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BACK PROPAGATION NEURAL NETWORK FOR OBJECT DETECTION AND CLASSIFICATION OVER VIDEO DATA

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ABSTRACT
The vehicle detection on roads becomes an important task when it comes to the urban surveillance and monitoring the traffic on the roads. The live monitoring of the tasks over the roads requires the specifically designed algorithm for vehicular movement tracking. The vehicular movement tracking enables the vehicle detection model to track the object from the points of its appearance in the video and till its disappearance out of the video. Each vehicular object must be tracked and localized for the efficient classification. The image processing techniques in this paper include the various object detection and classification methods. The neural network has been incorporated for the vehicular detection and classification on the basis of the knowledge-driven application. The accuracy of the object algorithm determines the robustness of the vehicular classification and categorization for the in-depth analysis. The performance of the proposed model has been evaluated after conducting the appropriate series of experiments. The proposed model has been found accurate and efficient on the limited data under the experiments performed.

KEYWORDS:. Object Classification, Mobility Tracking, Object Localization, Appearance-Based Object Detection.

INTRODUCTION
Due to the increase in the number of vehicles plying on roads , it is the need of the hour to monitor the traffic with the help of proper techniques for traffic management so as to avoid jamming of vehicles on roads . In order to record vehicular traffic data it is required to understand the type and no of vehicles plying on the road

Vehicle detection has been an important research field for years as there are a lot of valuable applications, ranging from the backing of the traffic planners to the real-time traffic management **.**Being able to constantly monitor the concentration of vehicles inside urban domain allows avoiding problems tied to traffic jams and congestions and consequently allows minimizing the complications of air pollution. Likewise , problems connected to surveillance could be faced by estimating the number of cars inside parking lots or along specific roads. to accomplish this task completely there are still some threats along the way like change in illumination, frame scale, frame quality, size and color. Vehicle detection plays a vital role in the surveillance control, traffic highway and planning of urban traffic[1]. Vehicle detection process on road is used for tracking and counting of vehicles, measuring each individual vehicle's average speed, analyzing traffic and also categorization of vehicles [2]. Vehicle detection can also be defined as the detection of single vehicle by selecting the vehicle chain from video data for traffic surveillance. The video data for traffic surveillance can be defined with the following figure1 taken from the working of system after the detection time i.e. it covers a relatively vast area [3].

In this study, vehicle classification methods established on computational intelligence methods such as genetic algorithms and neural networks have been researched. Neural networks are capable of lear.ning and adapting complex non-linear patterns and complex questions can be solved using genetic algorithms. Various surveillance systems employ these methods Traffic data can be captured in different ways and with varying characteristics. In order to face all aspects of traffic, several acquisition techniques are used to achieve the complementary information. Widely used are induction loops which are a low-priced solution to accumulate traffic data continuously, but limited to isolated spots. In contrast to induction loops, stationary video cameras allow us to exploit geometric information and identification, but also just locally. They are mostly installed on highly frequented streets, only.

The fleet of vehicles in cities continues to increase and monitoring vehicles fleet is an emerging necessity. A number of cities especially in the developed countries make use of field based equipments such as cameras which are installed at fixed locations or weigh-in motion sensors on pavements to monitor traffic. Recently video imaging and airborne imaging is tested especially to provide the more synoptic view of the traffic and to monitor traffic trajectories. Aerial photography has also been evaluated and the newly available vehicle surveillance dataset at very high resolution provides us a new opportunity and a start also to be considered. The comparison of optical, infrared and SAR data shows obviously they are both advantages and bottlenecks. For example the SAR sensor is independent of day/night and weather condition but its oblique view causes distortion, the presence of some buildings hides some roads and its analysis is very much affected by the experience of the interpreters.

Rest of the research paper is organized as follows: In section II we describe the literature review which shows the various analyses and research made in the field of vehicle classification and detection and the results already published, taking into account the various parameters of the proposed research . Section III describes the Experimental Design in which we discuss the various algorithms used in this research. Section IV discusses the analysis of neural network workflow Section V defines the Result Analysis which provides the results of the proposed model that have been obtained after performing the several experiments over the input imagery data.Section VI defines the conclusion and the future scope of the proposed work.

LITERATURE REVIEW

In this section we discuss the previous work done in this field and the improvements made in the proposed model.The previous work done in this field is described in the following papers:

Jazayeri et al. [4] proposed the detection and tracking of the vehicles in car for the purpose of safety, auto driving and target tracing. It is based on the motion information. It describes the localization of target vehicles in video. Some features that are used to characterize the vehicles are extracted in the video in a robust manner. The positions of these extracted features are projected on a 1D profile in order to speed up the tracking and identification of the vehicle. Hidden Markov Model (HDD) is defined to separate the target vehicles from background in such a way that the vehicles can be tracked probabilistically.

Cao et al. [5] described a method in order to detect the moving vehicles in urban traffic surveillance. The algorithms used must be efficient so that they can be used in a real time environment. In order to tackle these problems, an approach to detect the moving vehicles from low altitude airborne videos is proposed.

Premebida et al. [6] defined the detection and classification of road users that describes an issue on safety systems for intelligent vehicles drive. It describes the analysis of pedestrian detection by using the laser based features in urban areas. The main objective is to explore the required information that can be extracted from LIDAR sensors. This can be used to define the pedestrian detection systems by using both LIDAR i.e. an object detector and vision sensors. Pedestrian detection is defined as a part of the perception system which consists of various modules such as data preprocessing, tracking and data association, feature extraction and pedestrian detection. There are various tasks that are performed in preprocessing of data i.e. pre- filtering, coordinate transformation and segmentation.

Sivaraman et al. [7] proposed a novel approach for localization of vehicles and tracking of vehicles that combines stereo- vision to the monocular vehicle detection. This system obtains the information from stereo- vision for 3D localization and also obtains monocular frames that are synchronized and hence calculate the depth maps. Then system detects the vehicles in image plane by using a vehicle detector i.e. monocular vision method that is based on the active learning. Then the system localizes vehicles by using image coordinates of detected vehicles. With the help of results of detection, the 3D location of vehicle is solved by using stereo- vision. Firstly the state of the vehicle is estimated and then tracked by using Kalman filtering. The complete system takes 46 ms in the processing of a single frame

Song et al. [8] described a system for vehicles that is based on sensor network. SVATS is used to detect the unauthorized movement of the vehicle and tracking the vehicle that has been stolen. Since the rate of theft of vehicle is high, so alarm systems or tracking systems have been defined. Such systems have disadvantage like high cost and high false alarm rate. This is a very large system for tracking of the vehicles. It also defines the implementation, design and evaluation of this system. In this, the vehicles that are parked in same parking area forms a sensor network and then it monitors and identify the vehicle thefts and this can be done by detecting the unauthorized movement of vehicle. This also describes the various technical issues such as theft and movement detection, connectivity management and intra- vehicle networking.

Arrospide et al. [9] described an approach for detecting the vehicles visually by using a gradient-based descriptor. This defines the classification performance of symmetry in a Bayesian decision framework. But it explained that the performance is limited. Hence to detect the vehicles, a new gradient- based descriptor is defined and it is tested under a similar Bayesian framework and this proved to yield high separability between classes as compared to symmetry.

Unzueta et al. [10] proposed a robust vision- based system used for tracking and classification of vehicles for traffic flow surveillance. A robust adaptive multicue segmentation method is defined to detect the foreground pixels. This system threshold the combination of luminance and chromaticity disparity maps. Then in order to improve segmentation of dark vehicles with casted shadows, it adds extra features to it that are derived from the gradient differences. The results show that this approach can count and classify the vehicles in real time containing high performance

Nedevschi et al. [11] defined a real time pedestrian detection system that is useful for detecting the pedestrians in urban scenarios. To protect pedestrians, they should be detected in a reliable manner. This system is designed so that it can behave as a sensor that can be used for road vehicles. This provides the information regarding driver warning systems and actuators. This system also defines a method in urban traffic conditions for the detection of various pedestrians. It uses pattern matching for detecting the pedestrian. In order to track the pedestrians that have been detected, Kalman filtering is used. For walking pedestrians, a motion-based validation is used that comprises of motion signature extraction and for analyzing the periodicity of the motion signature.

Tsai et al. [12] proposed a technique for detecting the vehicles and tracking using an intelligent vision- based on-road system. In order to improve the reliability and stability of the system, a pre- processing video stabilization method is defined that is used to remove the unwanted oscillation from a shaky video stream. This method defines the global motion estimation (GME) which is used to estimate global motion and also is used to separate motion to an intentional motion (IM) and unwanted motion (UM). Therefore a stabilized video is achieved by removing the unwanted motion from a shaky condition.

:EXPERIMENTAL DESIGN

The model based upon the object detection in the video traffic surveillance dataset has been proposed in this paper. The proposed model has been based upon the appearance based object detection and classification over the given dataset. The knowledge discovery based object detection and localization method has been utilized for the object detection in the proposed model for the object classification. The back propagation neural network classifier has been utilized for the vehicular object classification from the video traffic surveillance dataset collected from the various sources across the network of institutes for research.

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Figure 1: The testing frame for the vehicular classification demonstration in the proposed model

The image shown above in figure 1 has been obtained from the image data from the Stanford university database for the evaluation of the object detection approach in the urban scenario. The vehicular objects has been detected and classified in the proposed model by using the pattern matching based upon the back propagation neural network (BPPNN) under this technique. The above image displays the scene of Oxford Circus square, London, which is a busy square. The Oxford circus square is the path for several vehicles and pedestrians everyday. The proposed model has been evaluated for its performance under the chain of experiments using this technique. The vehicular object detection incorporates the knowledge-driven approach, which utilizes the slider window function based pattern discovery within the image matrix to localize the vehicular objects. The vehicular objects are further classified using the second level pattern classification model after the region of interest (ROI) extraction from the given image matrix.

The proposed neural network approach is entirely based upon the concept of the back propagation paradigm for the discriminate method based neural network training. The automatic weight computation for the object classification has been incorporated under this proposed model to evaluate the probability of the found match in order to determine the final decision. The flexible weight tracking has been applied using the neural network for the purpose of gradient descendent based decision logic calculation:

$$Q_{ij}(\mathrm{t+1}) = Q_{ij}\ (\mathrm{t}) + \ n\frac{\partial b}{\partial q_{ij}}$$

Where the b defines the cost function, Q defines the training coefficient, n is the number of input variables, ∂ denotes the initial probability and t defines the current index count. The supervised methods require the weight calculation to determine the best match out of the available matches from the given set of training vectors. The softmax function is prominently utilized to evaluate the neural weights by using the optimal cost function as it defined in the following equation.

$$q_j = \frac{\exp(y_j)}{\sum_k \exp(y_k)}$$

Where $q_j$denotes the probability of the class and y_k and y_k gives the overall number of unit inputs to the neural network denoted by the variables j and k. The cost entropy function plays the vital role in the successful execution of the neural network classification. The cross entropy examines the pattern strength and realm the strong patterns to the fore. The cross entropy can be given by the following equation.

$$\mathrm{C} = -\sum d_j \log(p_j)$$

where d_j gives the target probability for the unit number of j. The p_j term denotes the output probability for the index j after the application of the activation function. In this algorithm, the application of knowledge-driven back propagation has been incorporated for the vehicular object localization and classification over the video traffic surveillance dataset. The algorithm flow has been clearly described in the following section:

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Algorithm 1: Back Propagation Neural network classification for object localization

1. The video acquisition is performed over the target video
2. Extract the video into the frames under the given folder
3. Start the iteration over the given number of frames
   a. Frame acquisition for the target traffic surveillance object
   b. De-noise the frame using the median filter to shun out the salt and pepper noise for better classification by removing the unexpected peaks and ravines in the frame pixel pattern
   c. Detect the target features in the frame using the knowledge-driven pattern matching over the input frame
   d. Extract the detect object regions (known as regions of interest or ROI) from the target frame
   e. Apply matrix factorization for the minimization of the frame features for quicker classification.
   f. Convert the triplet streamed factorized data to the 1-D vector
   g. Create neural network with 10 layers and programmed with multiple objective input
   h. Submit the training matrix obtained from the knowledge-discovery database
   i. Perform the neural network classification
   j. Return the decision logic
4. If it's the last frame
   a. Quit
5. Otherwise return to the step 3.

Algorithm 2: Hybrid deep neural network (HDNN)

1. Initiate the activation function for the neural networks denoted by → phi
2. Define the derivative of the activation function {phi} → phid
3. Begin the Forward Propagation network
   i. Define the Input data in the form of input nodes (i) over the given input (x).
      a. Run the iteration for each input object or node (i)
      b. Return the output vector $result_i$ which equals x_i stands for calculated cost.

4 .Compute the Hidden layer processing over the given nodes j

   a. Run the iteration for each given object j
   b. $result_j = \sum_i phi(w_{ji} \cdot result_i)$

5. Define the output layers of the neurons
   a. Run the iteration for each given neuron k
   b. $result_k = \sum_k phi(w_{kj} \cdot result_j)$

Algorithm 3: Activation Function

1. Being the activation function
2. Activate the Layers (**input** and **output**)
3. Run the iteration for each object i and neurons k
   a. calculate $result_i$
4. Run the iteration for each hidden neuron j
   a. calculate $result_j$
5. Run the iteration for each hidden neuron k
   a. calculate $result_k$
   b. **result** = $\{result_k\}$

Algorithm 4: Define the Output Error

1. CalcError()
2. Run the iteration for each **input** in given InputSet
   a. $CalcError_{\mathbf{input}} = \sum_{k\ result\ neuron} (target_k - result_k)^2$

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NEURAL NETWORK WORKFLOW ANALYSIS

Hybrid Deep Neural Network (HDNN)

In the hybrid deep neural network (HDNN),as shown in Figure 4.1 we tend to divide the maps of the last convolutional layer and the maxpooling layer of the deep neural network into multiple blocks of variable receptive field sizes or max-pooling field sizes, to enable the HDNN to extract variable-scale features. The extracted features are passed over the HDNN for the vehicle type classification. Comparative experimental results indicate that our proposed HDNN significantly outperforms the traditional methods on vehicle detection.

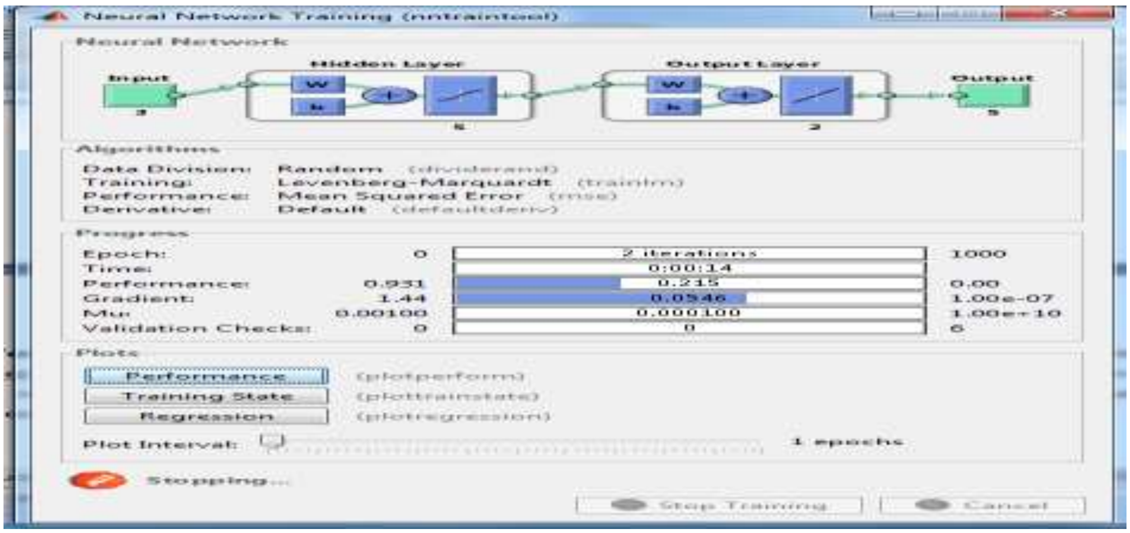

Figure 4.1: HDNN

Performance Plot

This graph provides performance of our system and shows the Mean Square Error (mse) of training, testing and validation. In following Figure 4.2 training is shown in blue color, testing in red color and validation in green color line. Best match in this figure meet at 11thepoch. Lowest mean square error indicates the best validation performance.

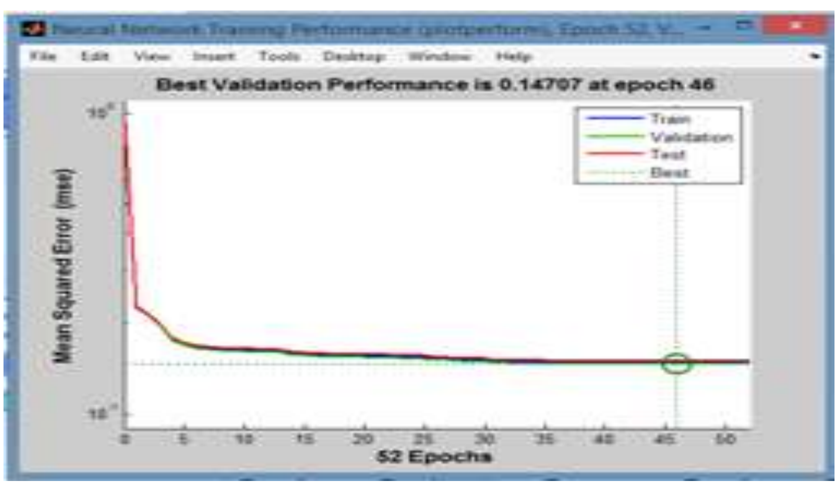

Figure 4.2: Performance Plot

Confusion Matrix

This matrix as shown in Figure 4.3 defines the actual and predicted values of the network and tells about the overall performance of this system for training, testing and validation. In above matrix green squares contain high number of correct response and red squares contains low no of incorrect response. Blue Square at the right bottom contains overall performance.

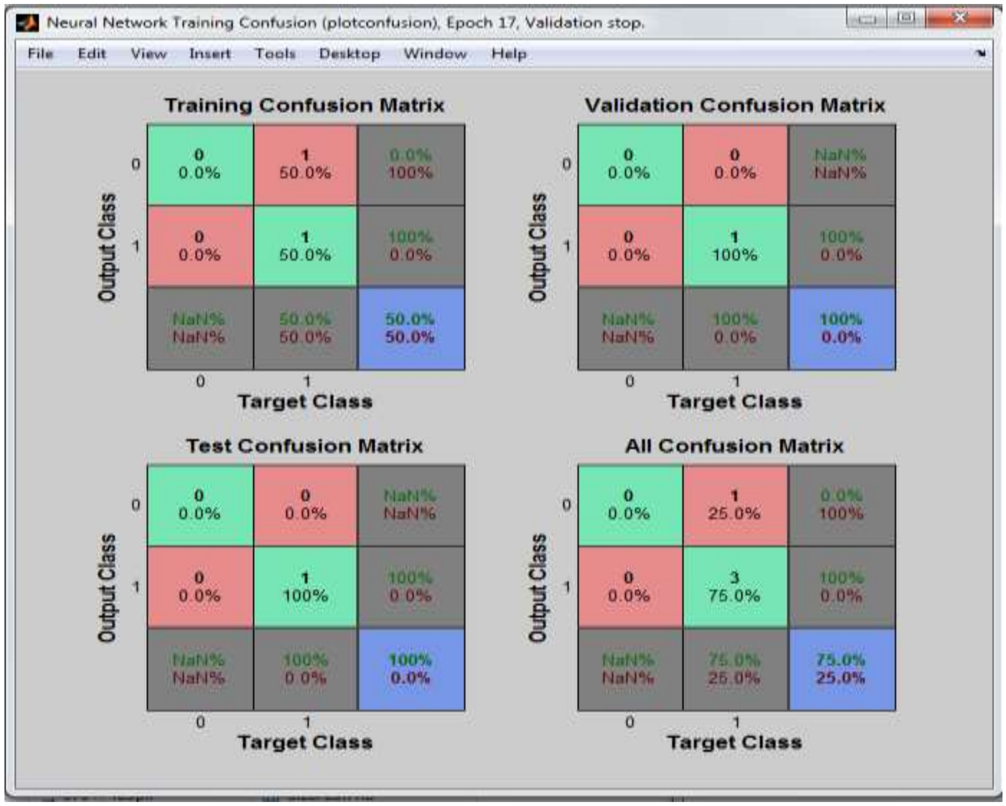

Figure 4.3: Confusion Matrix

ROV Curve

In Figure 4.4 we define the Receiver Operating Characteristic (ROC) curve. Network performs very well for this problem. In this figure, colored lines represent the ROC curve in every axis. This curve is a graphical representation of the true positive rate (sensitivity) versus the false positive rate (1 - specificity) as the threshold is changed. A perfect test would show points in the upper-left corner, with 100% sensitivity and 100% specificity.

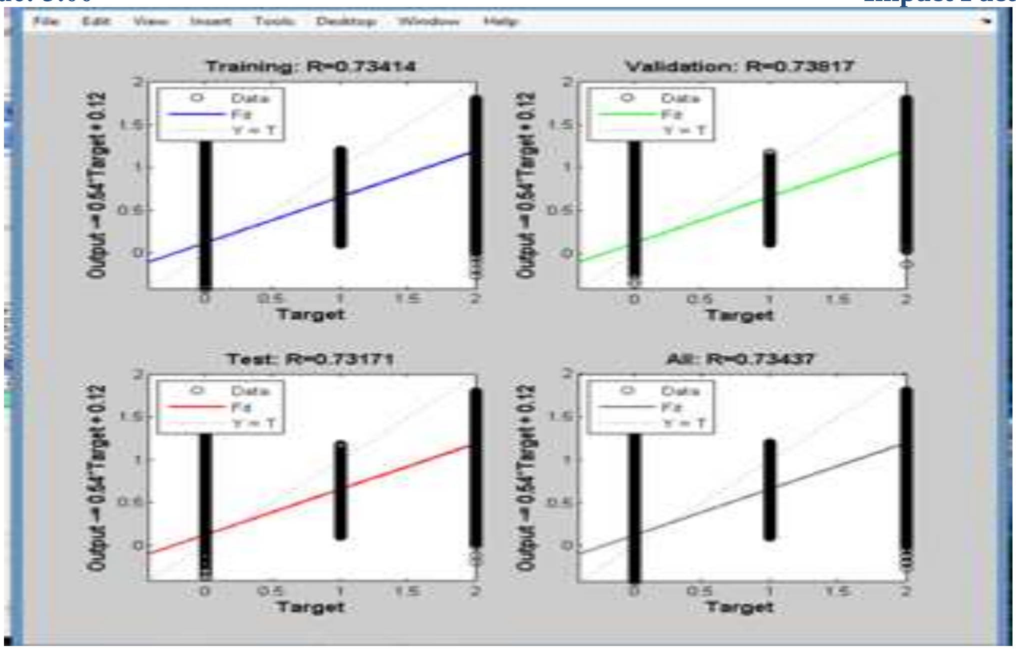

Figure 4.4 ROV Curve

Training State

Training state as shown in Figure 4.5 shows the gradient value of back propagation at each of the iteration. Gradient value shows the very closest point of goal. Validation fails iterations are those iterations whose Mean Square Error values are increased. MATLAB automatically stops after 6 regular validation fails.

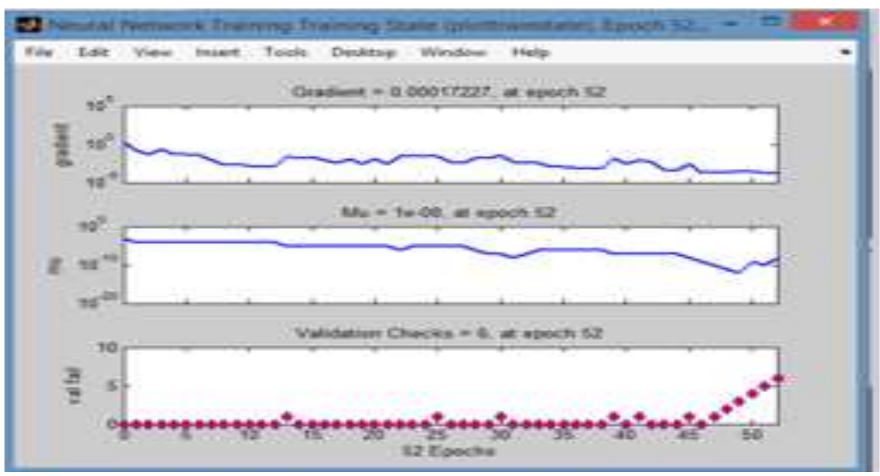

Figure 4.5 Training State

Error Histogram

This plot shown below in Figure 4.6 shows the training in blue color, testing in red color and validation in green color. This plot shows the errors at first bin are both training and testing errors. One training error lies at 7th bin and validation error lies at last bin.

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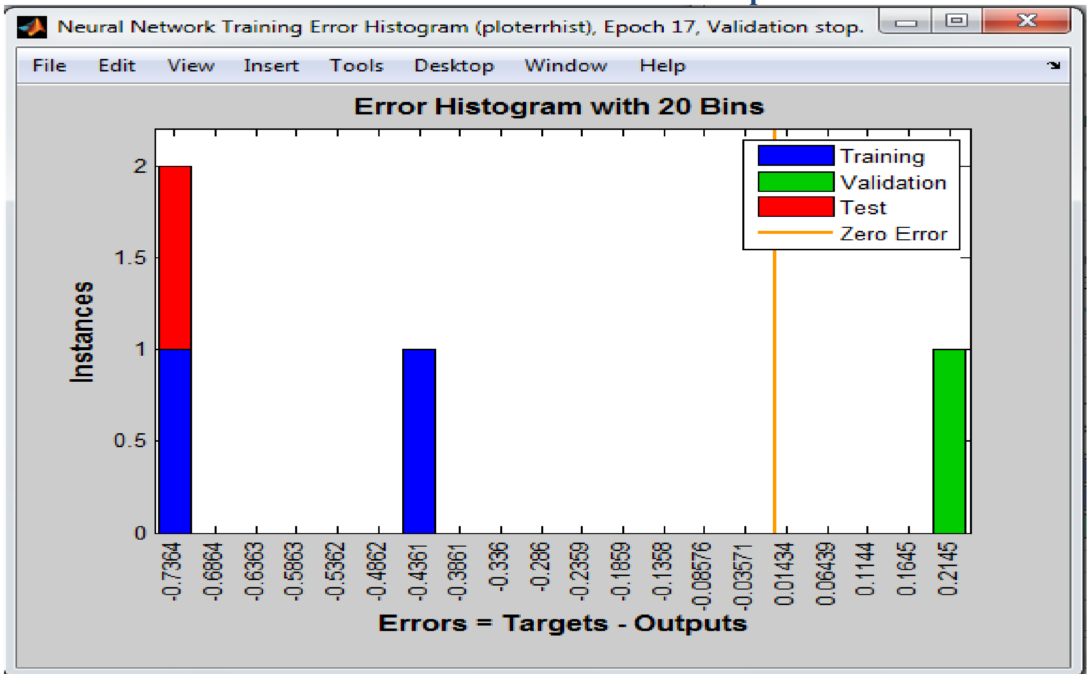

Figure 4.6: Error Histogram

return the Average after averaging function over (CalcError$_{input}$, and the InputSet)The results and discussion may be combined into a common section or obtainable separately. They may also be broken into subsets with short, revealing captions.

RESULT ANALYSIS

The results of the proposed model have been obtained after performing the several experiments over the input video and image data obtained from the datasets comprising the videos of traffic on the roads and squares. The proposed model results have been obtained in the form of recall, precision and accuracy of the vehicular object detection in the target objects. The proposed model has been designed for the mobility tracking among the video data obtained from the road traffic surveillance cameras. The following section clearly describes the performance of the proposed model over the video data specifically. The performance parameters are the specified entities which defines the result of the implemented model. The performance parameters have to be selected on the basis of the nature of the project, algorithms being used and the testing data. The proposed model is based upon the vehicle detection and classification, which always requires the high accuracy in order to use it in the real time applications. Hence, the accuracy becomes the major parameter, which is being calculated in the various ways using the statistics. The proposed model accuracy can be measured in the terms of precision, recall and accuracy. The possibility of the false results also becomes important in the case of performance evaluation. Hence, the parameter selection also includes the results concerned with the appearance of the false results. The parameters of false rejection rate (FRR) and false acceptance rate (FAR) has been selected as the parameters to measure the possibility

Precision

The parameter of the precision as shown in Table 1 is one the parameters to measure the accuracy of the system, which is entirely based upon the percentage of the total matches founds from the input data according the user requirement. The higher precision value signifies the robustness of the proposed model applied over the video data. The manual classification has been performed to measure the statistical type I and type II errors, which defines the overall results in the various categories or selection or rejection. The precision is also termed as the sensitivity and given by the following equation:

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P = Alpha / (Alpha + Lambda) * 100

Where P is the precision, Alpha stands form the true positive and beta for false negative.

PARAMETER	VALUE	95% CI
Precision	94.08%	75.29% to 100.00%

Table 1: Evaluation of the proposed model using precision

Recall

Recall as shown in Table 2 gives the overall probability of the test among the matching samples out of the total selected and rejected cases. The false rejection cases significantly reduces the overall accuracy of the system, hence the impact of the false rejection cases is studied with the parameter of recall.

Recall = Alpha / (Alpha + Gamma) * 100

PARAMETER	VALUE	95% CI
Recall	91.10%	75.29% to 100.00%

Table 2: Recall based evaluation of the proposed model

Positive Predictive Value

Positive predictive values as shown in Table 3 *are influenced by the prevalence* of correct results in the population that is being tested. If we test in a high prevalence setting, it is more likely that people who test positive truly have matching probability than if the test is performed in a population with low prevalence.

Positive Predictive Value = A/(A+B) × 100

PARAMETER	VALUE	95% CI
Positive Predictive Value	93.50%	75.29% to 100.00%

Table 3: Positive predictive value calculated from the simulation results

Accuracy

The overall accuracy of the system as shown in Table 4 is measure by dividing the correct number of the detection samples (True positive and true negative) by the total number of the test cases. The accuracy clears the overall performance of the system unlike the specific cases defined by the precision or recall. The following table defines the accuracy of the system**:**

Accuracy = (Total correct results/ Total test cases) *100

PARAMETER	VALUE	95% CI
Accuracy	93.41%	75% to 100%

Table 4: Accuracy based evaluation of the proposed model.

False Acceptance Rate (FAR)

It can be defined as the fraction of the system that donot matches the patterns of input correctly to the template that is non matching. It defines the percentage of inputs that are not valid. False acceptance rate as shown in Table 5 is dependent on the threshold. It is also defined as the measure that an attempt by the user that is unauthorized will be accepted by the biometric security system.

PARAMETER	VALUE	95% CI
False Acceptance Rate	0.025	0.025

Table 5: False acceptance rate calculated from the simulation results

False Rejection Rate (FRR)

False rejection rate as shown in Table 6 is defined as the probability of a system to detect the matching between the pattern that is given as input and the matching template. It is the fraction of number of false rejections to the number of attempts that are identified. It defines a measure that an attempt by the user that is unauthorized is rejected by the biometric security system.

PARAMETER	VALUE	95% CI
False Rejection Rate	0.00	0.05

Table 6: False Rejection rate calculated from the simulation results

The above tables under the different parameters show the significantly higher performance of the proposed model in the statistical terms of recall, precision and accuracy. The proposed model can be evaluated as the highly accurate object detector and classifier in the urban traffic surveillance scenario, when equipped with the efficient population of the training samples. Total of 235 vehicles has been detected in the target video data, which is collected from the Standford university's video surveillance Database. The video represents the traffic over the various points in the US or Europe, which are either busy or not busy points of the traffic and several or adequate number of vehicles pass through every day. The object extraction is based upon the supervised appearance model, which detect the visible objects looking like vehicles. The vehicles are then classified using the neural network classifier and have been defined using the different colors.

Method	Given Recall Rate
DNN [2]	**23.5**
HOG+SVM [19]	**67.5**
LBP+SVM [20]	**87.6**
Adaboost [21]	**91.6**
Proposed	**93.1**

Table 7: The table of comparison of FAR of different methods on vehicle test set

The above table (Table 7) has been recorded with the overall false acceptance rate, which in terms describes the ability of the proposed model to correctly find the required results. The proposed model has been recorded with recall rate more than all of the previous models considered under the comparative study. The proposed model has been described with the deep neural network, which creates the brighter chances for the deep learning, which straight forwardly enhances the performance of the proposed model. The results in above table have shown the effectiveness of the proposed model in the case of vehicle detection and classification. The proposed model has been proved to be efficient and robust object classification system. In the future, the proposed model can be applied on some of the standard vehicular dataset. The proposed model can be also tested with the video data for the vehicular detection and classification purposes.

CONCLUSION AND FUTURE SCOPE

The video traffic surveillance data under the observation in the proposed model is the video data collected over the busy points across the roads during the day time from the geo-stationary high resolution cameras during the day. The proposed model has been tested to classify the heavy vehicles and light vehicles in the given videos. The testing videos contains total of 253 vehicular objects, out of which the many are the heavy vehicles and others are the lightweight vehicles. The proposed model has been designed in the multi-layered model for the detection and classification of the vehicular objects in the satellite images. The proposed model results have been recorded on the basis of elapsed time for the vehicle recognition and vehicle detection transactions performed in the proposed model. The average classification time has been found around 234 seconds in the all 253 transactions to recognize the all vehicular objects in the simulation. Also the detection time has been recorded from the simulation, which has been recorded around less than 1 second on an average for the all individual transactions. The proposed model have correctly identified the all of the vehicular objects in the given test video test sets for the experiments. The experimental results have shown the effectiveness of the proposed model in the case of vehicle detection and classification. The proposed model has been proved to be efficient and robust object classification system.

In the future, the proposed model can be applied on some of the standard vehicular dataset. The proposed model can be also tested with the video data for the vehicular detection and classification purposes

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