doi: 10.53446/actamednicomedia.1195719

Acta Medica Nicomedia

Cilt: 6 Sayı: 2 Haziran 2023 / Vol: 6 Issue: 2 June 2023
https://dergipark.org.tr/tr/pub/actamednicomedia

Research Article | Araştırma Makalesi

ARTIFICIAL INTELLIGENCE BASED RATING OF CARPAL TUNNEL SYNDROME EFFICACY IN CLINICAL DIAGNOSIS

KARPAL TÜNEL SENDROMUNUN DÜZEYİNİN YAPAY ZEKA TEMELLİ DERECELENDİRİLMESİ

Elif Sarıca Darol[1], Yıdız Ece[2*], Süleyman Uzun[3], Murat Alemdar[4]

[1]Sakarya Training and Research Hospital, Department of Neurology, Sakarya, Türkiye. [2]Sakarya University, Vocational School of Health Services, Department of Therapy and Rehabilitation, Sakarya, Türkiye. [3]Sakarya University of Applied Sciences, Faculty of Technology, Department of Computer Engineering, Sakarya, Türkiye. [4]Sakarya University, Faculty of Medicine, Department of Neurology, Sakarya, Türkiye.

ABSTRACT

Objective: The most common entrapment neuropathy seen by the clinician is Carpal tunnel syndrome (CTS). CTS is graded as mild, moderate, and severe according to the results obtained on electroneuromyography (ENMG) by clinicians. We aimed to show the effectiveness of the use of artificial intelligence in clinical diagnosis in the grading of CTS.

Methods: In our study, the data of 315 people with a pre-diagnosis of CTS were used and classified into four classes based on AI as CTS grade. Machine Learning (ML) algorithms Ensemble, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Decision Tree (Tree) algorithms were used in classification processes. 10% Hold-out validation was used and the learning rate was determined as 0.1. As a result of the classification, accuracy, precision, sensitivity, specificity, and F1-score performance values were obtained.

Results: SVM made the best estimation and KNN made the worst estimation in the 0 class. The best estimate in class 1 belongs to the Support Vector Machine. Ensemble and Tree made the best guesses in the 2nd and 3rd grades. In our study, the best algorithm with an overall success rate is SVM with 93.55%.

Conclusion: The results showed that ML algorithm models consistently provided better predictive results and would assist physicians in determining the medical treatment modality of CTS. Artificial intelligence (AI) techniques are reliable methods that assist clinicians to deliver quality healthcare.

Keywords: Carpal Tunnel Syndrome, Electromyography, Artificial Intelligence, Grading

ÖZ

Amaç: Karpal tünel sendromu (KTS), median sinirin karpal tünelde sıkışması sonucu en sık görülen tuzak nöropatisidir. Elde edilen veriler sonucunda hastada mevcut KTS kliniği hafif, orta ve ağır olarak gradelenir. KTS derecelendirmesinde klinik tanıda yapay zeka kullanımının etkinliğini göstermeyi amaçladık.

Yöntem: Çalışmamızda KTS ön tanısı ile başvurmuş ve electroneuromyography yapılmış olan 315 bireyin, demografik ve electroneuromyography sonuçlarından elde edilmiş sinir ileti verileri kullanılmıştır. Sınıflandırma işlemlerinde makine öğrenmesi algoritmalarından Topluluk, Destek Vektör Makinesi, K-En Yakın Komşu ve Karar Ağacı algoritmaları kullanılmıştır. %10 bekletme doğrulaması kullanılmış ve öğrenme oranı 0.1 olarak belirlenmiştir. Sınıflandırma sonucunda doğruluk, kesinlik, duyarlılık, özgüllük ve F1-skor performans değerleri elde edilmiştir.

Bulgular: Çalışmamızın sonucunda 0 sınıfında en iyi tahmini Destek Vektör Makinesi, en kötü tahmini K-En Yakın Komşu yapmıştır. 1. sınıfda en iyi tahmin Destek Vektör Makinesine aittir. 2. ve 3. sınıflarda en iyi tahmini Topluluk ve Karar Ağacı yapmıştır. Çalışmamızda, genel başarı oranı en iyi algoritma %93,55 ile Destek Vektör Makinesidir.

Sonuç: Makine öğrenme algoritma modellerinin tutarlı bir şekilde daha iyi tahmin sonuçları sağladığını ve doktorlara KTS'nin tıbbi tedavi yöntemini belirlemede yardımcı olacağını gösterdi. Yapay zeka teknikleri, klinisyenlerin kaliteli sağlık hizmeti sunmalarına yardımcı olan güvenilir yöntemlerdir.

Anahtar Kelimeler: Karpal tünel sendromu, elektromiyografi, yapay zeka, derecelendirme

***İletişim kurulacak yazar/Corresponding author:** Yıldız Ece; Sakarya Üniversitesi Sağlık Hizmetleri Meslek Yüksekokulu , Sakarya, Türkiye.
Telefon/Phone: +90 (545) 716 06 68 **e-posta/e-mail:** yildizece@sakarya.edu.tr
Başvuru/Submitted: 27.10.2022 • **Kabul/Accepted:** 29.03.2023 • **Online Yayın/Published Online:** 30.06.2023

Introduction

Neurological diseases are acute, chronic or progressive clinical manifestations that occur as a result of neurodegeneration in the central and peripheral nervous system. The increase in the elderly population and the inadequacy of treatments in chronic processes increase the cost of neurological diseases day by day. In recent years, deep learning algorithms have been used to increase the early diagnosis and treatment possibilities of neurologists.[1] The recognition of artificial intelligence (AI) dates back to the 1950s.[2] AI aims to develop a method for capturing and solving complex problems based on large amounts of data.[3] It also has the effect of changing the current model in the diagnosis, treatment, prediction, and economics of neurological diseases.[2] It has been understood that with the use of artificial intelligence, it becomes easier to diagnose permanent neurological damage and even guides the prevention of diseases.[1] Studies in stroke, dementia, epilepsy and movement disorders have shown that machine learning will contribute greatly to the future of neurologic diseases[4], but there has not been enough studies on peripheral nerve diseases yet. Carpal tunnel syndrome is one of the most common peripheral neuropathies in the active working adult population, affecting daily activities and reducing work efficiency. It occurs by compression of the median nerve in the carpal tunnel and causes sensory and motor complaints in the first three fingers of the hand.

It is known that the common risk factors of CTS are; female gender, high body mass index (BMI), advanced age, and repetitive hand movements.[5] The incidence of CTS is approximately 3.0% in women and 2.1% in men.[6] Electroneuromyography (ENMG) is the most frequently used auxiliary diagnostic tool in the diagnosis of CTS. It is also helpful in following up on the disease progress by grading the severity of median nerve compression.[7-11] The severity of CTS is graded as mild, moderate, or severe based on the results of the data obtained in ENMG.[12] The treatment option is mostly determined according to this grading result.[13] The treatment options for CTS are, in order, from mild to severe; medical treatment, rest splints and surgical treatments. If severe CTS is left untreated, it can cause irreversible damage of median nerve, causing atrophy and weakness in the hand muscles.

Before AI systems can be used in healthcare applications, they need to be trained using data from clinical activities such as screening, diagnosis, treatment assignment, etc., so that similar subject groups and relationships among them can be learned. Machine learning (ML) creates data analytics algorithms to extract features from data.[14,15] The use of algorithms with high predictive power and success rate increases the accuracy of early diagnosis. The studies on this subject and the success of the applied devices emphasize the importance of machine learning in the field of medicine.[16] It enables ENMG to be used as a guide in following the course of the disease and determining the treatment method. However, the reliability of the ENMG test can be very variable due to factors such as the experience of the person performing the test, the technical characteristics of the device used, and the patient's compliance with the test. Considering these factors, there are studies conducted with machine learning algorithms.[14]

There are several algorithms in different libraries of machine learning. The ML algorithms used in this study are Ensemble, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Decision Tree (Tree).

The ensemble can improve classification performance. Findings of classifiers with varying accuracies are combined with an ensemble-based approach.[17] Even when using multiple sets of measures with ML algorithms, classification performance may not necessarily improve. In this context, Ensemble methods are multi-classifier systems in which individual weak classifiers are combined to create a more robust classification system.[18]

SVM is a fairly robust classification method for disease diagnosis.[19] According to other machine learning algorithms; It is widely used in medical research due to its many advantages such as being effective in cases where the sample size in the study is less than the number of dimensions, using different kernel functions in the decision mechanism, having unbalanced data, giving more effective and successful results in big data, and working with a large number of independent variables.[15,20,21]

KNN is a lazy learning approach as there is no clear training process. There is a K value determined in the study to classify KNN, and this value indicates the number of elements that the algorithm will look at in the data set. It is a statistics-based method.[17,18] It is one of the highly preferred machine learning algorithms because of its simplicity and resistance to complex training data.[17]

Decision Tree is an algorithm whose structure is based on probability and statistics. Decision trees consist of general-specific and downward-trained data.[22,23] Classification of data in decision trees consists of two stages, namely learning and classification. The training data known before the learning phase is examined by the classification method to reveal the model. This learned model is specified as classification rules. In the second stage, the classification stage, the test data is used to query whether the decision tree is correct.[21,23]

Hold-out validation is recommended to eliminate the overfitting problem. Here, the data is divided into two non-overlapping parts and one is trained while the other is tested with the trained model. People often don't understand this very clearly, and they consider waiting for validation to be dividing data into two equal parts. While it's true that it could be called a hold verification, it's a very specific standby verification case where 50% of the data held for testing is. Therefore, wait validation may have different percentages.[24]

Methods

In our study, the original data of 315 people who applied to Electroneuromyography laboratory of Sakarya University Training and Research Hospital with a preliminary diagnosis of CTS and underwent electromyography examination were used. Demographic data such as age, gender, height, weight, dominant hand, body mass index (BMI) and EMG conductions were recorded by the author M.A. and database were prepared by him. BMI is classified according to the criteria determined by the World Health Organization.[25] The motor and sensory latency, sensory and motor amplitude, and conduction velocity values of the median and ulnar nerves were evaluated by EMG, and CTS was graded by the clinician. NCSs were made by a specialist neurologist using the same EMG device at 24°C using standard conduction procedures. CTS grading was performed by the same specialist neurologist according to the electrophysiological parameters stated by Padua.[26] From the Carpal Tunnel Syndrome data used in the experimental study, it was classified based on artificial intelligence in 4 classes as CTS grade (0 normal, 1 mild, 2 moderate, 3 severe). Ensemble, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Decision Tree (Tree) algorithms from ML algorithms were used in classification processes. 10% Hold-out validation was used and the learning rate was determined as 0.1.

Table 1. Dataset

Attribute	Definition
Age	
Gender	Male / Female
Height	cm
Weight	kg
Dominant Hand	Right / Left
Side	Right / Left
BMI	Body mass index
BMI Group	18 underweight weak
	18.6-25 normal
	25.1-30 overweight
	30.1-35 degree obese
	35.1-40 2. degree obese
	40.1'in üstü 3. degree obese
Median SNAP	>6 mV
Median SCV	>49 m/s
Median MDL	<4.20 ms
Median CMAP	>4,5 mV
Median MCV	>50 m/s
Ulnar SNAP	>4 mV
Ulnar SVC	>49 m/s
Ulnar MDL	<4,0ms
Ulnar CMAP	>5.0 mV
Ulnar MCV	>47m/s

The data set is explained in Table 1 above. Carpal Tunnel Syndrome (CTS) severity data;

GRADE 0: 157 pieces of data with zero intensity (normal)
GRADE 1: 92 data at an intensity (mild)
GRADE 2: 55 pieces of data in two (moderate)
GRADE 3: 11 data at three severity (severe)

In the figure 1 below, the ratio of the total number of female/male samples to the overall sample number is given.

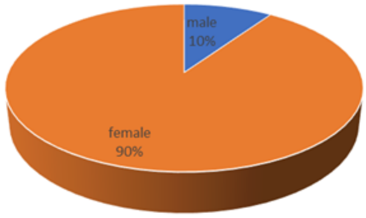

Figure 1. Gender distribution

BMI distribution is given in figure 2 below.

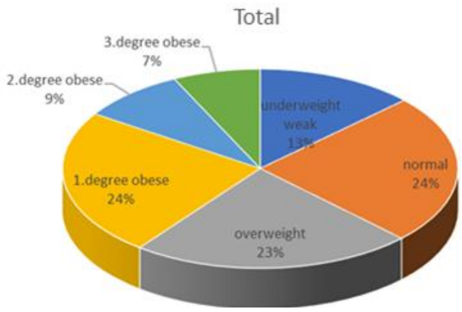

Figure 2. BMI distribution

Simulation Results and Performance Evaluation

As a result of the classification in the experimental study, accuracy, precision, sensitivity, specificity, and F1-score performance values were obtained. To better present these results, ROC (Receiver Operating Characteristic) curves graphics were drawn. The complexity matrix shown in Table 2 is used to calculate performance metrics (Table 2).

Table 2. Confusion Matrix

Predicted Class	Actual Class	
	Positive	Negative
True	[1]TP	[2]TN
False	[3]FP	[4]FN

[1]True Positive, [2]True Negative, [3]False Positive, [4]False Negative

Mathematical equations of performance metrics used in the study are given in equations 1, 2, 3, 4 and 5 given below.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

$$Precision = \frac{TP}{TP+FP}$$

$$Sensitivity = \frac{TP}{TP+FN}$$

$$Specificity = \frac{TN}{TN+FP}$$

$$F1 - score = \frac{2*TP}{2*TP+FP+FN}$$

The complexity matrix obtained as a result of the study is shown in Figure 3. In this matrix, each algorithm is classified into 4 different groups as the CTS grade of the algorithm (0 normal, 1 mild, 2 modarete, 3 severe).

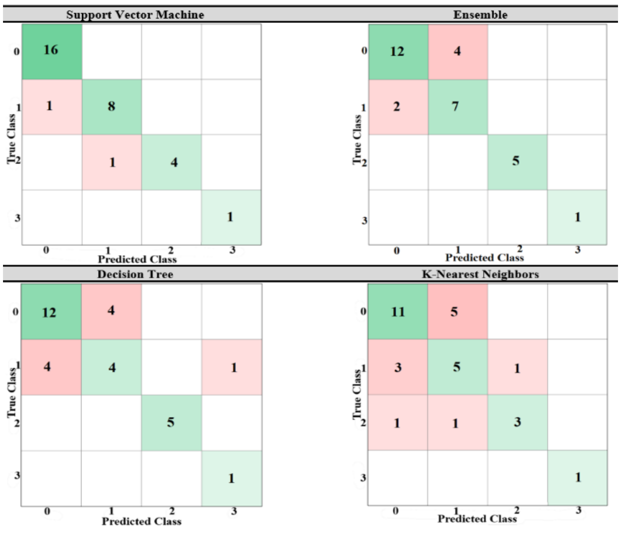

Figure 3. Confusion matrix

While the SVM algorithm correctly classified all the data in the "0 normal" class, the Ensemble and Tree algorithms predicted 4 of the data in the "1 mild" grade and misclassified them, while KNN predicted 5 of them in the "1 mild" class and classified them incorrectly. Likewise, their performance in other classes can be seen in Figure 3 (Figure 3). If we evaluate the results in Figure 3 in general, SVM made the best prediction in 0 grade and KNN made the worst prediction. The best estimate in grade 1 belongs to SVM. Ensemble and Tree made the best guesses in the 2nd and 3rd grades. Using the numerical values obtained from the complexity matrix given in Figure 3, when substituting in equations 1, 2, 3, 4, and 5, the overall performance results of the Carpal tunnel syndrome grade classification data are calculated in Table 3 (Table 3).

Table 3. Carpal tunnel syndrome performance results of the classification

Classifier	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
Support Vector Machine	93.55	95.75	92.22	97.20	93.69
Ensemble	80.65	87.34	88.19	92.12	87.50
Decision Tree	70.97	68.75	79.86	87.95	72.18
K-Nearest Neighbours	64.52	73.45	71.08	85.55	71.91

When we evaluate Table 3, the best overall success is SVM with 93.55%. This is followed by Ensemble with 80.65%, Tree with 70.97%, and KNN with 64.52%. Besides, the Carpal tunnel syndrome ROC curve graph is shown in Figure 4. Data classification performances of classification algorithms are clearly shown on this graph.

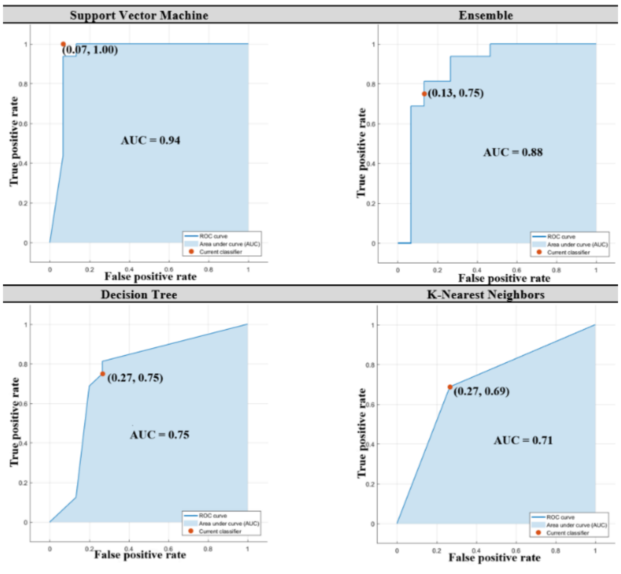

Figure 4. Carpal tunnel syndrome ROC curve graph

It is seen that SVM has the best area in the ROC curve graph, which is a different graph showing the performances of the algorithms (Figure 4). This is followed by Ensemble, Tree, and KNN, respectively.

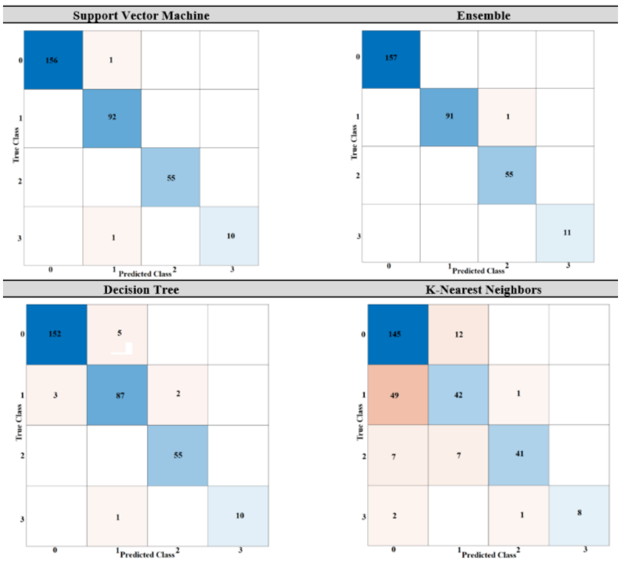

Figure 5. Training confusion matrix

The confusion matrix obtained at the end of training the data is shown in Figure 5 (Figure 5). When the confusion matrices obtained at the end of the trainings were compared, SVM predicted 156 data belonging to the zero class correctly, while it predicted only one data to be one class incorrectly. Likewise, while it correctly predicted ten data belonging to three classes, it achieved a high performance by estimating only one data as one class incorrectly. Likewise, while Ensemble correctly predicted 91 data belonging to the 1 class, only 1 data was incorrectly predicted to have two classes. He predicted

all other data correctly. The performances of other algorithms are as seen in Figure 5.
Datasets analyzed during the current study are available from the corresponding author by appropriate request.

Discussion

ENMG is used not only to determine the treatment modality in CTS but also to determine the severity of median nerve entrapment. This enables the usage of ENMG in following up on the progress of the disease and guiding the determination of the treatment modality. However, the reliability of the ENMG test can be very variable due to factors such as the experience of the person performing the test, the technical characteristics of the device used, and the patient's compliance with the test. In addition, the value of the test may vary according to the purpose of the test, for example, the sensitivity of the test should be maximized in order not to miss any case in the CTS screening to be performed in the industry sector.[27] The exponential increase in publications on AI in recent years and the focus on artificial intelligence in professional and scientific meetings in recent years emphasize the importance of this issue.[14] Diagnosing and managing diseases is a difficult task that cannot be obtained from textbooks or classroom information. It is gradually acquired through years of observation and experience.[28] CTS is an entrapment neuropathy with a wide range of symptoms and signs. Accurate grading of CTS is important, as choosing the right treatment option may vary depending on the severity of CTS.[29,30] Using computer-assisted techniques in medical applications can reduce cost, time, human expertise, and medical error.[28]
Kunhimangalam et al. reported that by designing an expert system, they were able to diagnose CTS and its severity using fuzzy logic to help the patient take appropriate therapeutic measures before the severity of CTS increases. They believe that the system they developed can help the GP or specialist to diagnose and predict the patient's condition.[28]
Park et al. using an ML-based modeling approach to investigate the feasibility of determining the severity of CTS based on personal, clinical, and sonographic characteristics, as in electrodiagnostic techniques, reported that the best ML models yielded greater than 70% accuracy. While ML-based models performed well in classifying mild and severe grades, model accuracies were relatively low when classifying moderate grades. They stated that Extreme Gradient Boosting (XGB) has the best performance among the evaluated ML algorithms.[31]
Faeghi et al. analyzed the accuracy of CTS diagnosis based on ML modeling by applying segmentation processes to sonographic images obtained at wrist level from CTS and control groups. They reported that the diagnostic accuracy of radiologists increased when the computer-assisted diagnosis was applied.[32]
Wei et al. determined that hand kinematics is important for CTS diagnosis and severity grading using Random Forest (RF) for hands with mild to moderate CTS in controls, in ML-based CTS assessment with predictive accuracy reaching 90.3%.[11]
Yaman et al. compared bagging and boosting ensemble learning methods to automatically classify EMG signals. Their experimental results showed that group classifiers perform better in diagnosing neuromuscular disorders. The results of the study reported that AdaBoost achieved 99.08% accuracy with the Random Forest Ensemble method, therefore using a smaller dataset provides a performance advantage.[22]
In our study, the best estimation was SVM and the worst estimation was KNN in the grade zero. Our best guess in grade 1 belongs to SVM. Ensemble and Tree made the best guesses in the 2nd and 3rd grades. SVM is the best algorithm with an overall success rate of 93.55%. As can be understood from the results of the algorithms we used in our study, the data type should be more to increase the success rate of the algorithms.
It is possible to talk about some difficulties in using machine learning in electrophysiological measurements. For example, the devices from which we receive the messages are not standardized and the data obtained according to the height, weight, gender and other demographic characteristics of the patients cannot be standardized. Similar limitations are seen in the studies of distinguishing neurologic and psychological diseases in machine learning.[33]
It should be kept in mind that AI can be used in different methods and in different combinations while diagnosing the disease, and it has different limitations and abilities in every direction.[34]
Although it facilitates clinical diagnosis, it is the best used It should be known that even AI algorithms tend to avoid negative side effects and test results, and it should not be overlooked that the safety of the patient cannot be fully ensured.[35]

Conclusion

The results of our study showed that the ML algorithm models provided better optimal training and prediction results, consistent with previous studies. Our ML-based classification system was able to accurately predict the severity of CTS using patient baseline, clinical information, and nerve conduction results. We believe that our study can play a supportive role in the clinic, allowing the surgeon or physician to determine the severity of CTS and decide on surgical or medical treatment accordingly, with minimal discomfort to the patient. The use of artificial intelligence can achieve very successful results in proportion to the regular and detailed recording of patient data in the digital system. However, it should be clearly known that; Artificial intelligence usage algorithms without positive findings obtained as a result of the examination by the clinician will always be incomplete in the diagnosis and treatment process.

Ethics approval

This study was carried out taking into account the principles of the Declaration of Helsinki. The study was approved by the Non-Interventional Ethics Committee of Sakarya University Faculty of Medicine with the date 04/03/2022 and number 52.

Conflict of Interest

The authors declare no competing interests.

Author Contributions

MA, YE and ESD designed the study, ESD and MA collected data, SU analyzed the data and ESD and YE wrote the study. MA and SU checked the results.

Financial support

The authors have not declared financial support.

References

1. Wahl B, Cossy-Gantner A, Germann S, Schwalbe NR. Artifcial intelligence (AI) and global health: howcan AI contribute to health in resource-poor settings? *BMJ Glob Health*. 2018;3(4):e000798. doi:10.1136/bmjgh-2018-000798
2. Pedersen M, Verspoor K, Jenkinson M, Law M, Abbott DF, Jackson GD. Artificial intelligence for clinical decision support in neurology. *Brain communications*. 2020;2(2):fcaa096. doi:10.1093/braincomms/fcaa096
3. Schweingruber N, Gerloff C. Künstliche Intelligenz in der Neurointensivmedizin. *Der Nervenarzt*. 2021;92(2):115-126. doi:10.1007/s00115-020-01050-4
4. Patel, UK, Anwar A, Saleem S, et al. Artificial intelligence as an emerging technology in the current care of neurological disorders. *Journal of Neurology*. 2021;268(5):1623-1642. doi:10.1007/s00415-019-09518-3
5. Genova A, Dix O, Saefan A, Thakur M, Hassan A. Carpal tunnel syndrome: a review of the literature. *Cureus*. 2020;12(3). doi:10.7759/cureus.7333
6. Atroshi I, Gummesson C, Johnson R, Ornstein E, Ranstam J, Rosen I. Prevalence of carpal tunnel syndrome in a general population. *JAMA*. 1999;282:153-158. doi:10.1001/jama.282.2.153
7. Padua L, LoMonaco M, Padua R. Neurophysiological classification of carpal tunnel syndrome: assessment of 600 symptomatic hands. Ital J Neurol Sci. 1997;18:145-50.
8. Aulisa L, Tamburrelli F, Padua R, Romanini E, Lo Monaco M, Padua L. Carpal tunnel syndrome: indication for surgical treatment based on the electrophysiological study. *J Hand Surg*. 1998;23:687-691.
9. Premoselli S, Sioli P, Grossi A, Cerri C. Neutral wrist splinting in carpal tunnel syndrome: a 3- and 6-months clinical and neurophysiologic follow-up evaluation of night only splint therapy. *Eura Medicophys*. 2006;42(2):121-126.
10. Karsidag S, Sahin S, Hacikerim Karsidag S, Ayala S. Long term and frequent electrophysiological observation in carpal tunnel syndrome. *Eura Medicophys*. 2007;43(3):327-332.
11. Iida JI, Hirabayashi H, Nakase H, Sakaki T. Carpal tunnel syndrome: electrophysiological grading and surgical results by minimum incision open carpal tunnel release. *Neurologia Medico-chirurgica*. 2008;48(12):54-559. doi:10.2176/nmc.48.554
12. Stevens JC. AAEM minimonograph# 26: the electrodiagnosis of carpal tunnel syndrome. Muscle & Nerve: Official Journal of the American Association of Electrodiagnostic Medicine. *Muscle Nerve*. 1997;20(12):1477-1486. doi:10.1002/(sici)1097-4598(199712)20:12<1477::aid-mus1>3.0.co;2-5
13. Wei Y, Gu F, Zhang W. A two-phase iterative machine learning method in identifying mechanical biomarkers of peripheral neuropathy. *Expert Systems with Applications*. 2021;169:114333. doi:10.1016/j.eswa.2020.114333
14. Lui YW, Chang PD, Zaharchuk G, et al. Artificial intelligence in neuroradiology: Current status and future directions. *American Journal of Neuroradiology*. 2020;41(8):E52-E59. doi:10.3174/ajnr.A6681
15. Jiang F, Jiang Y, Zhi H, et al. Artificial intelligence in healthcare: past, present, and future. *Stroke and Vascular Neurology*. 2017;2(4). doi:10.1136/svn-2017-000101
16. Cramer JS. The origins of logistic regression. 2002.
17. Subasi A, Mian Qaisar S. The Ensemble Machine Learning-Based Classification of Motor Imagery Tasks in Brain-Computer Interface. *Journal of Healthcare Engineering*. 2021. doi:10.1155/2021/1970769
18. Chilla GS, Yeow LY, Chew QH, Sim K, Prakash KN. Machine learning classification of schizophrenia patients and healthy controls using diverse neuroanatomical markers and Ensemble methods. *Scientific Reports*. 2022;12(1):1-11. doi:10.1038/s41598-022-06651-4
19. Yousefi J, Hamilton-Wright A. Characterizing EMG data using machine-learning tools. *Computers in Biology and Medicine*. 2014;51:1-13. doi:10.1016/j.compbiomed.2014.04.018
20. Wang Z, Dreyer F, Pulvermüller F, et al. Support vector machine-based aphasia classification of transcranial magnetic stimulation language mapping in brain tumor patients. *NeuroImage: Clinical*. 2021;29:102536. doi:10.1016/j.nicl.2020.102536
21. Demirel Ş, Yakut SG. Karar Ağacı Algoritmaları ve Çocuk İşçiliği Üzerine Bir Uygulama. *Sosyal Bilimler Araştırma Dergisi*. 2019;8(4):52-65.
22. Yaman E, Subasi A. Comparison of bagging and boosting ensemble machine learning methods for automated EMG signal classification. *BioMed Research International*. 2019. doi:10.1155/2019/9152506
23. Aksu MÇ, Karaman E. Karar Ağaçları ile Bir Web Sitesinde Link Analizi ve Tespiti. *Acta Infologica*. 2017;1(2):84-91.
24. Yadav S, Shukla S. Analysis of k-fold cross-validation over hold-out validation on colossal datasets for quality classification. In the 2016 IEEE 6th International conference on advanced computing (IACC). 2016;78-83. IEEE. doi:10.1109/IACC.2016.25
25. World Health Organization. Obesity and overweight. Accessed at https://who.int/news-room/fact-sheets/detail/ obesity-and-overweight on May 6, 2020.
26. Padua L, LoMonaco M, Gregori B, Valente EM, Padua R, Tonali P. Neurophysiological classification and sensitivity in 500 carpal tunnel syndrome hands. *Acta Neurologica Scandinavica*. 1997;96(4):211-217. doi:10.1111/j.1600-0404.1997.tb00271.x
27. Szabo RM, Slater Jr, RR., Farver TB, Stanton DB, Sharman WK. The value of diagnostic testing in carpal tunnel syndrome. *The Journal of Hand Surgery*. 1999;24(4):704-714. doi:10.1053/jhsu.1999.0704
28. Kunhimangalam R, Ovallath S, Joseph PK. A novel fuzzy expert system for the identification of the severity of carpal tunnel syndrome. *BioMed Research International*. 2013. doi:10.1155/2013/846780

29. Eslami S, Fadaei B, Baniasadi M, Yavari P. Clinical presentation of carpal tunnel syndrome with different severity: a cross-sectional study. *American Journal of Clinical and Experimental Immunology*. 2019;8(4):32.
30. Hirani S. A study to further develop and refine the carpal tunnel syndrome (CTS) nerve conduction grading tool. *BMC Musculoskeletal Disorders*. 2019;20(1):1-7. doi:10.1186/s12891-019-2928-y
31. Park D., Kim B.H., Lee S.E., et al. Machine learning-based approach for disease severity classification of carpal tunnel syndrome. *Scientific Reports*. 2021;11(1):1-10. doi:10.1038/s41598-021-97043-7
32. Faeghi F, Ardakani AA, Acharya UR, et al. Accurate automated diagnosis of carpal tunnel syndrome using radiomics features with ultrasound images: A comparison with radiologists' assessment. *European Journal of Radiology*. 2021;136:109518. doi:10.1016/j.ejrad.2020.109518
33. Vasta R, Cerasa A, Sarica A, et al. The application of artifcial intelligence to understand the pathophysiological basis of psychogenic nonepileptic seizures. *Epilepsy Behav*. 2018;87:167–172. doi:10.1016/j.yebeh.2018.09.008
34. Arani LA, Hosseini A, Asadi F, Masoud SA, Nazemi E. Intelligent computer systems for multiple sclerosis diagnosis: a systematic review of reasoning techniques and methods. *Acta Inf Med*. 2018;26(4):258-264. doi:10.5455/aim.2018.26.258-264
35. Brzezicki M A, Kobetić MD, Neumann S, Pennington C. Diagnostic accuracy of frontotemporal dementia. An artificial intelligence-powered study of symptoms, imaging and clinical judgement. *Advances in Medical Sciences*. 2019;64(2):292-302. doi:10.1016/j.advms.2019.03.002