minimum has supposedly been reached). Moreover, there exist a variety of decision boundaries achievable each time a neural network is trained and the particular solution arrived at during any one learning process does not guarantee optimum classification boundary and generalization power of the trained neural network maybe at risk; this is exemplified in the figure below with some of the possible decision planes a neural network can converge to for two categories (class A and B) classification problem shown .

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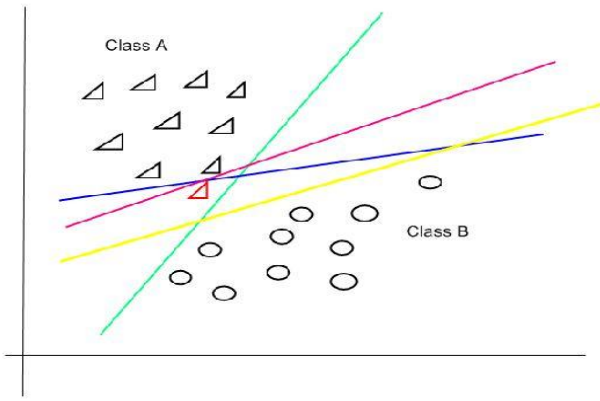

Fig. 1. Various achievable decision boundaries for classes A and B

It can be seen from fig. 1 that there are a number of different solutions that a trained neural network can arrive at (straights lines with different colours), and during test or simulation with data that were not part of the training set, some instances may lie outside the decision boundary and hence lead to wrong classification.

Assuming that training samples belonging to class A are denoted with triangles and class B denoted with circles, a typical misclassification problem has been exemplified using a test sample denoted with a red triangle which actually belongs to class A by inspection (closer to the class A cluster) but is wrongfully classified by neural network as belonging to class B when the pink or blue decision boundaries are considered (fig.1); such problems raises concerns over the best possible decision boundary a neural network can converged to after training, especially in classifying new data.

Given a linearly separable training set for a binary classification problem, it is perhaps intuitive that the optimal decision surface is equidistant from the class boundaries[4].
Support vector machine reviews the above mentioned problem with the maximum-margin classifier model algorithm in which a hyperplane of widest margin from a set of training samples classes is achieved; these set of points are called support vectors. Only they determine the position of the hyperplane. All other points have no influence [5].

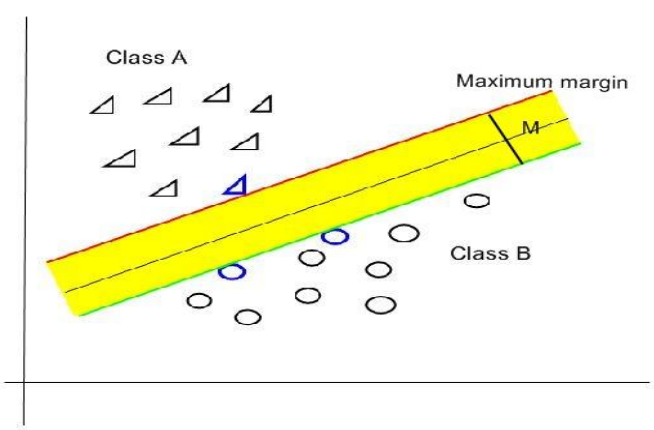

Fig. 2. Support vector machine as maximum margin classifier

The maximum margin for optimum decision boundary is achieved from these support vectors and the separation hyperplane is the centre line of the margin. Support vectors for the described problem in fig. 1 are shown above in fig. 2 as the blue triangle and two blue circles.
Mathematically, some fundamental equations for obtaining support vector machines are shown below.

Triangle-plane = $w \, . \, x_i + b = +1$ (red line, fig.2) (1)

Circle-plane = $w \, . \, x_i + b = -1$ (green line,fig.2) (2)

Decision Hyperplane = $w \, . \, x_i + b = 0$ (black line, fig.2) (3)

Hyperplane Margin width , $M = 2/ \| w \|$ (4)

Where the triangle plane, circle plane and decision plane are shown respectively as red, green, and black lines in fig.2. Also, x_i are input vectors, and vector w is perpendicular to both the Triangle Plane and Circle plane

The maximum margin can be obtained as seen from equation (4) by minimizing the term $||w||$. Minimizing $||w||$ is equivalent to minimizing $½||w||^2$ and the use of this term makes it possible to perform Quadratic Programming (QP) optimization later on [6]; and after which Lagrange multipliers can be used to resolve minimization constraints.

3 Competitive Neural Network (CNN)

Artificial neural networks are an attempt at modeling the information processing capabilities of nervous systems[7]. They form enormous parallel interconnections between the basic components.

The basic building component of neural networks are called artificial neurons and the most commonly used model is the perceptron. A perceptron operates by computing a value known as the total potential (T.P); which is sum of the products of inputs and corresponding weights. The total potential is then compared against a reference value called the threshold; after which the neuron could be fired or not[8]. The rules used to activate neurons are shown below.

T.P ≥ Threshold value: Neuron activates
T.P < Threshold value : Neuron does not activate

It allows using very simple computational operations (additions, multiplication and fundamental logic elements) to solve complex, mathematically ill-defined problems, nonlinear problems or stochastic problems[9]. Various configurations of neural networks exist but one common feature is learning; the phase where examples are shown to the network so that experiential knowledge can be acquired.

Competitive neural networks (CNN) employs unsupervised learning .i.e. training data do not have to be labelled as in the case of supervised learning.

In competitive neural networks, the output neurons compete among themselves to become active[10]. Learning is

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achieved based on a "winner-takes-all" rule where only the weights connected to the winner neuron are updated each epoch; all other weights are left not updated. This has the effect of gradually strengthening the relation (correlation) between a particular input pattern supplied to the network and the winner neuron.

Fig. 3 shows a typical competitive neural network with n input neurons and two output neurons. It is worthy of note that competitive neural networks have no hidden layer (or neurons); output layer neurons only compete to become fired when the network is stimulated with patterns. From fig. 3, it is shown that output neuron 2 (total potential of output neuron 2 exceeds that of output neuron 1) won at a particular time staple when network was stimulated and hence only weights connected to it (blue connections) are updated in the next epoch. i.e. the winner neuron is favoured to win again in next epoch.

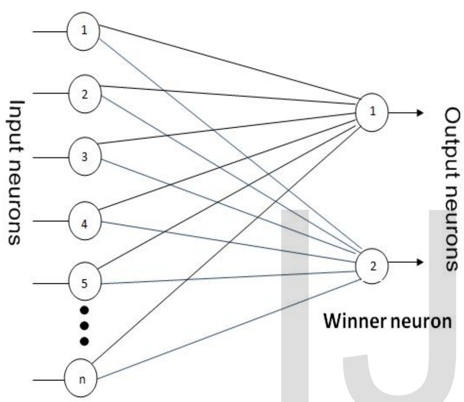


Fig. 3. Competitive neural network

Let the w_{kj} be weight connection from neuron j to neuron k; hence from fig. 3, the only weights interconnections that are updated in next epoch are w_{21}, w_{22}, w_{23}, w_{24}, w_{25},….,w_{2n} (blue connections from input to output neuron 2).

The constraint on the update of weights during learning is that sum of all weights connected to the winner neuron must be 1. e.g. $w_{21} + w_{22} + w_{23} + w_{24} + w_{25} + \ldots + w_{2n} = 1$

Learning rule used to update weights is shown below [10].

If neuron k wins, then $\Delta w_{kj} = \eta(x_j - w_{kj})$ (5)

If neuron k loses, then $\Delta w_{kj} = 0$ (6)

Weight update, $w_{kj}^{new} = w_{kj}^{old} + \Delta w_{kj}$ (7)

Where, x_j and w_{kj} are inputs and weights connected to winner output neuron k respectively; η is known as the learning rate and determines how fast the algorithm converges to a solution.

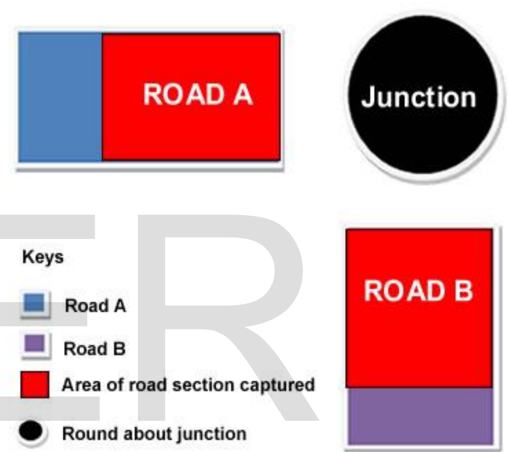
4 Input Layer Design

A modeled two road scenario (road A and road B) used in the earlier work has also been considered for this research; images captured from suitable sections of the roads are processed to reflect features of interest (fig. 4), classified using the designed systems and the output then used to drive traffic lights.
The classification of images has been coded as shown below.

Class 1: road A more congested than road B
Class 2: road A less congested to road B

Output of class 1 will drive traffic lights such that road A is passed, while an output of class 2 will drive traffic lights such that road B is passed.

Cameras stationed at the junction capture images simultaneously and synchronously from suitably considered section of road A and road B. The images are processed to filter out features of interest (foreground from background). The images used in this research work are software simulated using a graphic drawing software.



[8] Fig. 4. Schematic diagram of modeled junction scene

Different levels of congestions are simulated such that learning can be achieved. It is the aim of this of work to design a decision system or classifier to determine which of the roads (A or B) is more congested (or denser).

In order to achieve this, is it crucial that feature of interest to be learnt for classification be extracted; this has been realized by processing the images in such a way that the background or unoccupied part of the roads are white and vehicle occupied parts as black. i.e. separating image into background and foreground. The classifier system will be required to compare the images from road A and road B, then output (categorize) which class it belongs to (which is denser).

The processing of the simulated images for road A and B have been carried out as shown below:

- Rescaling: images rescaled to 40×40 i.e. 1600pixels (to relieve computational stress)
- Gray scaling: rescaled colour images converted to gray
- Thresholding: gray images are converted to binary by uniformly thresholdimg them at 0.75 level to separate background from foreground.

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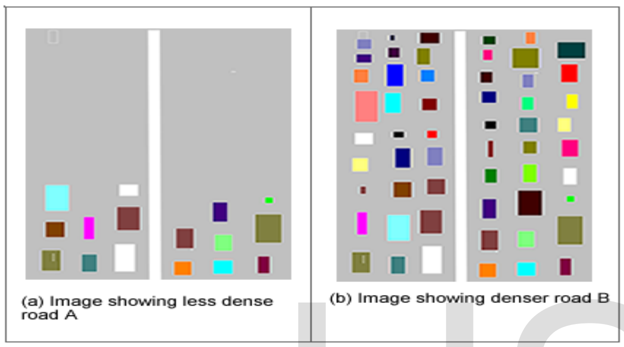
• Reshaping: the thresholded binary images were reshaped to 1600×1 (column vector) such that they are now suitable as inputs to be fed to the classifier system.

The modeling logic has been simulated as shown below.

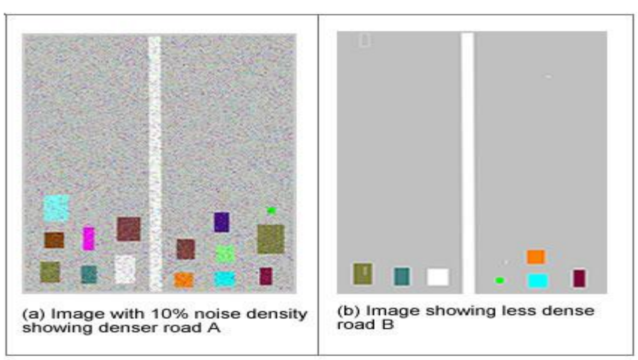
• Asphalt: grey background
• Lane divider: a white line at road centre
• Vehicles: solid shapes of different colours

A simulated traffic scenario is shown in fig.5 in which road A less congested or dense compared to road B. Here, the designed classifier system should output class 2 i.e. decision to pass road B.

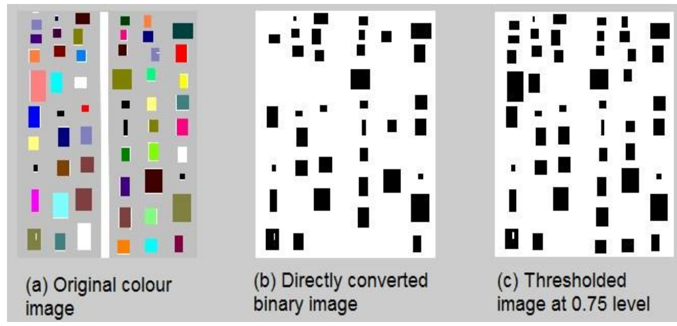


[8] Fig. 5. Simulated traffic showing road A less congested compared to road B

Fig. 6 is another of the several simulated images of various possible congestion levels for road A and road B; here road A is denser compared to road B, hence the classifier system should output class 1 i.e. decision to pass road A. Furthermore, road A (figure 6a) image have has been simulated with added salt & pepper noise of 10% density; other images for road A and road B have also been simulated with noise level within the range 5-10%. This has been done so that noisy data are part of learning in order to develop a robust classifier relatively immune to noise when deployed in noisy environments.



[8] Fig. 6. Simulated traffic with road A more congested than road B



[8] Fig. 7. Comparison of directly converted binary image and thresholded binary image

The figure above shows a simulated road colour image (fig. 7a), directly converted binary image (fig. 7b), and thresholded binary image version (fig. 7c). It will be seen that separation of background from foreground is best achieved in the thresholded image compared to the directly converted binary version where some crucial features were lost (some vehicles disappeared); this is due to the range of values for simulated vehicle colours which maybe high when converted to gray and greater than 0.5 and when directly binarized; hence disappear (classified as white, therefore merges with the background); since direct binary image conversion is simply thresholding a gray image at 0.5 level. Consequently, the technicality behind thresholding the images at a suitable value high (0.75 level) enough to preserve the simulated vehicles. In uniform thresholding, pixels above a specified level are set to white, those below the specified level are set to black[11].

An image intensity histogram has been used to facilitate the level at which images were thresholded. Intensity histogram is a distribution of grey level values of all pixels within an image[12].

Furthermore, as it is the intent of this research to design a classifier that accepts two image frames, makes comparison to determine which is denser; the same system of vertical concatenated images used in the earlier research work has also been used as shown below.

Processed images from road Ai : 1600×1
Processed images from road Bi : 1600×1
Concatenated images of road A & B, Ci : 3200×1

Since images of road A and road B are taken simultaneously and synchronously at a specified interval, hence the subscript i above to differentiate various time dependent synchronously captured images to be concatenated as whole images and therefore now suitable to be supplied to the designed systems for classification. C_i shows time dependent and final concatenated images to be supplied to the designed systems for learning. The whole input analogy is shown in fig. 8.

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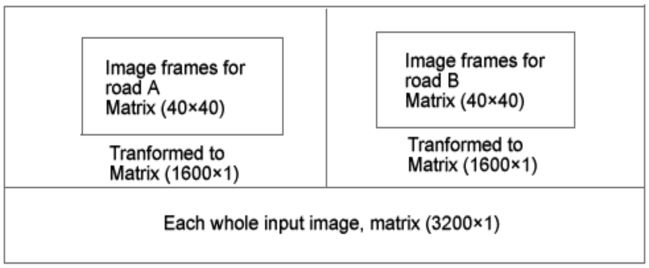

[8] Fig. 8. Whole image to classifier for each input.

The labeling of input images for classification has been such that e.g. fig. 5 is labelled class 2 and fig. 6 is labelled class 1. The logic of traffic control will be that an output of class 1 drives or passes traffic of road A while an output of class 2 drives traffic of road B.

Fig. 9 shows another of the several simulated traffic scenario for road A and B with their respective processed images, it is obvious by visual inspection that road A is more congested compared to road B and hence should be classified by the designed systems as class 1 after training.

5 Congestion Learning and Classification

5.1 Support Vector Machine Model

For purpose of learning, several images simulating different levels of traffic for road A and road B were created; and as support vector machine is a supervised learning algorithm, the final processed concatenated images to be supplied for learning have been labelled as either class 1 or class 2.

500 samples (each with 3200pixels) of input images have been used to train the SVM, hence input matrix is 3200×500; and therefore class labels for the input data is of dimension 1×500.

The training of the SVM model has been achieved using MATLAB programming; and the 'fitcsvm' function was used. It generates a SVM model for the training, and also performs an important aspect of machine learning which is validation (reducing the possibility of over-fitting curves to data and hence trained model losing generalization) ; the function uses a default 10-fold cross validation [13]. The training and performance parameters for the model are shown in table 1.

It will be seen that 29 support vectors have been used to realize the decision hyperplane of maximum margin after training, a linear kernel (dot product) has also been used.

Testing of the SVM model was done using 300 samples (matrix 3200×300) that were not part of the training data and a recognition rate of 98% was achieved. Simulated outputs were visually crossed checked for classification accuracy.

Table 1: Trained SVM model parameters and performance

Number of training samples	500
Number of support vectors	29
Bias	-0.0605
Kernel function	linear
K-fold cross validation	10
Correctly classified training samples	500
Number of test samples	300
Correctly classified test samples	294
Recognition rate	98%

5.1 Competitive Neural Network

Here, the designed neural network is required to learn appropriate clustering of congestion levels and put each whole supplied image into class 1 (road A more congested than road B) or class 2 (road A less congested to road B). Considering the number of pixels of images to be supplied to the network, it follows that the network should have 3200 neurons at the input layer. Also, there should be two neurons at the competitive output layer since it is the aim to classify processed traffic scene into two classes. i.e. two ouput neurons compete with each other to respond to either class. Training and performance parameters are shown in table 2.

Table 2: Trained CNN parameters and performance

Number of training samples	500
Number of input neurons	3200
Number of output neurons	2
Learning rate (η)	0.1
Number of training epochs	100
Training time (seconds)	38
Number of training samples correctly classified	500
Number of test samples	300
Number of test samples correctly classified	285
Recognition rate	95%

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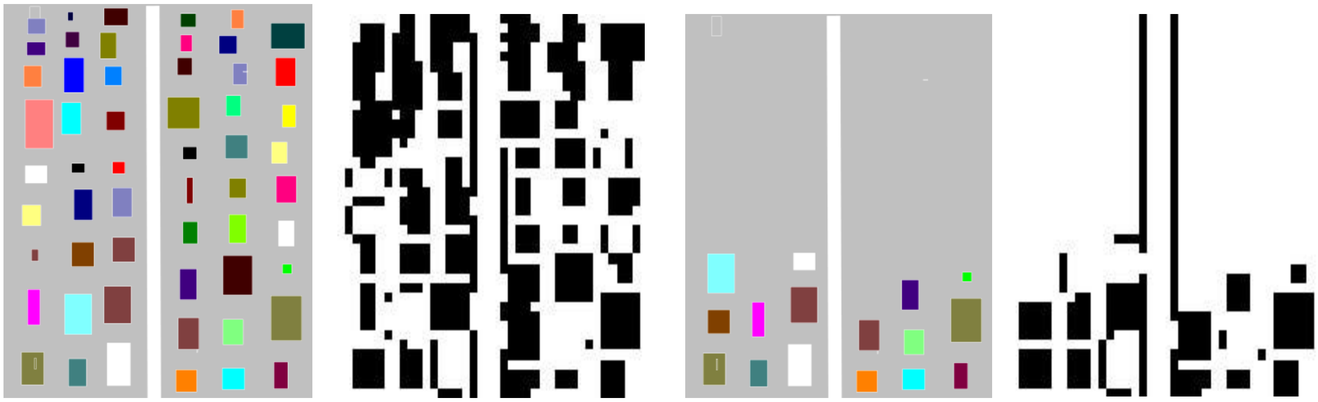

(a) Unprocessed image sample of test data- road A

(b) Processed binary image sample for fig (a)- fed into network

(c) Unprocessed image sample for test data- road B

(d) Processed binary image sample for fig (c)- fed into network

[8] Fig. 9. First test data sample showing road A and B with their respective features extracted images to be classified with the trained models (i.e. which is more congested or dense).

It can be seen from the table above that the number of training and test samples used in the SVM model has also been used in the CNN designed; and a recognition rate of 95% was achieved.

5.2 Comparative analysis of classification Models

An earlier work of the same task which was achieved using a feedforward neural network is analyzed below basing main considerations on recognition rate, computational efficiency and manual input (labelled data) required. Table 3 shows the comparison analysis.

Note that N/A in the table means Not Applicable.

Table 3: Trained CNN parameters and performance

Factors	Feedforward neural network	Support vector machine	Competitive neural network
Recognition rate	93%	98%	95%
Number of training epochs	500	<5000	100
Training time (seconds)	196	10	38
Active size of model	2 layers	N/A	1 layer
Labelled data	Yes	Yes	No

6 Conclusion

It will be seen from table 3 that SVM model outperforms both feedforward and competitive neural networks considering the recognition rates achieved. A thorough examination of some misclassified data showed that feedforward network had problems classifying quite a number image samples with close level of simulated traffic congestion for road A and road B; while SVM had best performance followed by competitive neural network in the situation.

Furthermore, it was noted that all the three models had no problem classifying data samples with added noise (noise tolerance).

Also, support vector machine has the least training time compared to competitive and feedfoward networks; network size is smaller too for the competitive neural network as against feedforward network and therefore boasts fewer hardware and reduced cost in implementation.

In addition, the enormous time in hand-labeling data can be seen in feedforward neural network and support vector machine. This process is quite manually intensive as each image to be used for training has to be visually inspected so that correct labeling is achieved; and for large data, this process may seem impossible, time consuming and cost unbearable.

Lastly, the world, including transport, is changing fast. We still encounter many of the same transport problems of the past: congestion, pollution etc [14]. Expanding road capacities is one option but unfortunately this is not always a feasible task due to barriers such as environmental aesthetics and annihilation. Hence, the designing of simple intelligent road traffic control systems which can quantify congestion levels and therefore drive traffic more efficiently as against systems that merely guess congestion levels, maybe too complex and cost ineffective to setup in certain environments or involve environmental degradation.

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