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Zebra Crossing Detection and Time Scheduling Accuracy, Enhancement Optimization Using Artificial Intelligence

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ABSTRACT

Zebra crossing detection is a fundamental function of the electronic travel aid. It can locate the zebra crossing and estimate its direction to help the visually impaired to cross the road safely. In contrast to the conventional methods, a regression approach is adopted to detect zebra crossing based on convolutional neural networks. Specifically, a fixed-size window slides across the image captured at the intersection. The image patches are sequentially fed to the logistic regression model to identify the zebra crossing. Then the image patch of zebra crossing is fed to the regression model to predict the direction. The parameters of models are optimized by the ANN back propagation algorithm before predictions. Compared with existing methods, the proposed method can improve the precision-recall performance of the zebra crossing identification and reduce the root mean square error of predicted directions.

Keywords : Visually Impaire, LYTNet Convolutional Neural Network, Machine Learning, Board Office M.P Nagar (BHOPAL)

I. INTRODUCTION

The zebra crossing detection technique is widely studied in several fields. In the advanced driving assistance system (ADAS), the technique is applied to detect the position of the zebra crossing. In the electronic travel aid (ETA), the technique is applied to help the visually impaired to cross the road independently [1]. The zebra crossing is an essential traffic sign, which represents a safe way to cross the road. The accessible region of zebra crossing should be provided to the visually impaired for safe travelling. In addition, the visually impaired demands the direction of zebra crossing to adjust the travelling orientation.

There are several works reported on zebra crossing detection. In Se [2], the Hough transform is used to pick out groups of parallel lines and the vanishing point constraint is used to check for concurrency. In addition, the pose estimation is adopted to distinguish the zebra crossing and the stair-case in their approach. In Wu et al.[3], the block-based Hough transform is proposed to provide the position and direction of the zebra crossing. In Uddin et al. [4], the zebra crossing is primarily recognized by its bipolar pattern, and then further confirmed by some of its distinguishing features. These features include crossing width, crossing direction, number of crossing bands, as well as bandwidth trend. In Ivanchenko et al. [5,6], a prototype 'Cross watch' is developed to provide the information of the zebra crossing using voice. In Wang et al. [7], zebra crossings and stairs are detected on RGB-D images. Pixels of R (red), G (green), B (blue) channel are utilized to extract concurrent parallel lines, and pixels of D (depth) channel are utilized to distinguish zebra crossings and stairs. In Ahmetovic et al. [8], a four-stage zebra crossing detection method is proposed, including image preprocessing, rectification matrix computation, line segment detection, line segment grouping and validation. In Mascetti et al. [9], a prototype 'Zebra Recognizer' is designed parallel on the GPU to speed up calculations. In Riveiro et al. [10], an automatic zebra crossing detection method is proposed based on the mobile LiDAR technology. In Berriel et al. [11,2], three convolutional neural networks (CNN) are adopted to perform crosswalk classification on vehicles. In Ghilardi et al. [3], the support vector machine (SVM) algorithm is adopted to perform crosswalk classification on the low-resolution satellite images. In Yu et al. [4], the LYTNet is proposed to provide the mode of the traffic light and the start-end points of the zebra crossing. Notwithstanding the good performances of the existing works in localizing the zebra crossing, the direct estimation of the zebra crossing still needs further studies. The classification methods cannot provide the direction of the zebra crossing. The Hough transform is a favorite method to fit lines and estimate their directions on binary image [5], but it will generate spurious lines under the influence of noise.

II. RELATED WORKS

There are several AI- and ML-based solutions in the literature for ITSs that serve different purposes. In [10], for example, a vehicle detection system based on bio inspired algorithms and autonomic computing, and IBM's MAPE-K is proposed to control the queues at traffic lights. In other applications, as in [11], historical data is used to detect accidents and generate alternative routes by combining radio frequency identification (RFID), 5G communication, and cloud services. These works use logistic regression (LR), multi-layer perceptron (MLP) neural networks, particle swarm optimization, adaptive boosting, and decision trees to release cognitive services over Microsoft Azure. Vehicle telemetry was also used to classify and detect abnormal situations on the roads (e.g., traffic jams) using a support vector machine (SVM) [4].

III. PROBLEMS FORMULATION

It can be difficult to guide yourself across a crosswalk when your visual capabilities are limited, which can be an everyday issue for someone with impaired vision. This paper aims to alleviate that issue for zebra stripe crosswalks by proposing an algorithm that incorporates multiple properties of zebra stripe crosswalks with a neural network to assist in quickly and accurately identifying a crosswalk in video and pictures taken from a smartphone camera. This method improves the accuracy of zebra crosswalk detection in images. In a large dataset, it correctly identified 76.5% of zebra crosswalks, while reducing the false discovery rate (q-value) from 20% without using neural networks to 2.21% using this neural network method. Only 2.04% of non-crosswalk images as crosswalks using the neural network method.

Objectives:

Our main objectives are as follows :-

1. To collection of zebra collection real time data for proposed location.
2. To observation of Scheduling time based on proposed method ANN tool.
3. To Identification of traffic flow prediction values and prediction model.

4. To Analyzing of ANN prediction Accuracy.
5. To computation of Traffic flow rate across zebra crossing.

IV. PROPOSED METHODOLOGY

Artificial Neural Networks (ANN)

ANN is the term used for systems that attempt to work the approach the human brain works. Suggests that system tries to perform a precise task the approach humans do. commonly computers do any work the approach it's educated within the sort of code, however it doesn't have the aptitude of finishing works that it absolutely was ne'er schooled of. however if we tend to contemplate an individual's brain, it's self-learning capability that makes it perform several processes that it's been neither performed nor schooled. So, ANN essentially tries to inherit this capability of the human brain to self-train itself for tasks that area unit ne'er been performed by it that too terribly with efficiency. Human brain's structure consists of neurons that area unit interconnected with one another and there by forming giant network that is well connected thereby helps in playing a awfully complicated task like voice and image recognition very simply. A similar task once performed mistreatment traditional pc will not offer an correct result. Hence ANN mimics neurons structure of the human brain to get the link between input and targets. Neurons have this ability to avoid wasting previous experimental information. The speed of human brain is many thousand-time quicker than ancient standard conventional pc as a result of in brain in contrast to traditional pc as whole data isn't passed from vegetative cell to vegetative cell they're rather encoded within the neuron network. This can be the explanation why the neural network is additionally named as connectionism.

A biological model of a vegetative cell is largely comprised of dendrites, a cell body or soma, And an nerve fiber as shown in Figure 4.1. The cell body, additionally known as the soma, holds the nucleus of neurons.

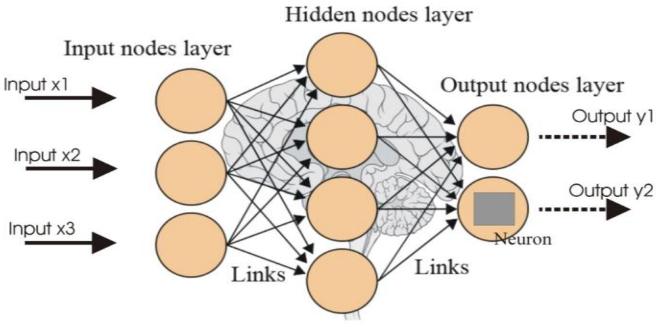

Figure 4.1 : Concept of ANN

The dendrites square measure the branches that square measure connected to the cell body and stretched in house round the cell body to receive signals from neighbour neurons. The nerve fiber works as a transmitter of the vegetative cell. It sends signals to neighbour neurons. The junction or conjunction terminal is that the association between the nerve fiber of 1 vegetative cell and therefore the dendrites of neighbour nucleon, that is that the communication link in between the 2 neurons. chemistry signals square measure communicated from the junction. once the entire signal received by a vegetative cell is over the junction threshold, it causes the vegetative cell to fireplace i.e., send Associate in Nursing chemistry signal to neighbour neurons. it's assumed that the alteration exhausted the strength of the conjunction association is that the main foundation of our brain's memory [11]. This modification is finished in ANN within the type of weights between neurons so as to perform any kind of action in our body, completely different components of the body (sense organs) send signals that travel through different components and reach the brain vegetative cell's wherever the neuron processes it and generates the specified output. It ought to be noted although that the output of a vegetative cell may be fed to a different vegetative cell. a group of such neurons is termed a neural network. The transformation of the biological model of vegetative cell into a mathematical model is shown in figure 4.2.

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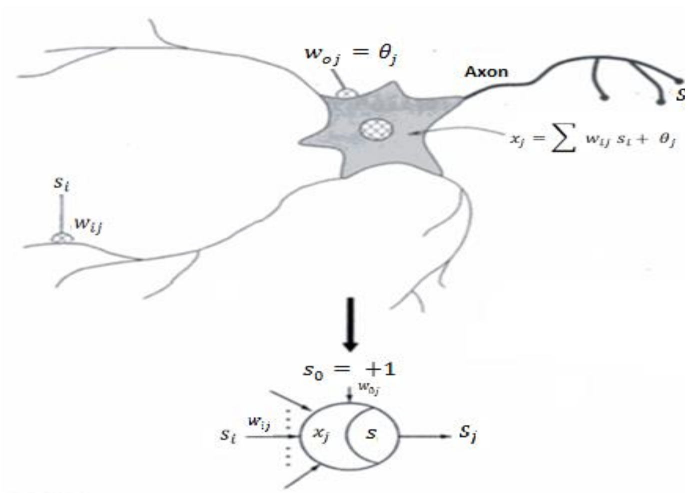


Figure 4.2 : Mathematical equivalent of Neuron

“x” are different inputs which are weighted by a weight corresponding to a path that the signal travels. The neuron is then expected to create a change in the form of an activation function ϴ and the complete signal then goes through a transformation S which produces the output of the neural network .Consider a signal s_1 traveling through a path p_1 from dendrites with weight w_1 to the neuron. Then the value of signal reaching the neuron will be $s_1 . w_1$.If there are "n" such signals traveling through n different paths with weights ranging from w_1 to w_n and the neuron has an internal firing threshold value of θ_n , then the total activation function of the neuron is given by equation 4.2.

$$Y = \sum_{i=1}^{n} \mathrm{X_i} . \mathrm{W}_i \quad + \quad \theta_i$$

4.2

Where,

X_i = the signals arriving through various paths

W_i = weight corresponding to the various paths

and θ = bias

The entire mathematical model of the neuron or the neural network can be visualized pictorially or the pictorial model can be mathematically modeled. The design of the neural network can be modeled mathematically. The more complex the neural design is, more will the complicated tasks that can be solved by the neural network. The above logic can be understood by the following diagram in figure 4.3:-

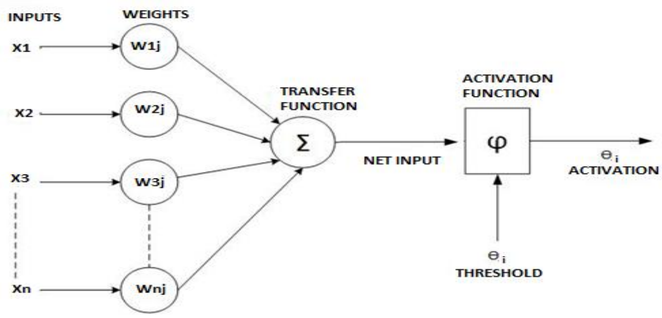


Figure 4.3 : The mathematical formulation of the neural model

The soul of the above model lies in the fact that the system so developed tries to mimic the working of the human brain in terms of the following

1) It works in a complex parallel computation manner.
2) High speed of performance due to the parallel architecture.
3) It learning and adapt according to the modified link weights.

Work on ANN has been roused directly from its commencement by the affirmation that the human cerebrum processes in an altogether extraordinary manner from the customary advanced PC.

ANN has a shocking capacity to discover a connection between totally non-straight information's which can be executed effectively to identify patterns and in this way discover the example followed by our objectives which are inconceivable for human minds to take note.

ANN poses great ability to train itself based on the data provided to it for initial training. It has the tendency of self-organization during learning period and it can perform during real time operation.

ANN process input data information to learn and get knowledge for forecasting or classifying patterns etc. type of works. All information processing is done within neuron only. In above figure connections between neurons is shown in which learning algorithm is applied to train using historical data [2].The links between neurons consist of some value which is termed as weights. These weights are responsible for scaling input values to a new value which will be responsible for forecasting accurate value. The value of weights is decided in the basis of input and target data and on the choice of activation function (usually nonlinear).The value of weight is utilized to successfully solve some certain complex forecasting or classification problem. The weights are continuously changed while training to improve accuracy [3] [4].

Through the input layer of neural network input data is passed first and then transferred to other layers through links after some alteration. This links possesses some strength whose value is also changed which is also called as weights. Our main aim is to calculate the most possible optimum values of these weights. Hidden layers neurons are further connected to output layer neurons. The activation function of hidden layer neurons is the main factor in deciding values of weights. The weight of this connection between hidden and the output layer is also needed to be optimized with prior weights.

The number of hidden layer neurons which will give the best result is difficult to find since there is no particular method to calculate that. Hence, we will vary the number of hidden layer neurons till we get required satisfactory result. A number of input layer neurons is equaled to a number of input signals and a number of output layer neurons is equal to the number of output variables which in our present case is one i.e. present load.

Below figure 4.4 depicts the working of a back propagation network in the form of the flow chart. From the chart, it is clear that after the initiation of training initial values of weights are to be assumed. Then input data is processed in sets. After all sets of input data are processed, then the error is calculated. If the error is within tolerant range, then network weights are saved and training is ended. If the error is not in the range of tolerance range, then check for a number of epochs. If epochs exceeded the maximum value, then show failure massage and end training else retrain network until required results are obtained.

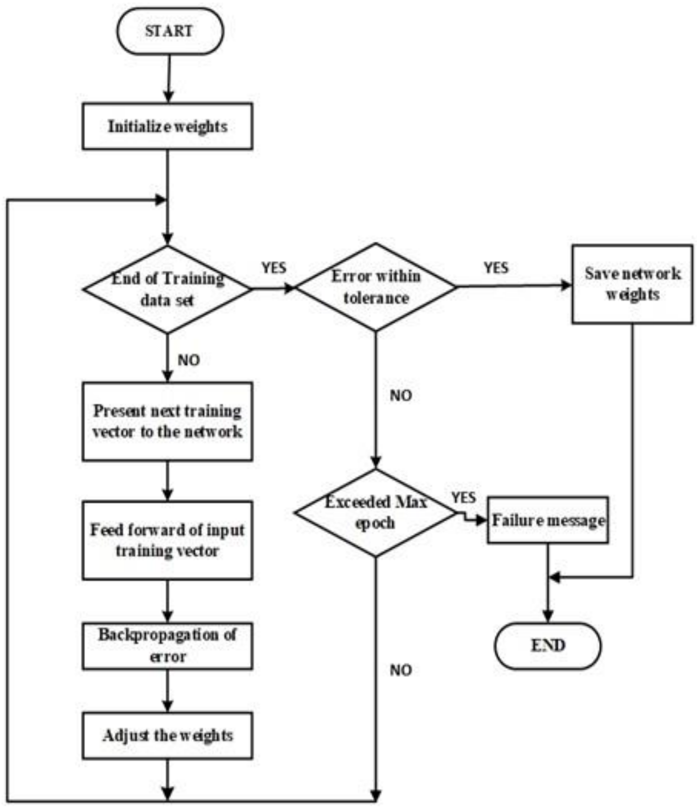


Figure 4.4 : Block Diagram of Back propagation Neural Network (BNN).[6]

Data Training Levenberg–Marquardt (LM) Algorithm

In present study, we have utilized this algorithm because of its good ability to reduce error function. This algorithm is first proposed by K. Levenberg in 1944 and then later it is further modified by D.

Marquardt in 1963 hence algorithm is named after both of them [2] [1].

Main advantages of this technique are that firstly it is very fast which makes processing large data set very fast and secondly convergence is very stable which take care of efficiency [5]. This algorithm is basic a well-organized blend of two different methods one is hessian and other is a gradient.

When the performance function is in the form of a sum of squares, then the two techniques are computed by the following relations,

$$H = {J_k}^T J_k \tag{4.3}$$

$$g = {J_k}^T e \tag{4.4}$$

Where J_k is the Jacobian matrix, which comprises of first order derivatives of the network errors with reference to the weights and biases, is denoting network errors. Hence producing a Jacobian matrix with the help of a back propagation technique is far less complicated than forming the Hessian matrix [3].

The Levenberg - Marquardt algorithm is a fine mixture of the steepest descent method and the Gauss–Newton algorithm. The following relation helps on understanding LM algorithm computation,

$$W_{k+1} = W_k - \left[{J_K}^T J_k + \mu I\right]^{-1} {J_K}^T e \tag{4.5}$$

Where,

W_k= current weight

W_{k+1} = next weigh

I = the identity matrix

e_k =last error

and μ = combination coefficient

LM method attempts to combine the benefits of both the SD and GN methods hence it inherits the speed of the Gauss–Newton (GN) method and the stability of the Steepest Descent (SD) method. The factor μ is multiplied by some factor (β) whenever iteration/epochs would result in an increase in present error e_{k+1} and when epoch leads to reduction in present error e_{k+1}, μ is divided by β. In this study, we have used value of β as 10. When μ is large the algorithm converts to steepest descent while for small μ the algorithm converts to Gauss-Newton [3].

Table 4.1 Comparison of three algorithms

Algorithm	***Rules***	***Convergence***
Gradient Newton algorithm	$W_{k+1} = W_k - \alpha g_x,\ \alpha = \frac{1}{\mu}$	Stable, slow
Gauss – Newton algorithm	$W_{k+1} = W_k - [{J_K}^T J_k]^{-1} {J_K}^T e_k$	Unstable, fast
Levenberg – Marquardt (LM) algorithms	$W_{k+1} = W_k - [{J^T}_k J_k + \mu I\ ]^{-1} J_k e_k$	Stable, fast

In order to evaluate the performance of generated models in this project three Performance Functions are used. Functions are Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE). MAE is used to measure how close predicted load by generated/trained model is to the actual loads. It is given by:-

$$MAE = \frac{1}{N} \sum_{t=1}^{N} |A_t - \hat{A}_t|$$

$$MAE = \frac{1}{N} \sum_{t=1}^{N} |e_t| \tag{4.6}$$

The mean absolute percentage error (MAPE) is used to calculate prediction accuracy of a generated/trained model. It is given by:-

$$MAPE = \frac{100}{N}\sum_{t=1}^{N}\frac{|A_t - \hat{A}_t|}{A_t} \qquad 4.7$$

The Mean Square Error (MSE) is given by

$$MSE = \frac{1}{N}\sum_{t=1}^{N} {e_t}^2$$

Where,

N = number of test samples

A_t = actual value

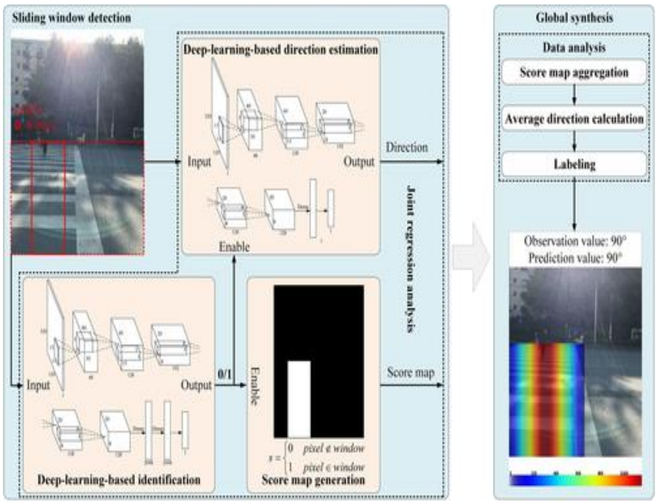
and $\hat{A}_t$ = forecasted value

Figure 4.5 shows the working of LM algorithm using block diagram. Initially, M=1 is considered and random initial values of weights and bias values are taken in calculations. Now for this weights and bias value, the respective output is generated and error is calculated. According to this error matrix, Jacobian matrix (J_k) is computed and on the basis of this Jacobian [/.matrix, next values or updated values of weights are calculated using equation 4.5. Now based on this updated weights and bias values updated or current error (e_{k+1}) is calculated.

Now in the next step comparison is made between present error and last error.

- If the present error is less than last error, then it indicates that the weights are updated in right direction. Hence combination coefficient (µ) will be divided by 10 and new weights now default initial weights i.e., $W_k = W_{k+1}$ and computation will repeat for this value of weight from step 1 again.
- If the new error is more than the last one than the previous values of weights are restored and combination coefficient (µ) will be multiplied by 10 and new weights are calculated using equation 6 with new combination coefficient with an increase in M by 1.
- Now if m > 5 then the new weight will be made the default initial weight and computation again shifts to step 1 and the whole process is repeated again in search of required result.
- If the value of the new error is less than the maximum allowed error value e_{max} than training is stopped at that moment and the current weights are saved as the desired weights and the network will be finalized for further testing.

The goal of the proposed method is to detect the accessible regions of the zebra crossing in front of the visually impaired. The regions of high scores are safe to travel, and the direction information can be utilized to adjust the travelling orientation. The framework of the proposed method is shown in Figure 2. The proposed method consists of two processes: the sliding window detection process and the global synthesis process. The region of interest (ROI) is at the bottom of the image, which represents the region in front of the visually impaired in natural scenes. Since the visually impaired cannot reach the region far from them, the zebra crossing at the top of the image is out of consideration. The window is sliding on the ROI to detect the zebra crossing. The positions and directions of the zebra crossings are analysed to inform the visually impaired. The window slides one pixel at a time, in order to find out all of the accessible regions. The image patch in the window is processed by the joint regression analysis one after another. The deep-learning-based identification is adopted to predict the presence of the zebra crossing. The position of the zebra crossing is recorded in the score map. The score map generation and the deep-learning-based direction estimation are triggered if the zebra crossing exists. The score maps and the directions of zebra crossings are utilized for computation in the global synthesis. After all image patches are processed, the score maps are aggregated and the average direction of the zebra crossings is calculated. The results are labelled to assist the visually impaired. Although the results are shown visually in this paper, audio (or vibration) reminders should be provided to help the visually impaired to be informed.



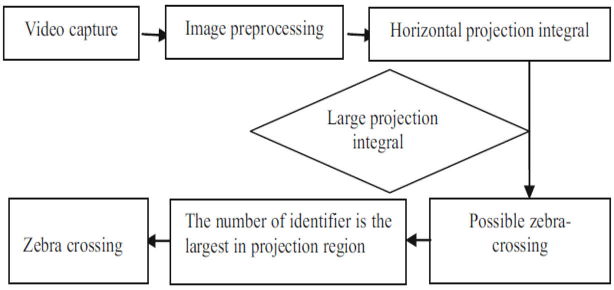


Figure 4.5 : Flow diagram

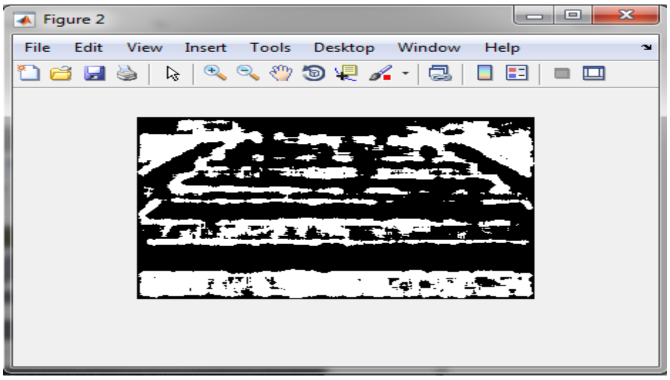
Pattern recognition

- Machine recognition, description, classification, and grouping of patterns are necessary issues during a form of engineering and scientific disciplines like biology, psychology, medicine, marketing, pc vision, artificial intelligence, and remote sensing [2]. A pattern may be a fingerprint image, a written cursive word, a personality's face, or a speech signal. This recognition concept is straightforward and acquainted to everyone within the real world surroundings however in the world of AI, recognizing such objects is a tremendous accomplishment.
- The practicality of the human brain is wonderful, it's not comparable any artificial machines or software system. [4] The term pattern recognition encompasses a large vary of data process issues of nice sensible significance, from speech recognition and therefore the classification of written characters, to fault detection in machinery and diagnosis. The act of recognition will be divided into 2 broad categories: recognizing concrete things and recognizing abstract things [5].

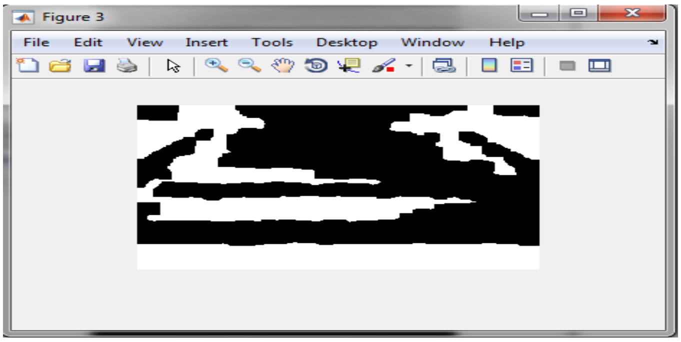
V. RESULT AND ANALYSIS

- To evaluate various indices of the proposed algorithm, we have conducted tests with 56620 sequence images from vehicle-based MMS taken in the BHOPAL.
- Those images, with the pixel of 1600*1200, were taken by a single-CCD camera mounted on the top of a vehicle, with an exposure interval of 0.5s. The test area stretches for 5 km, covering single crossings, among which 243 were seriously impaired.
- The time-consuming of the classifier training varies considerably depending on the classifier class and the rigor of the training end condition, which takes about 80 hours when hierarchical learning classifier of level 17 is used. And the detection of the crossing takes about 9 hours. According to equations 4.2, the Recall of the detection accuracy is 90.78%, and Precision is 94.51%.

(a)



(b)



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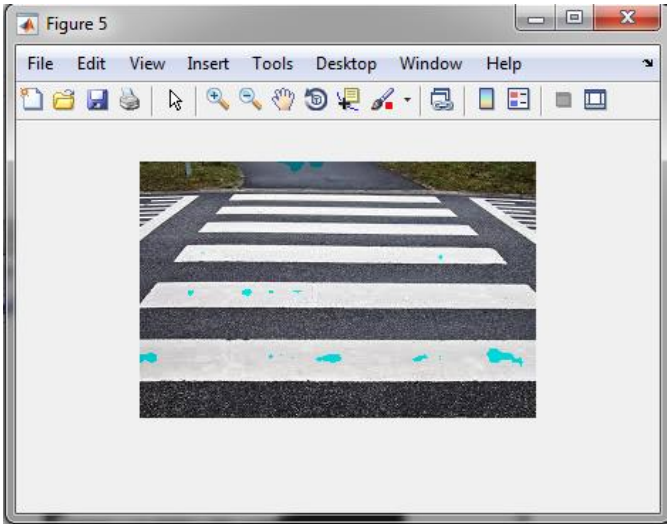

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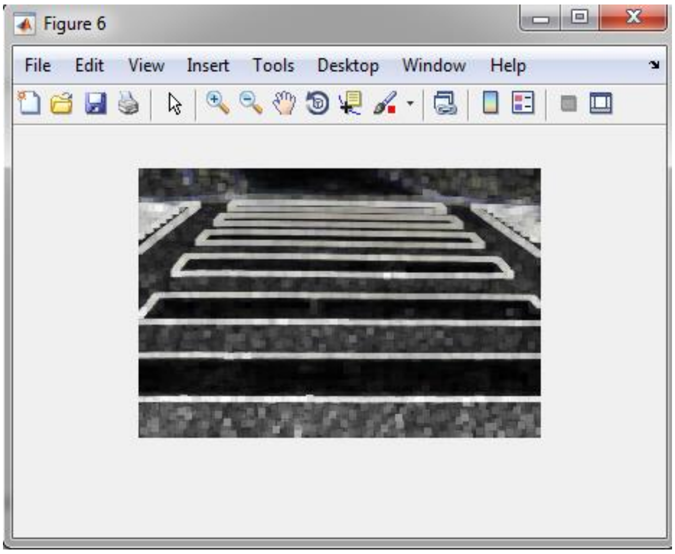

Figure 5.1 : AOI map, contour map, crossing line map of a serious impaired crossing, with strip number calculated

Direction :	Bothways													Location:	Average of all 2 locations				
Location	Motorised Traffic											Non-Motorised Traffic						Grand Total	
	Passenger Vehicles					Goods Vehicles				Agricultural		Passenger		Goods Vehicles					
							Ord. Trucks							Animal Drawn					
	Two Wheeler	Three Wheeler	Car/Jeep	Mini Bus	Bus	Tempo / LCV	2 Axle	3 Axle	M Axle	Tractor with Trailor	Tractor	Cycle	Cycle Rickshaw	Animal Drawn	Horse Drawn	Hand Cart	ADT	PCU
PCU Factor	0.5	1.0	1.0	1.5	3.0	1.5	3.0	3.0	4.5	4.5	1.5	0.5	2.0	8.0	4.0	3.0		
KM 5+000	4915	93	1517	380	310	193	138	171	118	40	23	46	0	3	6	11	7964	7886
KM 45+000	5756	15	1500	449	380	130	123	127	59	172	42	23	0	27	4	0	8808	8695
AVG OF ALL LOCATIONS	5335	54	1509	415	345	162	131	149	88	106	32	35	0	15	5	5	8386	8291

Figure 5.2 : Data collection

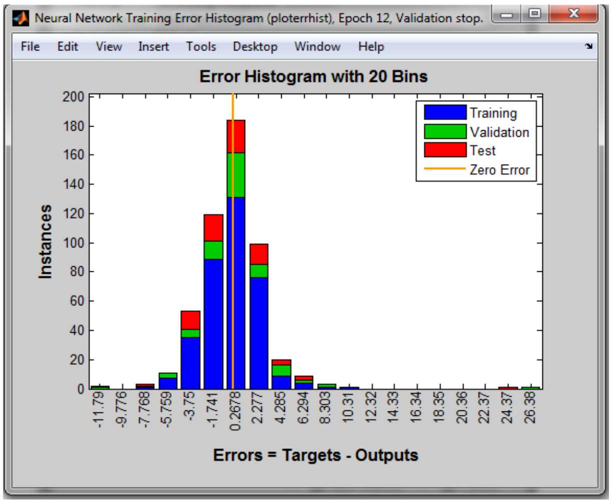

Figure 5.3 : ANN Error for zebra crossing detection

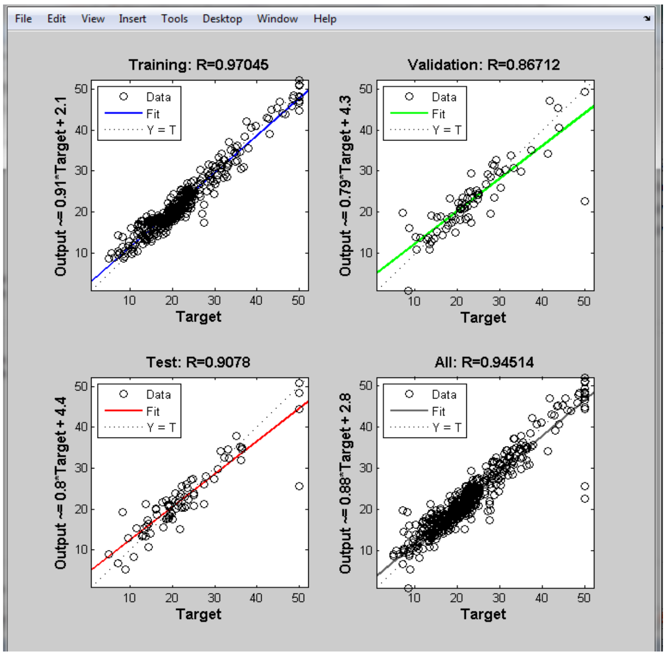

Figure 5.4 : Accuracy prediction and scheduling time prediction accuracy

MSE Analysis represent histogram for multiple layer option. The irregular result provide to neural network. So 0.2678 Error (traffic flow rate) histogram with 20 bins is the highest value of this graph represent.

VI. CONCLUSION

The method presented in this paper is not only simple but also easy to implement. In addition, less time is consumed, it is only 0.0039 s, so, it can meet real-time requirement. Of course, this paper also has some problems. Firstly, the zebra crossings are severely blocked, this method will fail. What's more, when the zebra crossings are severely damaged, our method is also not enough to solve these problems.

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