TAF Journal of Advances in Technology and Engineering Research JATER
2024, **10**(1): 46-55

PRIMARY RESEARCH

Recognition of traffic signs based on feature extraction vector and using support vector machine classifiers and neural networks

Behzad Soltani*
Islamic Azad University, South Tehran Branch, Tehran, Iran

Keywords
Neural network
Traffic signs
Support car vector
Extraction vector

Received: 13 January 2024
Accepted: 10 March 2024
Published: 21 April 2024

Abstract
In this research, the detection of traffic signs based on the feature extraction vector and using support machine vector classifiers and neural networks has been done. In this project, we intend to use methods to identify and reset traffic signs. In this study, a fast and robust method for detecting symptoms using algorithms in machine vision is presented. The classification and recognition of signs is also done using smart classifiers such as neural network and vector machine support. To get the right result, we categorize traffic signs into different categories such as mandatory signs or warning signs. The proposed model for recognizing traffic signs consists of two parts. The first part has the task of identifying the type of sign according to the categories done. And the second part is responsible for identifying the type of sign in each of the categories obtained from the first part.

I. INTRODUCTION

Intelligent transportation system or ITS for short is the use of information and communication technology to improve the performance of the transportation system. "The word ITS refers to a set of tools, facilities and expertise such as traffic engineering concepts, software, hardware and telecommunication technologies that are used in a coordinated and integrated manner to improve efficiency and safety in the transportation system. ". In recent years, transportation engineers, together with experts in the fields of telecommunications and communications, electronics, computers, etc., have created intelligent transportation systems or ITS by using information technology. (Bahlmann C, 2005).

In today's modern world, traffic management and road safety are of particular importance. One of the key aspects of this management is the detection and identification of traffic signs. These signs act as vital tools to guide and control traffic and play an important role in reducing accidents and increasing road safety. Due to the ever-increasing growth of cars and the need for intelligent transportation systems, the use of advanced technologies for automatic detection of these signs has become a necessity. (GUO H-r, 2011)

Traffic sign recognition can be a big challenge in image processing and machine vision, especially in different lighting and atmospheric conditions. In this context, feature extraction from symptom images plays a vital role in the performance of recognition systems. Among the common methods for extracting features, we can mention the use of vector feature extraction techniques that can help to uniquely identify different symptoms. (Mogelmose, 2012).

After the features, the next step is to use advanced classifiers such as vector machine (SVM) and neural networks. These algorithms are well able to identify complex patterns in data and distinguish between different symptoms. As one of the most powerful methods in classification, Support Vector Machines (SVMs) have received much attention due to

*Corresponding author: Behzad Soltani
†email: Soltani.behzad1988@gmail.com

their high ability to work with high-dimensional data and insensitivity to noise. (Jang, 2000) On the other hand, neural networks, especially deep neural networks (DNN), with the ability of deep learning and detailed analysis of features, represent tremendous advances in the field of machine vision and image recognition. In this paper, we will seek to investigate the most efficient methods of traffic sign detection, focusing on feature extraction techniques and applying SVM classifiers and neural networks. Considering the applications and benefits of each of these methods, we will also analyze their performance and results in a real environment. It is hoped that this research can help improve road safety and reduce traffic accidents in the future. (Stallkamp, 2012).

Today, due to population growth, the expansion of the road network, the development of intra-urban and road transportation, as well as the increase of the speed parameter in vehicles; The traffic environment for road users, including drivers of passenger cars, heavy vehicles, public vehicles, motorcycle and bicycle riders, should be defined and specified in such a way that drivers can visualize the route in advance and with sufficient confidence and knowledge to Let them continue on their way. This brings comfort to car occupants as well as pedestrians. But despite the presence of intelligent navigation systems, traffic information, route maps, traffic signs, we still see the occurrence of accidents by drivers, which is mostly due to the lack of attention to the current traffic signs on purpose or It is unintentional. The important issue is to what extent drivers can be helped to avoid possible accidents and dangers. To what extent do the visual elements in the environment affect the amount of violations and traffic accidents? Can we take an effective step in reducing accidents by using faster and more correct recognition of graphic elements?

A. Statement of the problem

In the digital era and with the ever-increasing expansion of the Internet, consumer behavior has become one of the determining factors in the success of marketing strategies. Companies and brands need to carefully analyze the behavior and needs of their customers to survive and grow in competitive markets. In this regard, one of the basic challenges that many organizations face is the lack of sufficient knowledge of consumer behavior in the online space and how it affects purchasing decisions. (Mogelmose, 2012).

The growing trend of online shopping, especially after the spread of the Corona virus, has made it easier for consumers to access products and services as quickly as possible. This change in purchasing behavior has not only affected the traditional variables, but also led to the emergence of new and more complex patterns of consumer behavior. As a result, the correct understanding of these patterns and how they interact with marketing strategies has become a major challenge for marketers. (Theodoridis, 2003).

The main problem of this research can be defined as follows: "How does consumer behavior in online marketing affect marketing strategies and how can companies optimize their strategies by analyzing and understanding these behaviors?" In other words, it is necessary for organizations not only to pay attention to the characteristics and needs of their consumers in the online space, but also to use the capacities available in this platform to design and optimize marketing strategies. (Barnes N, 2008).

With changing consumer behavior and new purchasing norms, organizations must be able to respond quickly to these changes. In this regard, it is very important to identify the new needs and preferences of customers in the online platform. The huge and diverse data that is collected through the online behavior of consumers needs to be analyzed carefully so that they can be used in designing marketing strategies. The lack of appropriate analytical tools and models can prevent the desired effect of marketing strategies (Bishop, 1996).

Optimizing marketing strategies according to consumer behavior requires a deep understanding of purchasing processes, customer pain points, and existing barriers. Failure to pay attention to these issues can reduce the effectiveness of marketing campaigns. In the highly competitive online market, understanding consumer behavior can be a competitive advantage for brands. Therefore, research in this field can also help to identify the strengths and weaknesses of competitors. As a result, understanding the impact of consumer behavior on online marketing strategies is a necessity for marketing managers and can lead to improved business performance and a better experience for customers. This article examines this issue in detail and tries to provide practical solutions for optimizing marketing strategies in the online arena by providing tangible data and a case study. (Chen Z, 2011).

Recognition of traffic signs is one of the most important challenges in the field of machine vision and image processing. These signs, which are linked to regular and identifiable cycles, play a key role in traffic management and ensuring road safety. With the ever-increasing number of vehicles and the complexity of transportation networks, the need for automatic systems to quickly identify and interpret these signs has become an inevitable necessity. (Zaklouta, 2012).

ISSN: 2414-4592
DOI: 10.20474/jater-10.1.5

Existing challenges and problems

Variety and complexity of signs: Traffic signs have various shapes, colors and sizes. This variability may cause diagnostic systems to make mistakes, especially in different environmental conditions such as light and weather changes.
Complicated background: Images of signs may interfere with backgrounds containing other materials and objects. These interferences can lead to misidentification or missing symptoms.
Lighting and atmospheric conditions: Factors such as sunlight, rain, snow and fog can have many effects on the quality of images and the ability to identify signs. These problems can significantly affect the accuracy and efficiency of detection systems.
The need for rapid learning and adaptation: Due to the constant changes in sign design and new designs, recognition systems must be able to quickly adapt to new information. This requires advanced machine learning algorithms that are capable of learning from new data and changing conditions.
Reliability and accuracy analysis: Since traffic signs are critical to maintaining road safety, high detection accuracy and system reliability are extremely important. An incorrect detection system can lead to severe and dangerous accidents. (MAZINAN, 2014).
In order to solve these challenges, this paper investigates and develops an approach based on advanced techniques in which feature extraction vector is used to identify the key features of traffic sign images and support vector machine (SVM) classifiers and neural networks are used.
Feature extraction: This section includes identifying and extracting important features from sign images, such as shapes, colors, and textures, which can help better identify signs.
Classification using SVM and neural networks: The use of classification methods based on SVM and neural networks can effectively identify different types of symptoms and increase accuracy even in difficult situations. (M. Lalonde and Ying Li, 1995).
Considering the challenges raised and the need for accurate and reliable detection systems, this research investigates and evaluates the combined performance of feature extraction vector techniques and SVM algorithms and neural networks in detecting traffic signs. The aim of this research is to increase the accuracy and efficiency of detection systems and ultimately improve road safety in real environments. It is hoped that the results of this research can be used in practice and help the development of intelligent transportation systems.

Necessity of conducting research

As a key research area in data science and machine vision, automatic traffic sign recognition has attracted much attention in recent years. This necessity can be examined from different aspects: (Minhaj, 1377)
Increase in road accidents With the increasing number of cars and the variety of road conditions, accidents and traffic accidents have become one of the serious problems of modern societies. According to global statistics, not paying attention to traffic signs is one of the main causes of accidents. With the development of smart technologies and automation systems, it is possible to reduce these incidents through quick and accurate detection of symptoms.
Optimum traffic management Traffic signs play a vital role in traffic management, especially in densely populated and high-traffic areas. By using intelligent systems capable of recognizing and interpreting these signs, it is possible to significantly improve traffic flow and reduce travel time. This capability, in turn, will lead to the reduction of pollution caused by traffic and the improvement of the quality of urban life. (Ruta A, 2010)
Technological advances The development of artificial intelligence and machine learning technologies allows us to use more complex algorithms to analyze and process data. The use of support vector machine (SVM) models and neural networks as advanced machine learning methods can significantly increase the accuracy and reliability of symptom detection. This research studies and evaluates the effectiveness of combining these two approaches in diagnosing symptoms. (Wang, 2012).
Variety and changes in the design of signs Traffic signs are constantly changing and updating. For this reason, recognition systems require safety and fast learning. New technologies must be able to easily adapt to changes in the design of their signs to avoid misdiagnosis and misdiagnosis. The current research seeks to develop adaptive and optimal algorithms.
Increasing the need for automation and intelligent systems Due to the growing trend of automation systems, such as self-driving cars, the need for fast and accurate recognition of traffic signs is felt more and more. Automation processes require intelligent systems that can make decisions independently. This research can help to improve the decision making process in these systems. (Stallkamp 2012)
Increasing the satisfaction and safety of road users Correct and accurate detection of traffic signs can directly lead to increased road safety and satisfaction of drivers, pedestri-

ISSN: 2414-4592
DOI: 10.20474/jater-10.1.5

ans and other road users. By improving the intelligence and accuracy of detection systems, the risk of accidents is reduced and the assurance of compliance with traffic laws is increased.
Considering the mentioned challenges and necessities, it seems necessary to conduct this research with the aim of developing and improving traffic sign recognition techniques. This research can be considered as an effective step towards improving the safety of road facilities and improving traffic management in urban and suburban complexes. It is hoped that the obtained results can be effective in developing smarter and safer systems for a better and safer future. (Stallkamp, 2011)

Basics and background of the research

The basics of research for "recognition of traffic signs based on feature extraction vector and using support vector machine classifiers and neural networks" can include several main parts. Below, these basics are explained:
All transportation systems need appropriate signs and signals to guide and control traffic. Automatic recognition of traffic signs is one of the important challenges in image processing and machine vision. This research examines various feature extraction techniques and classification algorithms such as support vector machines (SVM) and neural networks. Feature extraction is the first basic step in an image recognition system, where important and visible features of each image are extracted. These steps include identifying and extracting key information from traffic sign images. (Ciresan, 2012)

B. Feature extraction methods

Edge-based methods: includes edge-based methods that operate using edge filters such as Canny.
Texture-based methods: using techniques such as Histogram of Oriented Gradients (HOG) to describe texture.
Color-based methods: such as extracting color features from HSV or LAB color space.

C. Technologies of intelligent transportation systems

Smart transportation system is not just a new tool or technology. In fact, ITS enables the integration of the transportation system. A transportation system generally includes networks, vehicles, people and goods. Each component of the transportation system has its own specifications, organs, and sometimes separate government agencies. But information technology is able to make all these components into an integrated system. An information-centric transportation system can help solve the old and false problems between transportation and communication. People, goods and information can be transferred from one point to another and in many cases, to achieve this goal more effectively, one can replace the other. For example, sending a letter electronically is faster, cheaper and more reliable than mailing it, or participating in a video conference instead of traveling and attending the conference in another place is much easier and more economical. Advances in information technology can help create a fully integrated system for years to come. (Cai Zi-Xing, 2013).
The percent reduction in accidents through the information obtained from the entrance and exit of the highway (ramp), speed control cameras, accident warning systems and the program to help the safety of motor vehicles is as follows: The results of the information obtained from the entrance and exit of the highway are about 24% to 51% show a reduction in accidents based on the 2 evaluated ranges. The percentage of accidents decreased due to the presence of speed cameras from 21% to 11%. Accident warning systems show a 33% to 41% reduction in accidents. Despite all these facilities and information and intelligentization of transportation, we still see accidents on the roads and paths, which are usually caused by human error or violations. To reduce road accidents, we must look for a solution to reduce human error and limit drivers to commit violations in order to minimize accidents, and naturally reduce financial and life costs. A simple solution for this is to put an intelligent system next to the drivers to recognize traffic signs on the roads or create automatic driving in cars. (Wang W, 2012)
History of traffic signs The first traffic light in its present form was used in 1921 in Detroit, Michigan. From this simple beginning, traffic control systems that include a wide range of equipment, such as: smart lights controlling intersections, variable signs, speed control systems, etc., were born. Over time, traffic control lights were upgraded from the primitive form or fixed timing to its current form, i.e., intersection control based on counting the available traffic, and in 1921, systems were installed in 5 points in the United States, using IBM 1800 computers at that time. It was planned. Doing the above tasks at that time was actually the beginning of using intelligent traffic control systems, because these methods followed the way of progress and systematization for traffic control. (Loy, 2004).
The ITS program, which received attention in the 1991s, has clear roots that go back to the research and development activities that began in the 1961s by the US federal government and industry-university cooperation. At that time, a project was defined by BPR Public Roads, now called the Federal Highway Administration FHWA, to improve the

ISSN: 2414-4592
DOI: 10.20474/jater-10.1.5

safety and efficiency of intercity travel. This program was significantly different from past research activities in terms of volume, perspective and concepts. (Zurada, 1992)

1) Advanced Vehicle Control Systems AVCS can actively help drivers in driving and inform them of sudden dangerous situations or intentional or unintentional maneuvers, or physically prevent them from continuing dangerous driving. The development of AVCS technologies is carried out by the following authorities: Vartak, 2005).

1- The government in the national plan, which wants to increase road safety, their capacity and system implementation.

2-Equipment and motor vehicle suppliers who are looking for new products and systems and resort to tools that provide easier and safer driving.

These two trustees differ in the amount of technological intervention in the active control of driving. In Europe, the eSafety initiative is a joint industry-government initiative aimed at reducing the number of accidents using ICT information and communication technologies. (Bayer, 1975))

Other AVCS technologies that are being developed include:

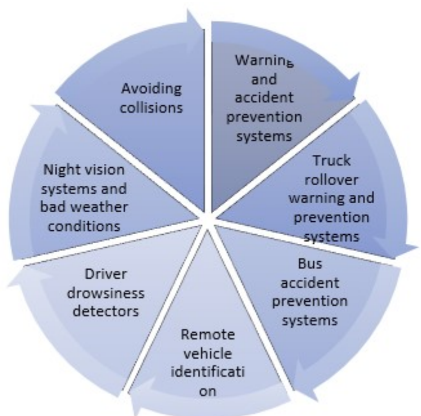

Fig. 1. Other AVCS technologies under development (Haykin, 1999)

Research background The most advanced system developed so far is called Traffic Sign Recognition -TSR, which was developed at the Image Recognition Laboratory of the University of Koblenz-Landau in Berlin. This system uses advanced color-based zoning methods to find traffic signs in the image. (Chandaka, 2008) In the classification stage, TSR uses neural networks and nearest neighbor methods. More than 6000 images of traffic scenes have been used to train this system. The accuracy of TSR identification is about 91% and the time is less than 200 milliseconds. The research group of the University of Genoa in Italy has also conducted a research in the field of identifying traffic signs in black and white images using the method of calculating the correlation coefficient. The accuracy of the designed system is between 92 and 96% and the total processing time is around 500 milliseconds. (Schalkoff, 2002).

Stallkamp and colleagues in 2012 applied multiple neural networks to classify different driving signs. In order to choose the appropriate network, the shape and color information available in the detection stage is used. The author presented only qualitative classification results. (Usama Fayyad, 1998).

Research method

Designing a traffic sign recognition system is associated with many problems. The images taken have noise for various reasons. The intensity and weakness of the ambient light affects the color of the image. The signs appear in different places on the image screen, also there are many objects in the scene, whose presence makes it difficult to detect the signs. Symptoms may not be exactly the same as the defined standard. The scale of the signs in the image is variable (depending on the distance of the car from the signboard, there is also a non-zero angle between the optical axis of the camera and the vector perpendicular to the surface of the signboard). The sum of the above factors complicates the identification of traffic signs.

Pre-processing

Before the images are given to the traffic sign recognition system, a pre-processing step is performed on the data. The block diagram of the pre-processing stage is as follows:

Fig. 2. Block diagram of the pre-processing stage (Avidan, 2004)

2) Convert the image to a gray image and apply a double threshold At first, color images are converted into gray images. The following algebraic relation is used to convert images to grayscale images.
where R is the value of red color, B is the value of blue color and G is the value of green color. The above relationship is related to the NTFS standard. This standard has three parameters of color components I and Q as well as brightness Y. The above relationship is related to the Y component or the gray signal. A value of zero for this component indicates a black pixel, and the higher its value, the closer it is to white. In the figure below, an example of a color image and its gray equivalent are displayed.
0.2989*R+0.5870*G+0.1140*B
Relationship number 1: from the algebraic relationship of converting images into gray images,

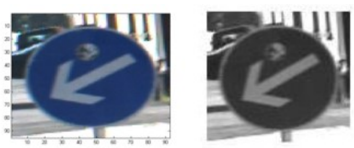

Fig. 3. An example of a grayscale image.

After the color images were converted to gray images with numerical values between 0 and 255 using the Otsu method. Error! Reference source not found We convert the images into binary images.

D. principal component analysis

PCA principal component analysis is among unsupervised linear methods for dimensionality reduction and feature extraction. PCA provides a set of orthogonal vectors, called loading vectors, ordered according to the size of the variance in the direction of that loading vector, suppose n samples of m variables in the training matrix X like relation.Error! No text of specified style in document-2.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ x_{na} & x_{n2} & \cdots & x_{nm} \end{bmatrix}$$

$$\max_{v \neq 0} \frac{v^T X^T X V}{v^T v}$$

$$\frac{1}{\sqrt{n-1}} X = U \Sigma V^T$$

Fig. 4. Relationship No. 2: Relationships to improve charts

If we want to minimize the effect of random noise on the PCA matrix so that it does not destroy the PCA matrix, we must obtain the variances of the data in an optimal way, in other words, the load vectors associated with a are kept from the most useful exceptional values in the PCA matrix. they become This action is similar to feature extraction in pattern classification.
Selecting the columns of the load matrix (V) is the same as selecting the load vectors, so after selecting a, the load vector becomes PER. The image of the samples in the matrix is

ISSN: 2414-4592
DOI: 10.20474/jater-10.1.5
TAF Publishing

a space with a smaller dimension containing the score matrix T = XP and the image T returned to the m-dimensional space of the samples is X = TP. The difference between X and the remainder matrix is EX. The subspace left in the E matrix has a low signal-to-noise ratio, and removing this space from the X matrix can lead to a more accurate representation of the process.

DISCUSSION AND CONCLUSION

The methods used are related to the set of "recognition standard of German traffic signs" which has been recently noticed. This dataset includes two data sets, training and testing. The training set consists of 39219 images that are in 43 classes, and the test set includes 12631. Road signs are characterized by a wide variation in their visual appearance in real world environments. For example, different weather conditions affect the perception of road signs Different classes of signs must be recognized with high accuracy. Road signs are designed to be easily readable by humans. However, for computer systems, the classification of traffic signs is still As a challenge in pattern recognition, both image processing and machine learning algorithms are constantly being refined and modified to improve this task. Videos are stored in a raw Bayer-pattern format (Bayer, 1925). Data collection, annotation, and image extraction were performed using the development and analysis of the ADAF32 advanced NISYS framework, based on a module-based software system. has been look at.

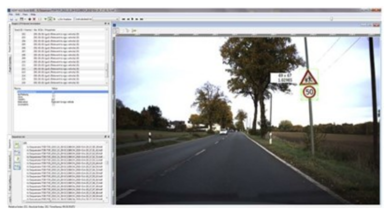

Fig. 5. Error! No text of specified style in documen

This collection of traffic signs includes images of more than 1700 examples of traffic signs. Traffic signs vary in size between 15 x 15 and 222 x 193 pixels. Images contain an 11% margin (at least 5 pixels) around the traffic sign to be used in edge detection. The original size and location of the traffic sign in the image (region of interest, ROI) in Error! No text of specified margin Presentation writing is preserved. Images are not necessarily square

Fig. 6. Presentation of random images of 43 GTSRB classes

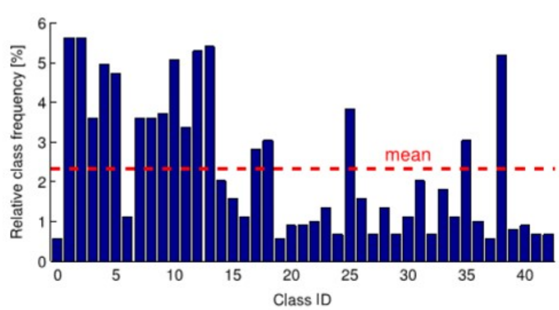

Fig. 7. Relative frequency of each class in the database

ISSN: 2414-4592
DOI: 10.20474/jater-10.1.5

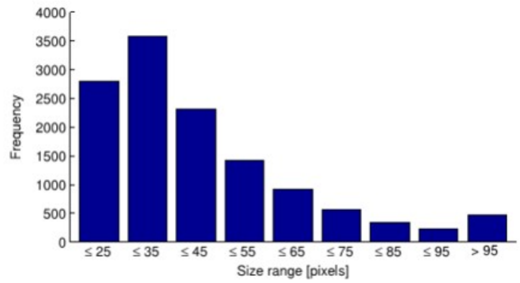

Fig. 8. Size distribution of traffic signs

It is divided into three different subsets (Figure GTSRB data set specified style in document-23). The division is done randomly but according to the account class and path membership. This ensures that (a) the overall distribution of each class is presented for each unique set and (b) all images related to a traffic sign sample are assigned to the same sets.

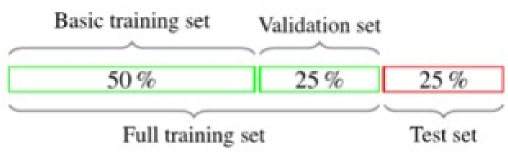

Fig. 9. : Classification of images in GTSRB database

The main division is separated into two categories: Full training set and Test set. The first set is created for classification training, where the samples are arranged in classes, although this full training is done in contrast to the test set, the classification is done by spatial information. The Basic collection is divided into two parts. Full training does not have location information. The training set is used to train the classifier and the Validation set is used to optimize and improve the parameters of the classifier.

According to the proposed structure, the simulation has two stages. The following table is related to the simulation results for the first step of the system, where the goal is to determine the subset related to the image, in other words, in the first step, it is determined which subset the image given to the system belongs to.

TABLE 1
DETECTION PERCENTAGE IN THE FIRST STAGE

Multilayer perceptron neural network	SVM
94/47	90/58

In the second part of the proposed system, there is a set of 6 different networks, each of which has the task of detecting symptoms related to their subset. The following table shows the results of each subset separately.

TABLE 2
DETECTION PERCENTAGE IN THE SECOND STAGE

Percentage of correct diagnosis	Multilayer perceptron neural network	SVM
Subset 1	95/75	95/72
Subset 2	91/34	97/50
Subset 3	96/49	97/06
Subset 4	80/03	84/91
Subset 5	91/57	95/95
Subset 6	93/40	91/34

ISSN: 2414-4592
DOI: 10.20474/jater-10.1.5

As can be seen in the above table, in most cases, SVM has provided a better result than multilayer perceptron neural network. Therefore, we have created the general structure of the proposed system with the SVM network and have trained and tested it. The following table presents the results of the final simulation.

TABLE 3
FINAL RESULTS OF SVM SIMULATION

	speed limit	Mandatory symptoms	End of limitation	warning	Specific symptoms	Other inhibitory symptoms
' Percentage correct	95/70	98/60	97/05	89/90	95/91	93/18

	Speed limits	Other prohibitions	Derestriction	Mandatory	Danger	Unique
Committee of CNNs	**99.47**	**99.93**	**99.72**	99.89	99.07	99.22
Human (best individual)	98.32	99.87	98.89	**100.00**	**99.21**	**100.00**
Human (average)	97.63	**99.93**	98.89	99.72	98.67	**100.00**
Multi-scale CNN	98.61	99.87	94.44	97.18	98.03	98.63
Random forests (HOG 2)	95.95	99.13	87.50	99.27	92.08	98.73
LDA (HOG 2)	95.37	96.80	85.83	97.18	93.73	98.63

Fig. 10. Table number 4: reference results

As can be seen in the tables, the results obtained in the article in question are better than the results obtained from the method proposed in this thesis. But the important point that should be stated is that the algorithms used in this article are of very high complexity and require high cost of calculations and time, if in the proposed method of this research, the input dimensions of the system have been significantly reduced. and the number of entries has been reduced to 30 entries, which reduces the number of calculations and duration. Considering that the traffic sign recognition system must be real-time and give the answer as soon as possible, and also this system is considered an assistance system for drivers, it can be said that due to the speed of the answer As if the proposed system can be used as an aid system for recognizing traffic signs.

REFERENCES

[1] Minhaj, Mohammad Baqer, "Computational Intelligence - Basics of Neural Networks", Volume 1, Dr. Prof. Hasabi Publishing Center, 1377.

[2] Mogelmose, A.; Trivedi, M.M.; Moeslund, T.B., "Traffic sign detection and analysis: Recent studies and emerging trends," Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on, vol., no., pp.1310-1314, 16-19 Sept. 2012. doi: 10.1109/ITSC.2012.6338900.

[3] M. Lalonde and Ying Li, Road Sign Recognition, Survey of the State of the Art, CRIM/IIT (Centre de Recherche Informatique de Montreal), 1995.

[4] GUO H-r, WANG X-j, ZHONG Y-x, LU P. Traffic signs recognition based on visual attention mechanism. The Journal of China Universities of Posts and Telecommunications 2011; 18:12-6.

[5] Bahlmann C, Zhu Y, Ramesh V, Pellkofer M, Koehler T. A system for traffic sign detection, tracking, and recognition using color, shape, and motion information. Intelligent Vehicles Symposium, 2005 Proceedings IEEE: IEEE; 2005. p. 255-60.

[6] Barnes N, Zelinsky A, Fletcher LS. Real-time speed sign detection using the radial symmetry detector. Intelligent Transportation Systems, IEEE Transactions on 2008;9:322-32.

[7] Ruta A, Li Y, Liu X. Real-time traffic sign recognition from video by class-specific discriminative features. Pattern Recognition 2010;43:416-30.

[8] Chen Z, Yang J, Kong B. A Robust Traffic Sign Recognition System for Intelligent Vehicles. Image and Graphics (ICIG), 2011 Sixth International Conference on: IEEE; 2011. p. 975-80.

[9] Stallkamp J, Schlipsing M, Salmen J, Igel C. Man vs. computer: Benchmarking machine learning algorithms for traffic sign recognition. Neural networks 2012;32:323-32.

[10] Wang W, Wei C-H, Zhang L, Wang X, Traffic-signs recognition system based on multi-features. Computational Intelligence for Measurement Systems and Applications (CIMSA), 2012 IEEE International Conference on: IEEE; 2012. p. 120-3.

ISSN: 2414-4592
DOI: 10.20474/jater-10.1.5

[11] Zaklouta F, Stanciulescu B. Real-time traffic sign recognition in three stages. Robotics and Autonomous Systems 2012.
[12] D. Ciresan, U. Meier, J. Masci, and J. Schmidhuber, "Multi-column deep neural network for traffic sign classification, " Neural Networks, vol. 32, pp. 333-338, 2012.
[13] Cai Zi-Xing, Gu Ming-Qin. "Traffic Sign Recognition Algorithm Based on Shape Signature and Dual Tree-Complex Wavelet Transform". Journal of Central South University of Technology (English Edition). Vol. 20, No.4, pp.433-439. 2013.
[14] Lin, C.C., Wang, M.S.: Road sign recognition with fuzzy adaptive pre-processing models. Sensors 12(5), 6415–6433 (2012).
[15] Stallkamp, J., Schlipsing, M., Salmen, J., Igel, C.: The german traffic sign recognition benchmark: a multi-class classification competition. In:Proceedings of the International Joint Conference on Neural Networks (IJCNN), pp. 1453–1460 (2011).
[26] Loy, G.; Barnes, N., "Fast shape-based road sign detection for a driver assistance system," Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on, vol.1, no., pp.70-75 vol.1, 28 Sept.-2 Oct. 2004.
[7] A H MAZINAN, M SARIKHANI. "Providing an efficient intelligent transportation system through detection, tracking and recognition of the region of interest in traffic signs by using non-linear SVM classifier in line with histogram oriented gradient and Kalman filter approach". Sadhana, Volume 39, Issue 1 , pp 27-37, Springer India, 2014.
[18] J.S.R. Jang, C.T. Sun, E. Mizutani, " Neuro-Fuzzy and Soft Computing," Prentice Hall Inc. 1997.
[19] H.J. Zimmermann, An application-oriented view of modeling uncertainty, European Journal of Operational Research 122 (2) (2000) 190–198.
[20] J. Han, M. Kamber, Data Mining: Concepts and Techniques, Morgan Kaufmann, 2006.
[21] J. M. Zurada, Introduction to Artificial Neural Systems.: West Publishing Company, 1992.
[22] S. Haykin, Neural Networks: A Comprehensive Foundation. 1999: Macmillan College Publishing Company Inc, New York.
[23] C. M. Bishop, Neural Networks for Pattern Recognition, 1st ed. USA: Oxford University Press, USA, 1996.
[24] R. J. Schalkoff, Artificial Neural Networks.: McGraw-Hill Companies, 1997.L. Robinson and S. Alves, New Parallel Algorithms for Back Propagation Learning., 2002.
[25] A. A. Vartak, M. Georgiopoulos, and G.C. Anagnostopoulos, On-line Gauss–Newton-based learning for fully recurrent neural networks.: Elsevier, 2005.
[26] Usama Fayyad, "A Tutorial on Support Vector Machines for Pattern Recognition," Data Mining and Knowledge Discovery, 2, 121–167, 1998.
[27] S. Theodoridis, "Pattern Recognition," Second Edition Academic Press an imprint of Elsevier Science, ISBN 0-12-685875-6, 2003.
[28] S. Avidan, "Support Vector Tracking," IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol.26, No.8, pp.1064-1072, Aug. 2004.
[29] S. Chandaka, A. Chatterjee, S. Munshi, "Cross-correlation aided support vector machine classifier for classification of EEG signals," Expert Systems with Applications, 2008.
[30] J. Stallkamp, M. Schlipsing, J. Salmen, C. Igel. "Man vs. computer: Benchmarking machine learning algorithms for traffic sign recognition". Neural Networks 32 (2012) 323–332.
[31] Bayer, B. E. US patent 3971065: color imaging array. Eastman Kodak Company. 1975.

ISSN: 2414-4592
DOI: 10.20474/jater-10.1.5