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Performance of different membership functions in stress classification with fuzzy logic

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ABSTRACT

Stress has become an indispensable part of today's world. Stress can have a very serious negative impact on human health. Knowing the intensity of stress on people is important in order to cope with it. In this research, 4 different Fuzzy Logic (FL) structures were used to classify human stress through sleep. In the established structures, the human stress detection data set in sleep and through sleep obtained from Kaggle was used. In the FL structures created, blood oxygen level and respiratory rate were taken as input and stress classification was made accordingly. Their performance in the classification of sleep stress was evaluated by using different membership functions in 4 different structures. In order to make a fair comparison in the established structures, the FL parameter was determined the same, except for the membership functions. As a result of experimental studies, the F model established with the generalized bell showed more successful results than the models established with other membership functions.

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1. Introduction

Stress, which has made a great impact on people from the past to the present and has become a popular disease in the technological age we live in, seriously affects human health (Deveci, 2017). Stress affects vital functions such as heart rate, blood pressure, breathing rate, blood sugar in humans (Yıldırım, 2008). In order to minimize these effects, knowing the stress level is important for taking the right steps. In addition, determining the stress situation requires time and cost. Decision support systems eliminate these disadvantages. Thanks to the developing new generation technologies and artificial intelligence, decision-making models are being developed in many areas (Adem et al., 2019; Bülbül et al., 2022; Bülbül and Öztürk, 2022; Işık et al., 2017; Işık et al., 2018; Pacal and Karaboga, 2021). These developed models can eliminate the disadvantages such as time, cost, and expert person requirements.

Looking at the studies in the literature, Kumar and Dhulipala, in a study they conducted (Kumar and Dhulipala, 2016), made a fuzzy logic-based stress classification as a result of the surveys they conducted on social networking sites. In the study, where blood pressure and heart rate were used as inputs, it was emphasized that devices that can access social networks increase stress. Rasgoo et al. (Rastgoo et al., 2019) proposed a model for classification of drivers' stress.

Successful results have been obtained in stress classification with this model, which uses convolutional neural networks and long short-term memory. Baumgartl et al. (Baumgartl et al., 2020) have proposed a model for diagnosing chronic stress. Random Forest Classifier was used in the model using EEG data. Successful results were obtained as a result of experimental studies. Shin et al. (Shin et al., 2002) used fuzzy logic to predict the stress situation on people. In the study using 5 different biosignals, a model was created that quickly evaluated the stress on humans and tested on healthy individuals. Nagvi et al. (Naqvi et al., 2021) used FL to perform stress measurement. Stress level was measured with the parameters of temperature, oxygen level, blood pressure, skin moisture and heart rate taken with physiological sensors and successful results were obtained. Zalabarria et al. (Zalabarria et al., 2018) used fuzzy logic to classify the stress level in humans. In the study, 3 physiological variables, respiration, galvanic skin response, and electrocardiogram, were used as input and stress was classified into 3 groups.

In the literature, FL is frequently used in stress classification. The studies used are generally based on a single model. There are many membership functions in the FL model. The use of different membership functions on the same model affects the success of the model. In this research, 4 different FL models were used to classify sleep and human stress. Classification successes of models established with different membership functions have been controversially compared.

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2. Material and Method

1.1. Fuzzy logic

Fuzzy Logic (FL) is a set of objects with uncertain boundaries that are separated from normal sets by the concept of membership (Awasthi et al., 2005). The fuzzy logic structure consists of four basic structures: fuzzification, rule base, inference mechanism and defuzzification (Bülbül et al., 2019). The FL model presented by these structures is shown in Figure 1.

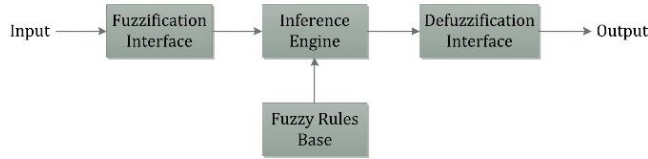


Figure 1. FL structure

In the FL model presented in Figure 1, the data is blurred with the first determined membership function. An inference is obtained according to the rule base determined over the fuzzy data. The resulting inference information is defuzzified and the output is obtained (Yıldırım et al., 2021).

1.2. Dataset

The data set used in the research was taken from kaagle and is used in the literature (Human Stress Detection in and through Sleep, n.d.). The data set includes snoring interval, respiratory rate, body temperature, limb movement rate, blood oxygen levels, eye movement, number of sleep hours, heart rate information and stress levels related to these measurements, collected from 630 individuals. Stress levels based on these criteria were classified into 5 groups as low/normal, medium low, medium, medium high, and high (Rachakonda et al., 2021).

1.3. Evaluation metrics

Performance evaluation in multidimensional classifiers can be measured with accuracy calculation (Heydarian et al., 2022). In order to make this calculation, the confusion matrix of the classifier must be created. An exemplary multidimensional confusion matrix is shown in Figure 2.

		Predicted Labels			
		C ₁	C ₂	C ₃	C ₄
True Labels	C ₁	TN	FP	TN	TN
	C ₂	FN	TP	FN	FN
	C ₃	TN	FP	TN	TN
	C ₄	TN	FP	TN	TN

Figure 2. Multidimensional confusion matrix structure

In Figure 2, TP stands for true positive, FP stands for true negative, TN stands for false positive, and FN stands for false negative. According to these expressions, the accuracy is calculated as presented in Equation 1 (Chen et al., 2022).

$$Accuracy(Acc) = \frac{TP+TN}{TP+TN+FN+FP} \quad (1)$$

3. Experimental Studies and Results

In this part of the research, FL models were established to classify the stress levels of individuals with Triangle (Model1), Trapezoid (Model2), Generalized Bell (Model3), Gauss (Model4) membership function. For each FL model, respiratory rate (RR) and blood oxygen level (BO) were used as inputs in the data set, while stress level (SL) based on these values was determined as output. The boundary values of the membership functions in FL are as shown in Table 1.

Table 1. Boundary values of the membership functions.

Parameters	Minimum	Maximum
RR (input)	82	97
BO (input)	16	30
SL (output)	0	4

Membership functions are classified as low(L), medium(M), high(H) in each model, and the rule base presented in Table 2 is used in each model for a fair comparison.

Table 2. Rule base used in models.

RR	BO		
	Low	Middle	High
Low	Low	Low	Low
Middle	Middle	Middle	Middle
High	High	High	High

The boundary values of the membership functions created in each model are kept the same for a fair comparison, and the membership functions created in different models for BO are shown in Figure 3.

Each model created was applied on the data set and the output values produced by the models were rounded for the clusters. In the established models, Mamdani inference method and center defuzzification method were used as they are frequently used in the literature with successful results. (Mohapatra and Lenka, 2016) In the Models were created on the MATLAB platform. Confusion matrix created for each model as a result of experimental studies is shown in Table 3-6.

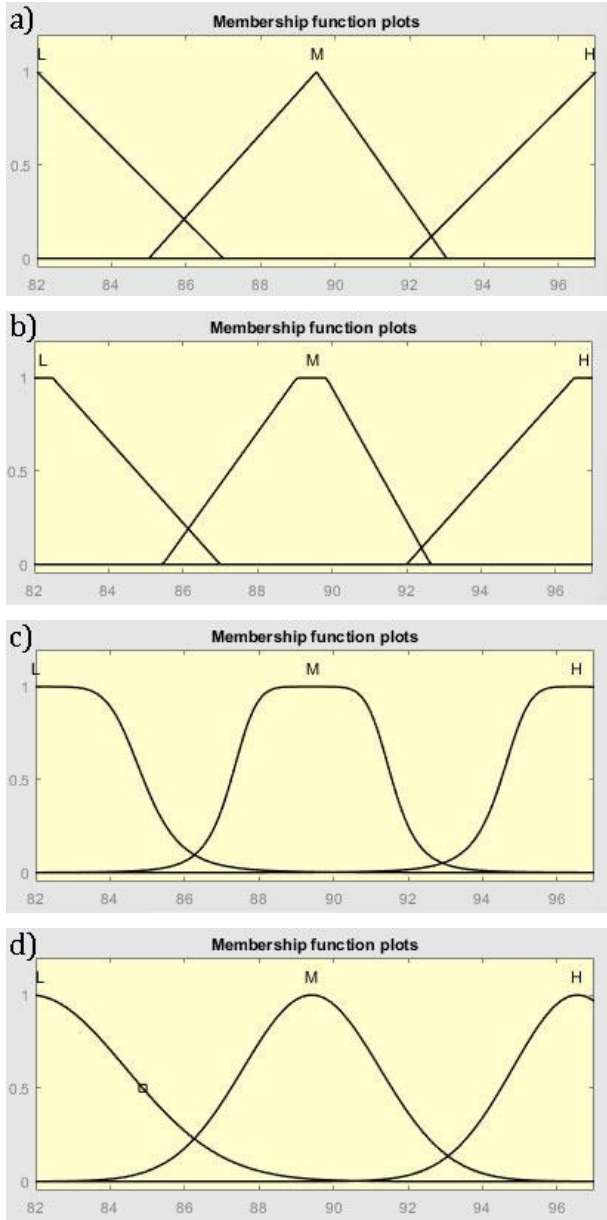


Figure 3. Membership functions used in the research a) Triangle membership function b) Trapezoidal membership function c) Generalized bell membership function d) Gauss membership function

Table 3. Confusion matrix for Model1.

Actual values	Predicted Values				
	Low / Normal	Medium / Low	Medium	Medium / High	High
Low / Normal	126	0	0	0	0
Medium/ Low	0	124	2	0	0
Medium	0	0	122	4	0
Medium/ High	0	0	56	70	0
High	0	0	0	78	48

Table 4. Confusion matrix for Model2.

Actual values	Predicted Values				
	Low / Normal	Medium / Low	Medium	Medium / High	High
Low / Normal	126	0	0	0	0
Medium/ Low	2	116	8	0	0
Medium	0	0	99	27	0
Medium/ High	0	0	59	67	0
High	0	0	0	52	74

Table 5. Confusion matrix for Model3.

Actual values	Predicted Values				
	Low / Normal	Medium / Low	Medium	Medium / High	High
Low / Normal	126	0	0	0	0
Medium/ Low	10	99	17	0	0
Medium	0	0	126	0	0
Medium/ High	0	0	32	94	0
High	0	0	0	33	93

Table 6. Confusion matrix for Model4.

Actual values	Predicted Values				
	Low / Normal	Medium / Low	Medium	Medium / High	High
Low / Normal	126	0	0	0	0
Medium/ Low	0	121	5	0	0
Medium	0	0	126	0	0
Medium/ High	0	0	32	94	0
High	0	0	0	94	32

Using the confusion matrices created in Table 3-6 for each model, the accuracy rates of the models were calculated according to the accuracy formula presented in Equation 1. The success of each model in stress classification is shown in Table 7.

Table 7. Accuracy rates of models.

Models	Accuracy (%)
Model1 (Triangle membership function)	78
Model2 (Trapezoidal membership function)	76
Model3 (Generalized bell membership function)	85
Model4 (Gauss membership function)	79

According to Table 7, the model established with the Generalized Bell membership function produced more successful results in stress classification than other models. In this model, as in other models, the respiratory rate and blood oxygen level were used as inputs, the mamdani method was used in the extraction step, and the centroid method was used in the defuzzification step.

4. Conclusion

Stress, which is an indispensable part of today's world, causes negative and serious problems on human health. The intensity level of the stress on the person is directly proportional to the damage done. Although it is important to know the stress level in order to eliminate stress, decision support systems used in this field are of great importance. In this research, FL-based models were created for the classification of human stress. Experimental studies were carried out on the data set used in the research by choosing different membership functions in the models created. The findings showed that the FL model established with the Generalized Bell membership function gave more successful results than the other models. In future studies, decision support systems can be created on different platforms. With the specified parameters, applications can be developed easily in mobile environments.

References

- Adem, K., Kılıçarslan, S., and Cömert, O., 2019. Classification and Diagnosis of Cervical Cancer with Stacked Autoencoder and Softmax Classification. *Expert Systems With Applications*, 115, 557–564. <https://doi.org/10.1016/j.eswa.2018.08.050>
- Awasthi, A. K., Dubey, O. P., Awasthi, A., and Sharma, S., 2005. A fuzzy Logic Model for Estimation of Groundwater Recharge. Annual Conference of the North American Fuzzy Information Processing Society – NAFIPS, Detroit, MI, USA, 26-28 June, p. 809-813. <https://doi.org/10.1109/NAFIPS.2005.1548644>
- Baumgartl, H., Fezer, E., and Buettner, R. 2020., Two-Level Classification of Chronic Stress Using Machine Learning on Resting-State EEG recordings. 26th Americas Conference on Information Systems, AMCIS, 15-17 August.
- Bülbül, M. A., Harirchian, E., Işık, M. F., Aghakouchaki Hosseini, S. E., and Işık, E., 2022. A Hybrid ANN-GA Model for an Automated Rapid Vulnerability Assessment of Existing RC Buildings. *Applied Sciences*, 12(10), 5138. <https://doi.org/10.3390/app12105138>
- Bülbül, M. A., and Öztürk, C., 2022. Optimization, Modeling and Implementation of Plant Water Consumption Control Using Genetic Algorithm and Artificial Neural Network in a Hybrid Structure. *Arabian Journal for Science and Engineering*, 47(2), 2329-2343. <https://doi.org/10.1007/s13369-021-06168-4>
- Bülbül, M. A., Öztürk, C., İlçi, V., and Özulu, İ. M., 2019. Two-Dimensional Error Estimation in Point Positioning with Fuzzy Logic. 2018 International Conference on Artificial Intelligence and Data Processing IDAP 2018, Malatya-Turkey, 28-30 September, p. 1-4 . <https://doi.org/10.1109/IDAP.2018.8620901>
- Chen, D., Lu, Y., and Hsu, C. Y., 2022. Measurement Invariance Investigation for Performance of Deep Learning Architectures. *IEEE Access*, 10: 78070-78087. <https://doi.org/10.1109/ACCESS.2022.3192468>
- Deveci, B., 2017. İş Stresi ve Turizm İşletmelerinde Yapılan Araştırmalara İlişkin Bir Değerlendirme. Mehmet Akif Ersoy University Journal of Social Sciences Institute, 9(20), 39-53. <https://doi.org/10.20875/makusobed.306671>
- Heydarian M., Doyle, T. E., and Samavi, R., 2022. MLCM: Multi-Label Confusion Matrix. *IEEE Access*, 10, 19083-19095. <https://doi.org/10.1109/ACCESS.2022.3151048>
- Human Stress Detection in and Through Sleep. (n.d.). Retrieved October 17, 2022, from <https://www.kaggle.com/datasets/laavanya/human-stress-detection-in-and-through-sleep>
- Işık, E., Işık, M. F., and Bülbül, M. A., 2017. Web Based Evaluation of Earthquake Damages for Reinforced Concrete Buildings. *Earthquake and Structures*, 13(4), 423-432. <https://doi.org/10.12989/eas.2017.13.4.387>
- Işık, M. F., Işık, E., and Bülbül, M. A., 2018. Application of iOS/Android Based Assessment and Monitoring System for Building Inventory Under Seismic Impact. *Gradjevinar*, 70 (12), 1043-1056. <https://doi.org/10.14256/JCE.1522.2015>
- Kumar, M. G. S., and Dhulipala, V. R. S., 2016. Fuzzy Logic Based Stress Level Classification Using Physiological Parameters. *Asian Journal of Research in Social Sciences and Humanities*, 6(cs1), 697-713. <https://doi.org/10.5958/2249-7315.2016.00990.4>
- Mohapatra, A. G., and Lenka, S. K., 2016. Neural Network Pattern Classification and Weather Dependent Fuzzy Logic Model for Irrigation Control in WSN Based Precision Agriculture. *Procedia Comput. Sci*, 78, 499-506. <https://doi.org/10.1016/j.procs.2016.02.094>
- Naqvi, S., Shaikh, A. Z., Altaf, T., and Singh, S., 2021. Fuzzy Logic Enabled Stress Detection Using Physiological Signals. Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST, Virtual Event, 04 November p. 161–173. https://doi.org/10.1007/978-3-030-90016-8_11
- Pacal, İ., and Karaboga, D., 2021. A Robust Real-Time Deep Learning Based Automatic Polyp Detection System. *Computers in Biology and Medicine*, 134, 104519. <https://doi.org/10.1016/j.combiomed.2021.104519>
- Rachakonda, L., Bapatla, A. K., Mohanty, S. P., and Kougiianos, E., 2021. SaYoPillow: Blockchain-Integrated Privacy-Assured IoMT Framework for Stress Management Considering Sleeping Habits. *IEEE Transactions on Consumer Electronics*, 67(1), 20-29. <https://doi.org/10.1109/TCE.2020.3043683>
- Rastgoo, M. N., Nakisa, B., Maire, F., Rakotonirainy, A., and Chandran, V., 2019. Automatic Driver Stress Level Classification Using Multimodal Deep Learning. *Expert Systems with Applications*, 138, 112793. <https://doi.org/10.1016/j.eswa.2019.07.010>
- Shin, J. W., Seongo, H. M., Cha, D. I., Yoon, Y. R., and Yoon, H. R., 1998. Estimation of Stress Status Using Biosignal and Fuzzy Theory. International Conference of the IEEE Engineering in Medicine and Biology Society, 01 November, Vol. 3 p. 1393-1394. <https://doi.org/10.1109/iembs.1998.747141>
- Yıldırım, E., Avcı, E., and Yılmaz, B., 2021. Serbest Basınç Dayanımının Tahmininde Sugeno Bulanık Mantık Yaklaşımı. *Uludağ University Journal of The Faculty of Engineering*, 26(1), 97-108. <https://doi.org/10.17482/uumfd.863121>
- Yıldırım, S., 2008. Muhasebe Öğretim Elemanları ve Meslek Mensuplarının Mesleki Stres Düzeyi Üzerine Bir Araştırma. *Journal of Accounting and Finance*, 38, 153–162.
- Zalabarria, U., Irigoyen, E., Martínez, R., and Arechalde, J., 2018. Acquisition and Fuzzy Processing of Physiological Signals to Obtain Human Stress Level Using Low Cost Portable Hardware. In International Joint Conference SOCO'17-CISIS'17-ICEUTE'17, León-Spain, 6–8 September, p. 68-78. https://doi.org/10.1007/978-3-319-67180-2_7