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Real-time Driver Drowsiness Detection Using Artificial Immune System

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ABSTRACT

Driver drowsiness is considered one of the primary causes of traffic accidents. Drowsiness detection systems are typically categorized into two types: monitoring-based and vehicle motion-based systems, each with its own advantages and disadvantages. Monitoring-based methods, which utilize driver performance sensors, are considered more practical than other methods due to their non-intrusive nature. In this study, images of open and closed eyes are initially provided to the designed system for training purposes. Then, using the trained system, prolonged eye closure is detected. The images used for the training phase were collected from 5 individuals, with 40 pictures from each person, including images of the left and right eyes. The PCA algorithm is first used to extract features, and the data is then fed to various classification systems. For the testing phase, the same number of new images were used. Four classification methods Euclidean Distance, Max Likelihood, Neural Networks, and Artificial Immune System (AIS) as the proposed method were compared and evaluated. The results showed that the first two methods, despite not requiring a training phase, needed more testing time. Neural networks, despite shorter testing times, required significant training time. On the other hand, the Artificial Immune System required short times for both the training and testing phases, with no significant difference in the recognition accuracy across the methods.

1. INTRODUCTION

The increasing number of vehicles worldwide, and consequently the rise in accident statistics, damages, and fatalities resulting from traffic accidents, has led researchers to investigate the main causes of traffic accidents. Driver fatigue is considered one of the primary causes of traffic accidents. Driver fatigue is a phenomenon that constantly casts a shadow over the spirit and well-being of travelers. Unfortunately, this issue has become a harsh reality on the roads of many countries, where we frequently witness the loss of our beloved fellow citizens in such incidents. Sadly, Iran holds the first rank globally in terms of road traffic fatalities, with approximately 30,000 people losing their lives annually in these accidents [1]. It is worth noting that this issue is not limited to our country but is

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a global problem. Various measures have been taken in different areas to address the issue of fatigue detection and to prevent such accidents.

2. REVIEW OF RELATED WORKS

This section provides an overview of the efforts made in the field of detecting driver awareness. Currently, one of the main causes of traffic accidents is driver fatigue and exhaustion. Generally, methods for detecting driver fatigue are categorized into the following two types:

a. **Supervisory Methods**,

which are further divided into two categories:

- Physiological indicator sensors
- Driver performance sensors

b. **Vehicle Movement-Based Methods**

In supervisory methods, the primary devices are sensors and cameras that record the physical signs of the driver. These signals are then sent to a system for processing, where the level of the driver's fatigue is determined. In vehicle movement-based methods, the behavior of the vehicle, such as the movement and angle of the wheels, is analyzed to assess the driver's level of alertness by studying the vehicle's behavior. Each of these methods has its own advantages and disadvantages.

Among these methods, those based on the natural physiological effects of humans are considered the best. These methods are classified into two categories: measuring changes in physiological signals and measuring changes in physical conditions. In the first type, because the sensors are directly attached to the body, they can cause discomfort to the driver, and over long periods, the sensor accuracy may decrease due to the driver's perspiration. Therefore, the most practical method for detecting fatigue is monitoring the driver's performance using a camera. This method, which is a form of remote monitoring, does not cause any inconvenience to the driver. Overall, the best method for detecting fatigue and lack of alertness is the measurement of brain waves and heart rate variability [3, 2].

When a person is fatigued, their appearance and facial features undergo noticeable changes, with the most significant alterations occurring in the eyes, mouth, and posture. By capturing images of the driver and applying image processing techniques, it is possible to extract visual features of fatigue. In conditions of exhaustion and drowsiness, individuals exhibit specific behaviors that can easily be observed through changes in their appearance, especially in their eyes. For instance, prolonged blinking, slow eyelid movement, the eyelids coming closer together, or even the eyes being fully closed, eye gazing, yawning, numbness, frequent dropping of the head, drowsiness, and sluggishness are among the most common visual features of a fatigued person [3].

3. PROPOSED METHOD

The process of falling asleep while driving can be viewed as a gradual decrease in alertness. The most important issue to consider regarding intelligent systems for detecting drowsiness is how accurately and quickly they can detect fatigue in the early stages. There is no precise and well-defined criterion for detecting drowsiness, so it must be determined based on its effects, assessing the level of alertness. Accordingly, various methods have been proposed for detecting drowsiness, each with its own strengths and weaknesses. In each of these methods, different parameters are used, which may relate to either the driver or the vehicle.

In this study, the apparent behavior of the driver is analyzed. A general overview of the work is shown in Figure (1). In the training phase, a dataset consisting of images of the left and right eyes in both open and closed states is input into the system. Then, using the PCA method, the features of each image are extracted. For each image, 10 features are extracted using PCA, which are then used to train the classifier system.

In the testing phase, a series of new images are input into the system, and the features of these new images are once again extracted using PCA. Using the classifier system designed and trained in the training phase, the new data is then evaluated in the testing phase.

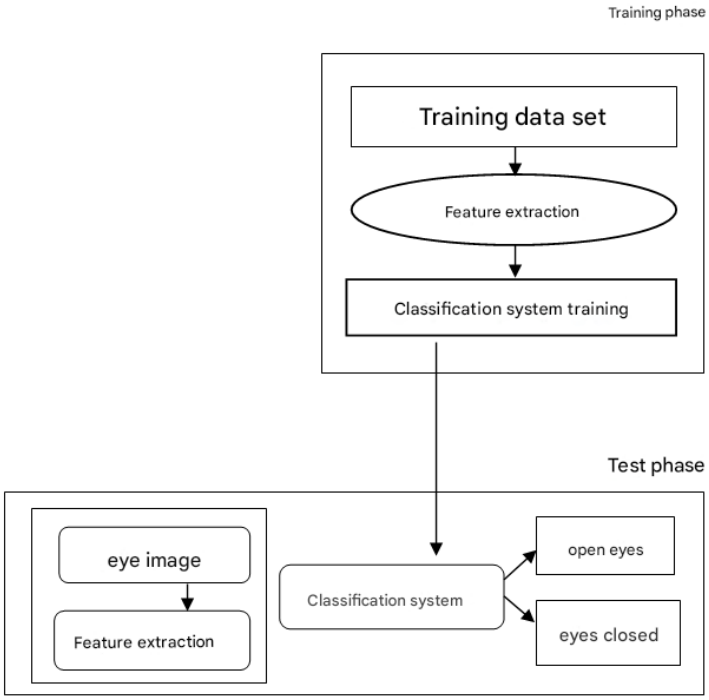

Fig. 1. Block Diagram of the General Workflow

3.1. Feature Extraction

Feature extraction is a process in which operations are performed on the data to identify its prominent and distinguishing features. The goal of feature extraction is to transform raw data into a more usable form for processing. To identify the pattern of an image, certain general or specific characteristics of the image must be extracted, which is known as feature extraction in image processing. Feature extraction methods map a multidimensional space to a lower-dimensional space. These methods are divided into linear and nonlinear categories, with linear methods being simpler and easier to understand. Examples of such methods include FA, PCA, DWT, and DFT. In this study, PCA is used for feature extraction.

PCA-based feature extraction is essentially the dimensionality reduction of the dataset. Dimensionality reduction means reducing the number of features of each data point. In addition to dimensionality reduction, another advantage of this method is that it retains the essential information of the image. Principal components are essentially the eigenvectors of the data covariance matrix. The largest variance in the data is along the direction where the corresponding eigenvector with the largest eigenvalue lies. Similarly, as the eigenvalue becomes smaller, the variance of the data along the corresponding eigenvector decreases. Ultimately, the components of the dataset that have the greatest impact on variance are retained.

In this research, 55x55 images were used, and these images have 3025 unique dimensions, with each pixel representing a unique feature. If classification is to be performed without dimensionality reduction, each of the 3025 dimensions of each image must be compared to the reference image, which is time-consuming and generally impractical. Therefore, techniques are needed to reduce the number of features, keeping only those that exhibit significant differences between the two classes in these features. Thus, an image can be written as a signal, and PCA can be used to extract its features. To do this, all the pixels of the image are arranged consecutively to form a vector. Therefore, for each image, a feature vector of size 3025 is obtained. Then, by applying PCA and specifying the desired final number of dimensions, new features are obtained. The final number of dimensions can be selected through trial and error to find the optimal number. In this case, we have chosen 10, reducing the 3025 dimensions to

10. Finally, the training and classification process is performed, where the feature data for the first and second classes are provided to the system for training.

3.2. Classification

In this research, four methods were used for classification: Euclidean distance, Maximum Likelihood, and Artificial Neural Networks, which were implemented and evaluated as traditional methods. Two sets of different images were used in the training and testing phases. The Euclidean distance and Maximum Likelihood methods do not require a training phase, but they extract features from the training phase images to compare in the testing phase. A multilayer perceptron artificial neural network was used, where the training images were employed to train the weights of the network, and the test images were used to test and evaluate the network.

In the proposed method, an artificial immune system (AIS) was used, which is inspired by the immune system of living organisms. This system prevents the growth of harmful cells in the body by replicating defensive cells (antibodies) at the appropriate time.

The first use of artificial immunity concepts to solve problems dates back to 1986. Since then, significant advancements have been made on this algorithm by Bersini and Forrest [4-7].

To date, this system has been applied in various fields such as pattern recognition [9, 10], data mining and machine learning [4, 5, 7, 8], optimization [13-15], artificial life [16], and other applications [17-20].

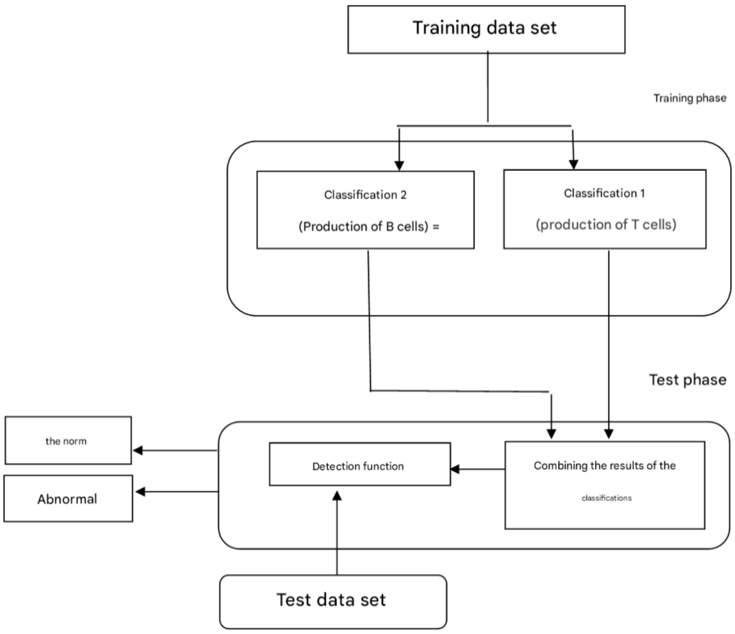

Fig. 2. Block Diagram of the Artificial Immune Network

In this algorithm, two classifications are used in the training phase. Classification number one employs a negative selection algorithm to cover the foreign sample space using the T antibody. The process works as follows: a random center, x, is selected in the feature space for the antibody, ensuring that this point is not within another antibody's region. Once the antibody's center is identified, its radius is gradually reduced until its boundary reaches the radius of the closest self-sample. If all the initial conditions are met and the reduced radius of the antibody exceeds a predefined threshold, the generated antibody is added to the set of mature antibodies. The algorithm terminates when a predetermined number of antibodies are generated, or a specific region of the non-self-space is covered by these antibodies.

In classification number two, a combination of positive selection and colony techniques is used to cover the self-sample space with antibody B. The process begins with randomly selecting a sample from the training dataset, then calculating the distance between the sample's center and the closest mature T cell. This distance is set as the initial radius for cell B. Next, the overlap between the new cell and the mature B cells is evaluated. If the overlap exceeds a permissible limit, the radius of cell B is reduced. Subsequently, N clones of the selected cell B are generated, and mutations are applied to these clones. The best clone is then selected and added to the mature cell set. This process continues until the training dataset is exhausted.

As shown in Figure (2), in the testing phase, the results of the classifications are merged, and the output, along with the test dataset, is fed into the detection function to determine whether the data is normal or abnormal.

To calculate the excitation level of cell B, the following equations are used.

$$\delta t = c[\sum_{j=1} m(ARB, xe_j) - k_1 \sum_{j=1}^{N} m(ARB, xp_j) + k_2 \sum_{j=1}^{N} m(ARB, y_j)] - k_3 \quad (1)$$

In this, ARB represents the detection radius of the B cell, m is the adjustment function, N is the number of antibodies, *N* is the number of antigens, and *c*, k_1,k_2 , k_3 , are constant coefficients (which are calculated based on the number of comparisons each time and the rate of production of activated B cells).

xe_j : The ***j***-th epitope of the B cell,
xp_j : The ***j***-th paratope of the B cell,
y_j : The ***j***-th antigen.
The second method is based on the Euclidean distance between the ARBs.

$$W_{ij} = exp(-\frac{d^2 ij}{2\delta i^2}) \quad (2)$$

The weight between ARB(i) and ARB(j) in the excitation surface network at each ARB(i) is equal to:

$$\delta t_i = \frac{\sum_{j=1}^{n} w_{ij}}{\delta^2 i} \quad (3)$$

Where n is the number of antigens and δ^2 is the radius of the ARB sphere, by maximizing the excitation surface at each excitation for each ARB and deriving from δt , we have:

$$\delta^2{}_i = \frac{\sum_{j=1} W_{ij} d_i^2}{\sum W_{ij}} \quad (4)$$

d_{ij}: The distance between antigen j and the center of ARB(i). The second method, using the normalized Euclidean distance formula, where distances and weights are mapped between 0 and 1. The excitation surface is equal to:

$$\delta t = \sum_{x=0}^{n} 1 - pd_x + \sum_{x=0}^{n} (1 - dis_x) - \sum_{x=0}^{n} dis_x \quad (5)$$

Pd is the normalized distance between the antigen and the ARB, where $0<Pd<1$, and dis_x is the normalized distance between the *x*-th neighbor and the ARB, with n being the number of antigens.

4. RESULT

The proposed algorithm is a new method for data classification. This algorithm has demonstrated unique capabilities in classification, particularly in terms of speed and training accuracy, showing significant improvements compared to previous methods. In this system, images from both training and testing datasets were used, each containing open and closed-eye images from 5 individuals, with 40 photos per person, including left and right eye images. The image size was 55x55 pixels. Initially, each individual's image dataset was trained using the desired methods, and then the test data was evaluated. To assess the methods, each individual was trained and tested separately in one phase. In the second phase, images from all five individuals were trained and tested together. Table 1 presents the recognition percentage of the test data using different methods.

As shown in Table 1, the recognition percentages across the different methods are nearly identical, with no major differences in this regard. Another important aspect that led to the use of artificial immune networks is the speed of training and testing. In the Euclidean distance and Max likelihood methods, unlike the other two methods, the data are not trained, and only the image features are extracted. Table 2 presents the average testing speed time.

Table 1. Percentage of Test Data Identification

Method	Eye Condition	All People	Mehdi	Moses	Hashem	Muhammad	Ahmed
Euclidean Distance	Left Eye Closed	94%	90%	100%	100%	100%	70%
Maximum Likelihood	Left Eye Closed	94%	90%	100%	100%	100%	80%
Neural Network	Left Eye Closed	96%	100%	100%	100%	100%	90%
Safety Net	Left Eye Closed	96%	90%	100%	100%	100%	90%
Euclidean Distance	Right Eye Closed	94%	100%	100%	100%	100%	100%
Maximum Likelihood	Right Eye Closed	96%	100%	100%	100%	100%	100%
Neural Network	Right Eye Closed	96%	90%	100%	100%	100%	80%
Safety Net	Right Eye Closed	98%	100%	100%	100%	100%	90%
Euclidean Distance	Left Eye Open	96%	70%	90%	100%	100%	100%
Maximum Likelihood	Left Eye Open	96%	70%	100%	100%	100%	100%
Neural Network	Left Eye Open	96%	70%	100%	70%	100%	100%
Safety Net	Left Eye Open	96%	100%	100%	100%	100%	90%
Euclidean Distance	Right Eye Open	90%	100%	100%	100%	100%	70%
Maximum Likelihood	Right Eye Open	90%	100%	100%	100%	100%	80%
Neural Network	Right Eye Open	96%	80%	100%	90%	100%	100%
Safety Net	Right Eye Open	96%	100%	90%	100%	100%	80%

Table 2. Average Test Speed (ms)

Method	All People	Mehdi	Moses	Hashem	Muhammad	Ahmed
Euclidean Distance	3.468	1.487	1.392	1.241	1.378	1.383
Maximum Likelihood	4.494	1.384	1.215	1.396	1.293	1.416
Neural Network	0.116	0.199	0.125	0.100	0.124	0.301
Artificial Safety Net	0.478	0.180	0.159	0.165	0.170	0.238

As shown in Table 2, the Euclidean distance and maximum likelihood methods demonstrate faster processing speeds during the testing phase compared to the neural network and artificial immune (safety net) methods. Despite the similar evaluation speeds of the neural network and artificial immune approaches, the neural network exhibits significantly slower training performance.

Table 3. Average Training Speed (ms)

Method	All People	Mehdi	Moses	Hashem	Muhammad	Ahmed
Neural Network	110.0	54.95	54.37	26.65	33.64	45.10
Artificial Safety Net	1.951	0.417	0.177	0.253	0.246	0.609

Table 3 compares the training times of the neural network and artificial immune network. Notably, the neural network requires substantially more time for training compared to the artificial immune network, highlighting a key performance trade-off between training efficiency and testing accuracy.

5. CONCLUSION

This study presents a real-time driver drowsiness detection system using the Artificial Immune System (AIS) as a novel classification approach. By utilizing image processing techniques, the system analyzes the driver's eye state to detect signs of fatigue. The Principal Component Analysis (PCA) method is employed for feature extraction, reducing the dimensionality of input data while preserving essential information. The performance of AIS was compared with three other classification methods Euclidean Distance, Maximum Likelihood, and Neural Networks demonstrating its efficiency in both training and testing phases.

The results indicate that all methods achieved comparable recognition accuracy, with minor variations among individuals. However, the AIS method outperformed traditional techniques in terms of training speed while maintaining a low testing time, making it a viable solution for real-time applications. Given the critical role of fatigue-related accidents, the proposed system offers a practical, non-intrusive approach to improving road safety. Future research could explore larger datasets and integrate additional physiological and behavioral indicators to enhance detection accuracy and system robustness.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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REFERENCES

[1] Ghafarian, H., & Hosinzadeh, A. (2005). Driver fatigue detection and warning system. *International Conference on Road Safety and Traffic Accidents, University of Tehran*.

[2] Sigarai, M. H., Fattahi, M., & Seryani, M. (2012). Design of a driver face monitoring system for the purpose of detecting fatigue and lack of attention. *Scientific Journal of Lahore, Ninth Year, (18).*

[3] Nasr Seraji, J., & Seraji, A. (2014). Using image processing in designing a proposed system for detecting drowsiness: A pilot study. *First Biennial Ergonomics Conference of Iran, Hamadan University of Medical Sciences, Hamadan*.

[4] Farmer, J. D., Packard, N. H., & Perelson, A. (1986). The immune system, adaptation, and machine learning. *Physica D, 22*(1–3), 187–204. https://doi.org/10.1016/0167-2789(86)90240-X

[5] Bersini, H., & Varela, F. (1993). The immune learning mechanisms: Recruitment, reinforcement, and their applications. In R. Patton (Ed.), *Computing with Biological Metaphors*. Chapman and Hall.

[6] Timmis, J., Hone, A., Stibor, T., & Clark, E. (2008). Theoretical advances in artificial immune systems. *Theoretical Computer Science, 403*(1), 11–32. https://doi.org/10.1016/j.tcs.2008.02.011

[7] Dasgupta, D., & Zhou, J. (2003). Reviewing the development of AIS in the last five years. *2003 IEEE Congress on Evolutionary Computation, Canberra, Australia, December 8–12.*

[8] Soltani Zadeh, H., Baradran Shohei, S., & Zarei, N. (2011). A new algorithm of artificial immune system for data classification in face recognition (IASI). *Seventh Conference on Machine Vision and Image Processing of Iran, Iran University of Science and Technology, Tehran.*

[9] de Castro, L. N., & Timmis, J. (2002). Artificial immune systems: A novel approach to pattern recognition. In L. Alonso, J. Corchado, & C. Fyfe (Eds.), *Artificial Neural Networks in Pattern Recognition* (pp. 67–84). University of Paisley.

[10] Lau, H. K., Timmis, J., & Bate, I. (2009). Anomaly detection inspired by immune network theory: A proposal. *CEC*.

[11] Courses, E., & Surveys, T. (2008). Intrusion detection system based on data mining. *Proceedings of the Knowledge Discovery and Data Mining, WKDD International Workshop on*.

[12] Dasgupta, D., Yu, S., & Majumdar, N. S. (2003). MILA—Multilevel immune learning algorithm and its application to anomaly detection. *Springer-Verlag*. https://doi.org/10.1007/3-540-45105-6_24

[13] Yongshou, D., Yuanyuan, L., Lei, W., Junling, W., & Deling, Z. (2007). Adaptive immune-genetic algorithm for global optimization to multivariable function. *Journal of Systems Engineering and Electronics, 18*(3), 655–660. https://doi.org/10.1016/S1004-4132(07)60144-3

[14] Gong, M., Jiao, L., & Zhang, X. (2008). A population-based artificial immune system for numerical optimization. *Neurocomputing, 72*(1–3), 149–161. https://doi.org/10.1016/j.neucom.2007.12.041

[15] Campelo, F., Guimaraes, F. G., & Igarashi, H. (2006). Overview of artificial immune systems for multi-objective optimization. *Lecture Notes in Computer Science, EMO*, 937–951. https://doi.org/10.1007/978-3-540-70928-2_69

[16] Chao, D. L., & Forrest, S. (2006). Generating biomorphs with an aesthetic immune system. In *Artificial Life VIII: Proceedings of the Eighth International Conference on the Simulation and Synthesis of Living Systems.* MIT Press.

[17] He, H., Maple, C., Watson, T., Tiwari, A., Mehnen, J., Jin, Y., & Gabrys, B. (2016). The security challenges in the IoT-enabled cyber-physical systems and opportunities for evolutionary computing & other computational intelligence. *2016 IEEE Congress on Evolutionary Computation (CEC)*, 1015–1021. https://doi.org/10.1109/CEC.2016.7743900

[18] Alonso, F. R., Oliveira, D. Q., & Zambroni de Souza, A. C. (2015). Artificial immune systems optimization approach for multi-objective distribution system reconfiguration. *IEEE Transactions on Power Systems, 30*, 840–847. https://doi.org/10.1109/TPWRS.2014.2330628

[19] Zhong, Y., & Zhang, L. (2013). Sub-pixel mapping based on artificial immune systems for remote sensing imagery. *Pattern Recognition, 46*, 2902–2926. https://doi.org/10.1016/j.patcog.2013.04.009

[20] Reddy, B., Kim, Y.-H., Yun, S., Seo, C., & Jang, J. (2017). Real-time driver drowsiness detection for embedded systems using model compression of deep neural networks. *2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 438–445. https://doi.org/10.1109/CVPRW.2017.59