Diagnosis of Mechanical Low Back Pain Using a Fuzzy Logic-Based Approach

Esmaeil Fakharian[1], Ehsan Nabovati[2], Mehrdad Farzandipour[3], Hossein Akbari[4]; Soheila Saeedi[5,*]

Abstract: *Back pain is one of the main causes of* disability, *and its proper diagnosis and treatment are difficult tasks. Intelligent methods can help physicians make a more precise diagnosis of diseases. The present study was conducted to diagnose the correct type of mechanical low back pain (LBP) using an Adaptive Neuro-Fuzzy Inference System (ANFIS). The diagnostic parameters of mechanical LBP were determined using library reviews and the views of experts based on the Delphi technique. Modelling was done in MATLAB R2012 using the ANFIS. After the modelling stage, the method was tested in terms of the percentage of corrected classification and diagnostic value indicators. Modelling is applied in the present study to diagnose different types of mechanical LBP, including back strain, spondylolisthesis, spinal stenosis, disc herniation, and scoliosis. The modelling input included 17 diagnostic parameters, and its output contained various types of mechanical LBP. The percentage of corrected classification varied from 80.9% to 83.8% (disc herniation and spondylolisthesis). The system test in the present study showed an appropriate accuracy in diagnosing different types of mechanical LBP. As a result, this system can be helpful in clinical settings for diagnosing different types of mechanical LBP presenting with similar symptoms.*

Keywords: Clinical Decision Support System, Diagnose, Fuzzy Logic, Mechanical Low Back Pain

1. Introduction

Back pain is one of the main causes of disability [1] and absenteeism from work [2]. Ten percent of all people in the world are affected by mild to very severe levels of this disorder [3]. The uncertainty in the diagnosis of this disorder is a dilemma for physicians that could lead to wrong treatments. Arriving at a definitive diagnosis can help care providers ensure the suitability of their treatment option and thus reduce the complications of improper treatment [4]. Diagnosing the patient's disease is the first and most complicated step in medical practice. According to studies, the rate of errors in the diagnosis stage varies from 10% to 15% [5]. Decision-making under conditions of uncertainty is one of the causes of medical errors [6]. A strategy for controlling these errors involves interventions offering cognitive assistance, including the use of electronic records and decision support tools that facilitate the access to information and specialists' opinions and knowledge [7].

Clinical Decision Support Systems (CDSSs) can help physicians in the diagnosis of diseases as tools that contain clinical knowledge and the patient's updated information [8]. These systems are designed to improve patient care [8] and are also meant to provide physicians and patients with consultations starting from the stage of diagnosis to the post-treatment follow-up. These tools can improve the performance of health care providers [9]. Various methods can be used for modelling knowledge in these systems' knowledge base, including neural networks, Bayesian network, rule-based reasoning, genetic algorithms, decision trees and the fuzzy logic [10-16].

Fuzzy sets can be used for modelling the uncertainty of a diagnosis and the imprecision of its symptoms [17]. The fuzzy logic is very close to natural language and therefore allows physicians to provide their findings in a natural form. This capacity makes fuzzy-based CDSSs more acceptable for humans [18]. A systematic review study conducted to assess fuzzy decision support systems designed to diagnose musculoskeletal disorders concluded that the median accuracy of the systems designed with this method was 90% and higher, which is indicative of the high accuracy of this system in the diagnosis of these diseases [19].

According to the results of a systematic review study, ANFIS had the highest diagnostic accuracy among all the different fuzzy methods applied [20]. ANFIS resolves the lonely-used problems of each of these methods by integrating a Fuzzy Inference System (FIS) and a neural network and thus improves the effectiveness of this method in different applications, such as modelling, control and classification.

Due to the ambiguous nature of mechanical LBP, the need for highly experienced physicians for the diagnosis of these diseases and the high similarity between the clinical symptoms of different types of mechanical LBP, it appears that developing a model can

[1] *Research Centre for Trauma, Kashan University of Medical Sciences, Kashan, Iran.   ORCID ID : 0000-0003-0115-8398*

[2] *Research Centre for Health Information Management, Department of Health Information Management & Technology, School of Allied Health Professions, Kashan University of Medical Sciences, Kashan, Iran ORCID ID : 0000-0003-0430-4637*

[3] *Research Centre for Health Information Management, Department of Health Information Management & Technology, Kashan University of Medical Sciences, Kashan, Iran, ORCID ID : 0000-0001-9738-7771*

[4] *Research Centre for Social Determinants of Health (SDH), School of Health, Kashan University of Medical Sciences, Kashan, Iran ORCID ID : 0000-0001-7486-8580*

[5] *Health Information Management Department, School of Allied Medical Sciences, Tehran University of Medical Sciences, Tehran, Iran. ORCID ID : 0000-0003-1315-794X*

* Corresponding Author Email: soheila.saeedi2021@gmail.com

be helpful in the diagnosis of these diseases.

The main purpose of the present study was thus to develop a model for the diagnosis of different types of mechanical LBP using ANFIS and to determine the diagnostic accuracy of developed model for each of these diseases.

2. Materials and Methods

Diagnosis of mechanical LBP was made in three stages in this study.

2.1. Stage One: Determination of diagnostic parameters

Knowledge acquisition was the first step of this study. Mechanical LBPs that are generally difficult to diagnose were identified by interviewing three neurosurgeons with a minimum practice experience of five years. A number of physicians were also asked to determine mechanical LBPs that were difficult to diagnose but could be diagnosed with the help of an intelligent system.

The symptoms that were necessary for the diagnosis of these disorders were then identified through a review of literature and reliable electronic databases, including PubMed, Scopus, UpToDate and ClinicalKey. To add the required diagnostic parameters to the tool, a questionnaire was designed based on the literature review and distributed among 12 neurosurgeons and orthopedists with a minimum practice experience of five years. The CVR and CVI of each item in the questionnaire were determined and the final version was thus designed. Each item in the questionnaire was scored based on a five-point Likert scale, from 'totally agree' to 'totally disagree'. The diagnostic parameters determined by this questionnaire and through the Delphi technique were discussed by the 12 neurosurgeons and orthopedists and then approved in the second round and entered as the system's input variables. In the Delphi technique, the diagnostic parameters that had been approved by less than 50% of the specialists were eliminated, and the parameters approved by 75% or more were accepted. The diagnostic parameters approved by 50% to 75% were debated again in the second round of the Delphi technique. After determining the ultimate diagnostic parameters, the linguistic variables related to each of these parameters were also determined by interviewing three neurosurgeons with at least five years of practice experience.

2.2. Stage Two: Modelling with ANFIS Method

A model was developed using the ANFIS in MATLAB R2012 software. ANFIS combines the advantages of two powerful methods, including neural networks and the fuzzy logic, and uses neural learning rules to identify and tune the parameters and structure of a fuzzy inference system (FIS) [21].

Based on Figure 1, the network structure of an ANFIS consists of five layers. The first layer is the input layer, and each node in this layer is equal to a fuzzy set and the output of each node is equal to the membership degree of the input variable in this fuzzy set.
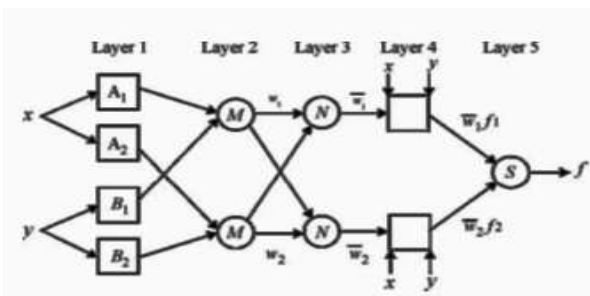

Figure 1. ANFIS architecture

In the second layer, each node output shows the firing strength of a rule.

In the third layer, nodes play an important role. The nodes of this layer determine the relative firing strength of a rule.

In the fourth layer, the output of each node is as in equation (1):

$$Q_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i), i=1,2 \qquad (1)$$

The fifth layer is the ANFIS output layer. Each node in this layer calculates the overall output value.

In this layer, the number of nodes is equal to the number of outputs. Finally, the overall output can be expressed as a linear combination of the resultant parameters as in equation (2):

$$f = (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_2 y) q_2 + (\overline{w}_2) r_2 \qquad (2)$$

The Sugeno method was used for the inference part [22]. The fuzzy if-then rules based on the Sugeno model are as follows:

Rule 1: if (x is A1) and (y is B1) then f1=p1x+q1y+r1

Rule 2: if (x is A2) and (y is B2) then f2=p2x+q2y+r2

The types of input and output membership functions were also determined in this step using the Gaussian membership function and a linear output.

A hybrid method that was a combination of back propagation and the least squares method was used for optimization. The number of epochs and the error tolerance were initially taken as 35 and 0.01, respectively. Epoch was increased to 250 if this condition was not satisfied. The model's convergence was assessed using the Root Mean Square Error (RMSE).

System training was performed using the data pertaining to 560 patients with mechanical LBP and controls (n=384 for those with mechanical LBP and n=176 for the controls).

2.3. Stage Three: Model performance determination

After creating the model, the system was tested using the data pertaining to 140 patients with mechanical LBP and controls (96 patients with and 44 people without mechanical LBP). The data pertaining to the patients with mechanical LBP were extracted from the medical records of the patients who had been hospitalized in a teaching hospital (Kashan University of Medical Sciences) in 2014-17 or had visited a neurosurgery outpatient clinic. The data pertaining to the controls were extracted from the medical records of heart patients who had visited a cardiovascular teaching hospital and did not suffer from back pain disorders. To test the model, the diagnoses it made were compared with the final diagnoses recorded by the physician in the patients' medical record. Finally, the percentage of corrected classification, sensitivity, specificity, positive and negative predictive values (PPV and NPV) were computed. Sensitivity indicated the level of correct diagnosis of patients with various types of mechanical LBP by the system. Specificity showed the system's ability to correctly diagnose people without mechanical LBP. Positive predictive value indicated the percentage of actual patients among the subjects who had been diagnosed with the disorder by the system. Negative predictive value showed the percentage of people without mechanical LBP who had been diagnosed by the system as non-patients. Corrected classification percentage showed the percentage of correct diagnosis by the system (patients with mechanical LBP and those without mechanical LBP) to the total number of subjects.

3. Results

After interviewing a number of physicians to determine the types of mechanical LBP, five types of this disorder were selected for developing the model, including back strain, spondylolisthesis, spinal stenosis, disc herniation and scoliosis.

The symptoms that were rejected by the physicians after two rounds of the Delphi technique and were eventually eliminated included gender, muscle spasm or tightness, redness, muscle weakness, asymmetry of shoulders, swelling, weakness in the legs, weight loss and family history.

The knowledge acquisition stage resulted in the identification of 17 diagnostic parameters for the diagnosis of mechanical back pain (Table 1). These 17 diagnostic parameters were taken as the input variables of the diagnostic system and were vital to the differentiation of these five types of mechanical LBP. The 17 input variables (disease symptoms) were described by two to 11 linguistic variables (Table 1). The type of mechanical back pain (back strain, spondylolisthesis, spinal stenosis, disc herniation and scoliosis) and the absence of mechanical LBP were defined as the output.

The lowest RMSE was obtained after 250 epochs, which was 0.029. Figure 2 presents the results of testing the model. The percentage of corrected classification varied from 80.9% to 83.8% (disc herniation and spondylolisthesis). Disc herniation had the lowest sensitivity (79.2%) and spondylolisthesis the highest (87.5%). The specificity for identifying people with no mechanical LBP was 81.8% to 84.1%
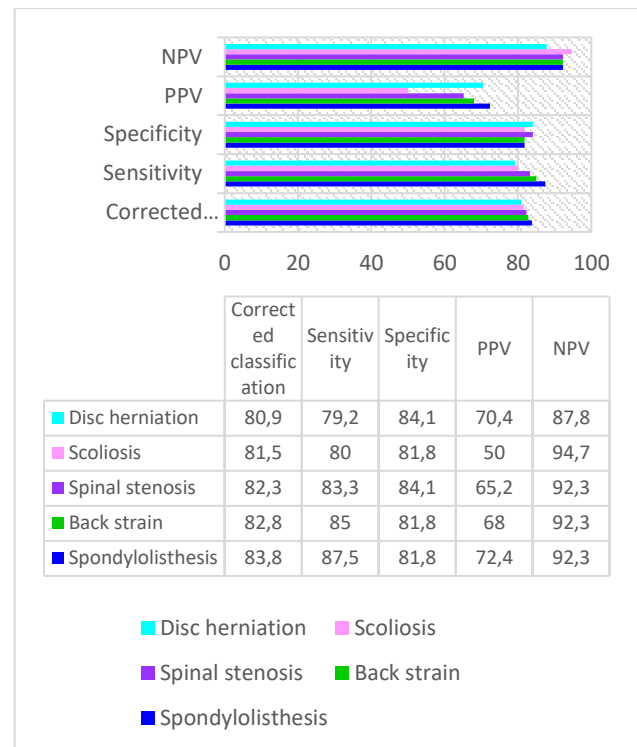

	Corrected classification	Sensitivity	Specificity	PPV	NPV
Disc herniation	80,9	79,2	84,1	70,4	87,8
Scoliosis	81,5	80	81,8	50	94,7
Spinal stenosis	82,3	83,3	84,1	65,2	92,3
Back strain	82,8	85	81,8	68	92,3
Spondylolisthesis	83,8	87,5	81,8	72,4	92,3

Figure 2. Values of statistical parameters of the result

Table 1. input variable and linguistic variable of mechanical LBP

Input variable	Linguistic variable
Age	first decade (age 0 to 9), second decade (age 10 to 19), third decade (age 20 to 29), fourth decade (age 30 to 39), fifth decade (age 40 to 49), sixth decade (age 50 to 59), seventh decade (age 60 to 69), eight decade (age 70 to 79), ninth decade (age 80 to 89), tenth decade (age 90 to 99), any age (age 0 to 99)
Pain pattern location	without pain, upper back, lower back, back, leg
Location of back pain	without pain, lumbar curve, thoracic, Low back, posterior Thigh, lower leg, sacroiliac joints, lumbar spine, buttock, back, low back to lower leg
Onset	without pain, acute, insidious, chronic
Pain with standing	without pain, increase, decrease
Pain with sitting	without pain, increase, decrease
Pain with bending	without pain, increase, decrease
Straight leg raising test	positive, negative
Quality of back pain	without pain, ache, spasm, sharp, shooting, burning, paraesthesia in lower leg, pins and needles
Range of motion	normal, decreased
Distribution of pain	without pain, localized, radicular
Duration of morning stiffness	without stiffness, considerable, non-considerable
Tenderness	absence, presence
Deformity	mild, moderate, severe
Duration of pain	without pain, days to weeks, days to months, months to years
Frequency of pain	without pain, daily, weekly, monthly
Severity of pain	without pain, mild, moderate, severe

4. Discussion

This study developed a model to diagnose different types of mechanical LBP, including back strain, spondylolisthesis, spinal stenosis, disc herniation, and scoliosis. The ANFIS technique was used for developing the model. Knowledge acquisition was carried out using a literature review, knowledge acquisition from medical experts and data analysis. The system input consisted of 17 diagnostic parameters, and its output was the type of mechanical LBP. Testing the model showed that disc herniation had the lowest percentage of corrected classification (80.9%) and spondylolisthesis the highest percentage (83.8%).

One of the main challenges in designing a system is knowledge

acquisition. Knowledge acquisition from experts involves certain problems, including: (1) The experts must be identified before designing the system –who is truly an expert in the field? (2) Are the experts willing to take part in the process of knowledge engineering? (3) Is there consensus among the experts on how to solve the problem? (4) How can this knowledge be obtained from the experts? (5) How can one be certain of the reliability, validity and completeness of the knowledge obtained from the experts [23]?

Knowledge acquisition from data also involves several challenges:, such as questions of which variables should be regarded as the system input, which cases should be used for the system training and who should determine the system variables and how [23].

To deal with these problems, different knowledge acquisition methods were used in the present study, including literature review, knowledge acquisition from medical experts and data analysis. The snowball method was also used for identifying experts in the field and entering them into the study. The Delphi technique was used to ensure that the knowledge created by the experts is reliable and valid and that the experts reach consensus among themselves, so that the variables that are most critical to diagnosis can be identified.

Evaluating the model performance showed that the percentage of corrected classification varies from 80.9% to 83.8%. In one study, Kadhim [24] designed a CDSS for the diagnosis of LBP using the fuzzy-neuro technique. The accuracy of this system was 83.6%. Comparing the results obtained by these two systems, both of which use a combination of fuzzy logic and neural networks, shows that they perform similarly in diagnosing LBP and there are no significant differences between them. In another study, Lin et al. [25] designed and evaluated a web-based CDSS for the diagnosis of LBP using the Bayes theorem. The accuracy of the designed system was 73.08%, which is lower compared to the present study. The high percentage of corrected classification in the present study could be attributed to the use of the ANFIS.

The present study had 17 diagnostic parameters as the system input variables, and testing the model showed that the percentage of corrected classification ranged from 80.9% to 83.8%. In a study conducted by Sari et al. [26] to design a CDSS for the prediction of LBP using the ANFIS, accuracy was measured as 0.972; however, the system input in that study included two variables. The low accuracy of the system designed in the present study compared to that designed by Sari et al. [26] could be due to the large number of input parameters used in the present study. In another study, Sidiropoulos et al. [27] designed a CDSS for the diagnosis of rare cancers and concluded that the number of features can affect the system accuracy. They demonstrated that the system offers the best results when the number of input features is the smallest possible. A study conducted by Nilashi et al. [28] also showed that using techniques such as PCA, which minimizes the number of input features, can improve the accuracy of the system.

Strengths and Limitations:

The present study had several strengths and limitations. Its strengths included developing a model for several types of mechanical LBP and also the use of various knowledge acquisition methods to create the system's knowledge base. Its weaknesses included the small sample size used in the training stage and the failure to implement the system in a clinical environment.

Implications of the findings for future research:

The system developed in the present study can be used by medical students for the purpose of training and also in remote areas with no access to specialists to assist GPs. The effects of the system on outcomes such as costs for patients and savings in time for physicians should be further examined.

A diagnostic system is recommended to be created for other types of mechanical LBP. In addition, some other capabilities can be added to the system, such as offering treatment solutions. This model is also recommended to be developed and evaluated using other knowledge modeling techniques, including the decision tree, neural network, rule-based reasoning, and the Bayesian network, and the results obtained should then be compared with the present findings. The number of input variables is also recommended to be reduced as much as possible in order to reduce the complexity of the designed system.

5. Conclusion

A model was developed in this study to help diagnose the type of mechanical LBP using the ANFIS. The model developed has a suitable accuracy in diagnosing mechanical LBP. Reducing the number of input parameters appears to improve the accuracy of the system. Moreover, combining literature review, knowledge obtaining from medical experts, and data analysis for the purpose of knowledge acquisition can have an effective role in the proper functioning of the model.

Conflicts of interest

The authors have no conflicts of interest to declare.

Acknowledgements

References

[1]   Tagliaferri SD, Miller CT, Owen PJ, Mitchell UH, Brisby H, Fitzgibbon B, et al. Domains of chronic low back pain and assessing treatment effectiveness: a clinical perspective. Pain Practice. 2020;20(2):211-25.

[2]   Lardon A, Dubois J-D, Cantin V, Piché M ,Descarreaux M. Predictors of disability and absenteeism in workers with non-specific low back pain: A longitudinal 15-month study. Applied Ergonomics. 2018;68:176-85.

[3]   Murray CJ, Lopez AD. Measuring the global burden of disease. New England Journal of Medicine. 2013;369(5):448-57.

[4]   Slade SC, Molloy E, Keating JL. The dilemma of diagnostic uncertainty when treating people with chronic low back pain: a qualitative study. Clinical rehabilitation. 2012;26(6):558-69.

[5]   Berner ES, Graber ML. Overconfidence as a cause of diagnostic error in medicine. Am J Med. 2008;121(5 Suppl):S2-23.

[6]   Zavala AM, Day GE, Plummer D, Bamford-Wade A. Decision-making under pressure: medical errors in uncertain and dynamic environments. Australian Health Review. 2018;42(4):3.402-95

[7]   Sung H-K, Jung B, Kim KH, Sung S-H, Sung A-D-M, Park J-K. Trends and Future Direction of the Clinical Decision Support System in Traditional Korean Medicine. Journal of pharmacopuncture. 2019;22(4):260-8.

[8]   Sutton RT, Pincock D, Baumgart DC, Sadowski DC, Fedorak RN, Kroeker KI. An overview of clinical decision support systems: benefits, risks, and strategies for success. npj Digital Medicine. 2020;3(1):17.

[9]   Brunner J, Chuang E, Goldzweig C, Cain CL, Sugar C, Yano EM. User-centered design to improve clinical decision support in primary care. International Journal of Medical Informatics. 2017;104:56-64.

[10] Ocak H. A medical decision support system based on support vector machines and the genetic algorithm for the evaluation of fetal well-being. Journal of medical systems. 2013;37(2):9913.

[11] Rossille D, Laurent J-F, Burgun A. Modelling a decision-support system for oncology using rule-based and case-based reasoning methodologies. International journal of medical informatics. 2005;74(2):299-3.06

[12] Chao C-M, Yu Y-W, Cheng B-W, Kuo Y-L. Construction the model on the breast cancer survival analysis use support vector machine, logistic regression and decision tree. Journal of medical systems. 2014;38(10):106.

[13] Constantinou AC, Fenton N, Marsh W, Radlinski L. From complex questionnaire and interviewing data to intelligent Bayesian network models for medical decision support. Artificial intelligence in medicine. 2016;67:75-93.

[14] Eslamizadeh G, Barati R. Heart murmur detection based on wavelet transformation and a synergy between artificial neural network and modified neighbor annealing methods. Artificial intelligence in medicine. 2017;78:23-40.

[15] Kunhimangalam R, Ovallath S, Joseph PK. A Novel Fuzzy Expert System for the Identification of Severity of Carpal Tunnel Syndrome. Biomed Research International. 2013.

[16] Jeddi FR, Arabfard M, Kermany ZA. Intelligent Diagnostic Assistant for Complicated Skin Diseases through C5's Algorithm. Acta Informatica Medica. 2017;25(3):182.

[17] Shukla AK ,Muhuri PK. Big-data clustering with interval type-2 fuzzy uncertainty modeling in gene expression datasets. Engineering Applications of Artificial Intelligence. 2019;77:268-82.

[18] d'Acierno A, Esposito M, De Pietro G. An extensible six-step methodology to automatically generate fuzzy DSSs for diagnostic applications. BMC bioinformatics. 2013;14(1):S4.

[19] Farzandipour M, Nabovati E, Saeedi S, Fakharian E. Fuzzy decision support systems to diagnose musculoskeletal disorders: A systematic literature review .Comput Methods Programs Biomed. 2018;163:101-9.

[20] Ahmadi H, Gholamzadeh M, Shahmoradi L, Nilashi M, Rashvand P. Diseases diagnosis using fuzzy logic methods: A systematic and meta-analysis review. Comput Methods Programs Biomed. 2018;161:145-72.

[21] Alizadeh M, Maghsoudi OH, Sharzehi K, Reza Hemati H, Kamali Asl A, Talebpour A. Detection of small bowel tumor in wireless capsule endoscopy images using an adaptive neuro-fuzzy inference system. Journal of biomedical research. 2017;31(5):419-27.

[22] Takagi T, Sugeno M. Derivation of fuzzy control rules from human operator's control actions. IFAC Proceedings Volumes. 1983;16(13):55-60.

[23] Sheikhtaheri A, Sadoughi F, Dehaghi ZH. Developing and Using Expert Systems and Neural Networks in Medicine: A Review on Benefits and Challenges. Journal of Medical Systems. 2014;38.(9)

[24] Kadhim MA. FNDSB: A fuzzy-neuro decision support system for back pain diagnosis. Cognitive Systems Research. 2018;52:691-700.

[25] Lin L, Hu PJ-H, Sheng ORL. A decision support system for lower back pain diagnosis: Uncertainty management and clinical evaluations. Decision Support Systems. 2006;42(2):1152-69.

[26] Sari M, Gulbandilar E, Cimbiz A. Prediction of Low Back Pain with Two Expert Systems. Journal of Medical Systems. 2012;36-1523:(3).7

[27] Sidiropoulos K, Glotsos D, Kostopoulos S, Ravazoula P, Kalatzis I, Cavouras D, et al. Real time decision support system for diagnosis of rare cancers, trained in parallel, on a graphics processing unit. Computers in biology and medicine. 2012;42(4):376-86.

[28] Nilashi M, Ibrahim O, Ahani A. Accuracy Improvement for Predicting Parkinson's Disease Progression. Sci Rep. 2016;6:34181.