Risk Assessment for Cardiac Arrest : A Deep Learning Approach

Atınç Yılmaz[*]

Correspondence:
atincyilmaz@beykent.edu.tr
Department of Computer
Engineering, Beykent University,
İstanbul, Turkiye
Full list of author information is
available at the end of the article
[*]Equal contributor

Abstract

Background: Risk of developing cardiovascular diseases, in the world, is increasing day by day. Accordingly, the number of deaths due to heart attacks is quite remarkable. Early risk assessment and diagnosis of heart disease are vital to prevent heart attacks by providing effective treatment planning and evaluation of outcomes. When a patient with high risk of heart attack is not treated correctly, chances of survival may reduce dramatically.

Methods: In this study, individuals who has heart attack risks are predicted by using a CNN method. A set of medical data from patients with heart attacks and healthy individuals are provided from the UCI database. Reinforced deep learning and ANFIS architectures are also applied to the same problem in order to compare the results and put forth the efficiency of applied method. In addition, ROC analysis and measurements of processing times for the applied methods were performed to reveal the performance, accuracy and efficiency of the study.

Results: The applied CNN method and other methods are tested and evaluated. The accuracy performance of the methods were 94.34% for the applied CNN method, 91.58% for the ANFIS, and 92.66% for the deep multilayer neural network. Highest accuracy has been obtained by using the applied CNN method, which is 94.34%. The reasons why the applied CNN method is better than other methods is the number of convolution and pooling layers, the filter size used in these layers, and the functions used in the loss and activation layers.

Conclusions: In the study, the applicability of proposed CNN method with images obtained from numerical data has been demonstrated. With the early prediction system proposed, it is now possible to take precautionary measures against possible cardiac arrest. In this study; a new method based on CNN is proposed for early detection of possible heart attack, which is a great risk for human life. Different from studies in the literature, it was used in the applied CNN method by converting all numerical data from dataset into 2D images. Afterwards, to show whether this the proposed method is applicable or not, the dataset which is numerical form was applied to other methods and compared.

Keywords: Cardiac arrest; Heart attack risk; Deep learning; Artificial intelligence; Image reconstruction

Background

Heart is a vital organ which has the task of pumping blood into circulatory system. In humans, it is located in the chest area under the rib cage and has the strongest muscles in body although it's about the size of a fist. Heart weighs less in women than men and beats about 100,000 times in one day. Circulation of the blood around the lungs where blood is oxygenated is called pulmonary circulation; and circulation around the body to provide oxygenated blood is called systematic circulation [1]. Although heart is composed of very strong muscles, it is vulnerable to many risk factors. Heart attack is the damage of the heart tissue due to the sudden blockage of the arteries that are feeding the heart. In the period that is called arteriosclerosis, the arteries shrink over time and clots develop on the cracks that clog the vessels. If not intervened in a timely manner, the damage results in loss of the heart tissue. If this loss is widespread, it affects the pumping power of the heart and causes failure. Heart attack is one of the leading causes of death both in Turkey and in the world. The World Health Organization (WHO) stated that 30% of the causes of death in the world are due to heart attack. In Turkey, studies show that the situation is even more serious with the ratio of 46%. Turkish Society of Cardiology, in a message issued on World Heart Day in 2015, stated that 300,000 heart attacks are observed every year in Turkey and 125,000 cases result in death [2]. Nausea, vomiting and cold sweat can be symptoms to detect the heart attack. Fainting and loss of consciousness can be added to these parameters. For patients over a certain age, shortness of breath is also among the symptoms. These symptoms are experienced in approximately 80% of individuals who has had a heart attack. It occurs quietly in the other 20% without any symptoms before. Eighty percent of cardiovascular diseases are developed due to smoking, hypertension, genetic predisposition, obesity, sedentary lifestyle and diabetes. Other causes are high cholesterol (Low-Density Lipoprotein-LDL [sometimes called "bad" cholesterol] and triglycerides), HDL (High-Density Lipoprotein - sometimes called "good" cholesterol), consume of alcohol, presence of various heart diseases (such as vascular occlusion, arrhythmia and experience a heart attack) and stress.

Another statistic shows that women have a lower risk of heart attack before menopause because of estrogen hormone. However, occurrence rate of complications is greater than that of in men. The earlier the heart attack is noticed, the less is the risk of loss of life. Because of this, it is very important to be able to save the life of the individual by determining the risk of heart attack in a timely manner. Only doctors can diagnose cardiac diseases today. Studies in the field of health informatics help doctors in this regard but they are not completely reliable. Misleading of the doctor's interpretation and diagnosis on a disease with a low error-threshold like heart attack might have irreversible consequences.

When analyzed in terms of computer and statistical sciences, health sector is one of the richest areas in terms of data. However, effective analysis methods are not used sufficiently to discover information and its relationship within the data. In recent years, Pattern Recognition, Data Mining and Machine Learning techniques have been applied to many areas of health informatics.

Related works

Nabeel Al-Milli developed a heart disease prediction system by using a neural network [3]. In this study, Al-Milli used 4 output classes and 14 parameters. The back propagation algorithm is used for the training of the network and the experiments performed in this study show that the proposed algorithm performs very well. Dr. K. Rani analyzed the heart disease dataset by using the Neural Network approach [4]. In this study, a parallel approach is adopted in the training phase in order to increase the efficiency of the classification process. Dangare et al. [5] proposed the Heart Disease Prediction System using neural network. In order to achieve better accuracy, the authors use 13 medical features such as gender, cholesterol level and stress testing in addition to smoking and obesity. The Heart Disease Prediction System estimates the probability of the patient having a cardiac disease. It is stated that the accuracy of this designed system is close to 100%. Chowdhury et al. applied an artificial neural network model for neonatal disease [6]. This proposed system accurately predicted the diagnosis of 75% of neonatal diseases.

Shankar et al. proposed an algorithm for the detection and division of S1 and S2 heart sounds using the Discrete Wavelet Transform and the Shannon energy envelope [7]. For classification, Shankar used an artificial neural network is to detect heart murmuring from heart sounds. Bahekar et al. used discrete wavelet transform for detection and division of S1 and S2 sounds among heart sounds [8]. For classification Adaptive-Network Based Fuzzy Inference Systems (ANFIS) is used.

M. Anbarasi tried to identify the important factors that cause heart diseases with the help of Genetic Algorithms [9]. Among the 13 factors that are responsible for heart diseases, genetic algorithms. determines the common factors, too. In addition, these factors are used in different classification algorithms. K. Srinavas et al. and M. Ghani et al. conducted two separate studies to estimate health status and heart attack by using data mining techniques[10, 11]. Heart-c, Heart-h and Heart-statlog are selected from UCI data sets and classification procedures are performed using Weka software [12]. In the experiments performed with UCI datasets, it is stated that best performance is obtained by using Information Gain and ANFIS [13]. Jin et al. monitored electrocardiogram (ECG) signals real time and continuously with a mobile phone based wearable device and the generated signal records were used to detect and prevent abnormal conditions [14]. Image processing-based measurement method that uses video sequences to measure the dynamic heart rate measurements by Link et al [15]. Panboonyuen et al. proposed a novel CNN for semantic segmentation with three main contributions called global convolutional network, channel attention and domain-specific transfer learning [16]. Some studies focus on the selection of the most effective feature in dataset and ability to classify with less complexity. Similarly, there are various studies on the detection of heart diseases by analyzing ECG signals. In some studies, methods on grouping the factors affecting different heart diseases are offered.

In this study, advanced artificial deep neural network approach is developed to predict deep coronary heart disease and improve diagnostic accuracy by using deep learning based classification and prediction models. In this study, a computer-assisted heart attack prediction system proposes to help potential patients who are at risk of heart attack and specialists identify the risk of heart attack through

Variable name	Operationalization	Mean	Standard deviation	Proportion of levels of Attributes
Age (Year)	Age at study	54.43	9.10	---
Sex	Gender : (Female = 1 ; Male = 2)	---	---	1= 32.22% ; 2= 67.78%
Chest Pain	Chest pain type (1 = typical angina; 2 = atypical angina; 3 = non-anginal pain; 4 = asymptomatic)	---	---	1= 7.41% ; 2=15.56% ; 3=29.26% ; 4=47.78%
Resting BP	Resting blood pressure (in mm Hg on admission to the hospital)	131.34	17.86	---
Cholesterol	Serum cholesterol in mg/dl	249.66	51.69	---
Fasting BS	Fasting blood sugar > 120 mg/dl (1 = False; 2 = True)	---	---	1= 85.19% ; 2=14.81%
Resting ECG	Resting electrocardiographic results (1 = Normal; 2 = Having ST-T; 3 = Hypertrophy)	---	---	1=48.52% ; 2=0.74% ; 3=50.74%
Max HR	Maximum heart rate achieved	149.68	23.17	---
Exercise Ang	Exercise induced angina (1 = No; 2 = Yes)	---	---	1=67.04% ; 2=32.96%
Oldpeak	ST depression induced by exercise relative to rest	1.05	1.14	---
Slope	The slope of the peak exercise ST segment (1 = Up sloping; 2 = Flat; 3 = Down sloping)	---	---	1=48.15% ; 2=45.19% ; 3=6.67%
Vessel	Number of major vessels (0-3) colored by fluoroscopy. (Treated as a discrete variable)	---	---	0=59.26% ; 1=21.48% ; 2=12.22%; 3=7.04%
Thal	Thallium heart Scan (1 = Normal; 2 = Fixed defect; 3 = Reversible defect)	---	---	1=56.30% ; 2=5.19% ; 3=38.52%
Heart disease	Diagnosis of heart disease (1= Absence; 2= Presence)	---	---	1=55.56% ; 2=44.44%

Figure 1 Dataset description.

personal data. The proposed system is based on Convolutional Neural Network architecture.

Methods

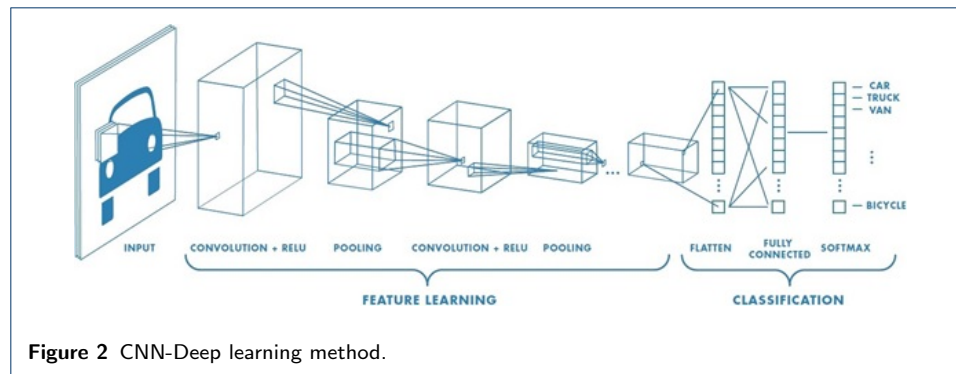
Dataset

The dataset used in this study is the heart attack dataset in the UCI machine learning database [17]. There are 270 data in the data set. In 150 of the total 270 data, a heart attack was not observed and other 120 had a heart attack. In the data set of containing 13 parameters that trigger the result of heart attack; the output column refers to the person's heart attack status. In this study, 270 heart disease patients are considered with 14 factors or variables. Description of the covariates, factors and their levels, summarized statistics such as the mean, standard deviation, and proportion of the levels are described in Figure Figure 1. The current data contains 5 continuous variables and 9 attribute characters. The description of each variable or attribute character, attribute levels, and how they are operationalized in the present report are also displayed in this figure. Presence or absence of heart disease in a patient is considered as a dependent variable (for regression) or output variable (for classification); and the rest of the variables are considered as independent variables/cofactors. Finally, entire data set of 270 total clinical instances are randomly separated into a training data set of 162 clinical instances (60%) and testing data set of 108 clinical instances (40%)

Method

Convolutional neural networks (CNNs)

Convolutional Neural Networks (CNNs), in contrast to the artificial neural networks, are a deep learning approach that has a layer, which allows the extraction of features

Figure 2 CNN-Deep learning method.

[18, 19, 20, 21, 22]. CNNs that produce good values for performance results in image processing [23, 24]. CNN architecture (Figure 2) consists of following layers [19] ;

*Convolutional neural networks models:*Models like Alex Net, Le Net, ZF Net, VGG-16, GoogLe Net, Microsoft RestNet are the most common CNN models in the literature. These models play an important role in improving deep learning. Therefore, they are very important. Le Net; It was published in 1998 and is the first successful CNN model. It was prepared by Yann Lecun et al. to read the numbers on the mails and bank checks. The LeNet architecture consists of full-connected layer, relu (activation) layer, pooling layer, and soft-connected layer.

AlexNet is a CNN model developed by Hinton, Krizhevsky and Sutskever. AlexNet won the ImageNet competition in 2012 and promoted deep learning around the world. It consists of a total of 25 layers with consecutive convolutional layers and pooling layers. The activation function (Relu) was used for nonlinear functions. This activation function was used to shorten the training time as it was faster than the classical function. The dropout layer was used to prevent excessive learning and hanging during the training process. Gradient descent model was used for weight delays and momentum values. Generally, after each convolution layer, the relu layer, which is an activation layer, is used. In addition, there are input layer, normalization layer, pooling layer, dropout layer, full connected layer, soft connected layer (SoftMax) and output layer. In this multi-layered structure, each layer has to complete its own process and then transfer the data to the next layer. When the input data is transmitted within the network, the amount of data between the layers is quite high. It takes a long time to execute these operations with a normal processor. By using GPUs, more process is performed at the same time, reducing the processing time. Therefore, GPU (Graphical Processing Unit) graphics processors are used in deep learning architectures.

ZF Net; It is a model that is an improved version of AlexNet architecture and won the ImageNet competition of 2013. In AlexNet, 11x11 filter is used for convolution in the input layer, while ZFNet has 7x7 matrix. RELUs function was used for activation, gradient descent was used for training and cross entropy loss was used for error loss. A visualization technique called Deconvolutional Network has been developed in ZFNet architecture. With this technique, a different dimension was brought to the architecture and the deep learning architecture was carried to a more successful point.

VGG-16; is a simple network model developed for better results. The most important difference that distinguishes VGG-16 from the previous models is that the pooling layers follow the double or triple convolution layers. Unlike in other deep learning methods, 2x2 and 3x3 filters are applied in the convolutions.

Google Net; It has a complex structure consisting of the combination of Inception modules that have won ImageNet-2014 competition. GoogleNet has 22 layers of depth and it has a structure consisting of 144 layers. It has created a different formation from the deep learning architectures that appeared before by filtering in different dimensions with the Inception module. Different sizes of filtering are done with the Inception module. These filters are filters, which used to reduce size. It contains 12 times less parameters than AlexNet. The number of layers used may differ according to the independent building blocks. Unlike the successive layered structure in other deep learning architectures, a depth structure was created. A modular filtering logic has been introduced that forms this depth.

Microsoft Rest Net; Designed to be deeper than all architectural structures, the model was the winner of the 2015-ImageNet competition. It is the first network that has 34 layer and consists of residual blocks. ResNet architecture, which has a depth above previous architectures, is more than the number of layers in other deep learning architectures. In the Microsoft ResNet architecture, Residual Block, which is fed with Residual Value between two RELUs and linear layers, has been created. With this architecture, it is thought that the learning process will take place more quickly.

The date of emergence of deep learning algorithms, number of parameters and error rates has shown in Table 1.

Table 1 Comparision of architectures.

Year	Deep Learning Algorithm	Error Rates (%)	Number of Parameters
1998	LeNET		60K
2012	AlexNET	15.3	60 Mil.
2013	ZFNet	14.8	
2014	GoogleNet	6.67	4 Mil.
2014	VggNet	7.3	138 Mil.
2015	ResNet	3.6	

Application

The computer that the application is modeled on has a 3.50GHz processor and 16 GB memory. MATLAB is used for programming. From the UCI dataset, digital data of 270 patients with heart attack risk are converted to image. Of the 270 images, 162 are used for training and 108 are used for testing. Selected inputs from the UCI dataset and other details are presented in Figure 1. The inputs of the proposed model are identified as; age, sex, chest pain, resting blood pressure, cholesterol, fasting blood sugar, resting ECG results, maximum heart rate achieved, exercise induced angina, ST depression induced by exercise, the slope of the peak exercise, number of major vessels and thallium heart scan. In order to create a model input pattern for each individual, an image is obtained from the values belonging to the inputs as a digital data in the data set (Figure 3). Column pixels for image; it consists of the values of the individual input parameters. When creating the image from the digital data, the related value is normalized by reducing it between 0-255. The obtained images are then used for training in the CNN model.

In the proposed work, the Alexnet CNN deep learning architecture was used for heart attack risk assessment. Dropout value was determined as 0.5% on fully connected layers, preventing the data from overfitting.

- 1 Convolution with 11×11 kernel size
- Rectified Linear Unit Layer Activation
- Response Normalization Layer
- 1 Maximum Pooling
- 2 Convolution with 5×5 kernel size
- Rectified Linear Unit Layer
- Response Normalization Layer
- 2 Maximum Pooling (3×3)
- 3 Convolution with 3×3 kernel size
- Rectified Linear Unit Layer Activation
- 4 Convolution with 3×3 kernel size
- Rectified Linear Unit Layer Activation
- 5 Convolution with 3×3 kernel size
- Rectified Linear Unit Layer Activation
- 3 Maximum Pooling (3×3)
- Fully Connected Layer (4096 nodes)
- Rectified Linear Unit Layer Activation
- Fully Connected Layer (4096 nodes)
- Rectified Linear Unit Layer
- Soft-max out

The application is coded in Python. In the proposed CNN model, Alex Net deep learning algorithm was used for classification. In addition, Deep Reinforced Network and ANFIS were applied to the same problem for the comparison. All algorithms are run in the Python development environment that is called 'Jupyter Notebook'. Also Keras, Tensorflow and matplotlib libraries are used for all models in the application section.

Results

In this study; a new method based on CNN is proposed for early detection of possible heart attack, which is a great risk for human life. Using the heart attack data set obtained from the UCI machine learning database, the classification performances of different classifiers and attribute groups on balanced and unbalanced datasets for the features triggering the heart attack are examined. A pattern consisting of 13 properties, five different feature groups, four different classifiers and a data balancing approach was created with 13x5x4x2 = 520 experiments. Experiment results are evaluated from different perspectives. In addition to the proposed CNN architecture, other architectures have been tested and evaluated numerically. Heart attack risk assessment statistics of proposed and other architectures are presented in Table 3. The mean accuracy performance of the architectures was 94.34% for the proposed deep learning method, 91.58% for the ANFIS, and 92.66% for the deep multilayer neural network. These results show that the proposed CNN architecture is more successful than other architectures. The performance of the proposed method is compared with similar previous studies and the performance of the proposed method is found higher.

Table 2 Comparision of architectures.

	Proposed CNN	Deep Reinforced Network	ANFIS
Accuracy	94.34	92.66	89.58
Sensivity	91.83	90.10	88.16
Specifity	92.65	91.24	88.31
False Positive Rate	0.03	0.04	0.06
False Negative Rate	0.05	0.06	0.08
RMSE	1.45	2.18	4.16

Traditional features are commonly used in the literature, the features obtained by transfer learning from a pre-trained model and their combinations are evaluated. Because of the experiments, it is concluded that different classification approaches and different feature groups should be considered separately for each heart attack feature. Moreover; variability is observed at the level of the classifiers' performance criteria, and results that make a particular classifier stand out in all criteria cannot be obtained. The data set obtained from the UCI database has an unbalanced distribution. This unbalanced distribution leads to a higher estimate of the dominant class and a lower estimate of the minority.

High classification performance and low sensitivity measurements confirm this conclusion. When the data sets are balanced, the decrease in the classification performance and the increase in the sensitivity value shows that the classes in the minority are better predicted and the relative prediction rate of the dominant class decreases. The increase in the minority class contributes little to the performance of the classification but high to the sensitivity rate. The reason for this is that the classification performance is calculated over the sum of the samples in the whole data set, and the sensitivity is calculated based on class and averaged. The certainty value is not affected much by the balancing process. This is due to the low false-negative rate in both conditions (balanced / unbalanced data). In terms of the classification methods, designed deep learning architectures provide high classification performance. ANFIS has a high accuracy rate of sensitivity. There is no significant difference between the classifiers in the value of certainty. Figure 5 using a single model structure while estimating mechanisms are being established. This study will contribute to the literature in terms of examining various mechanisms and combinations thereof.

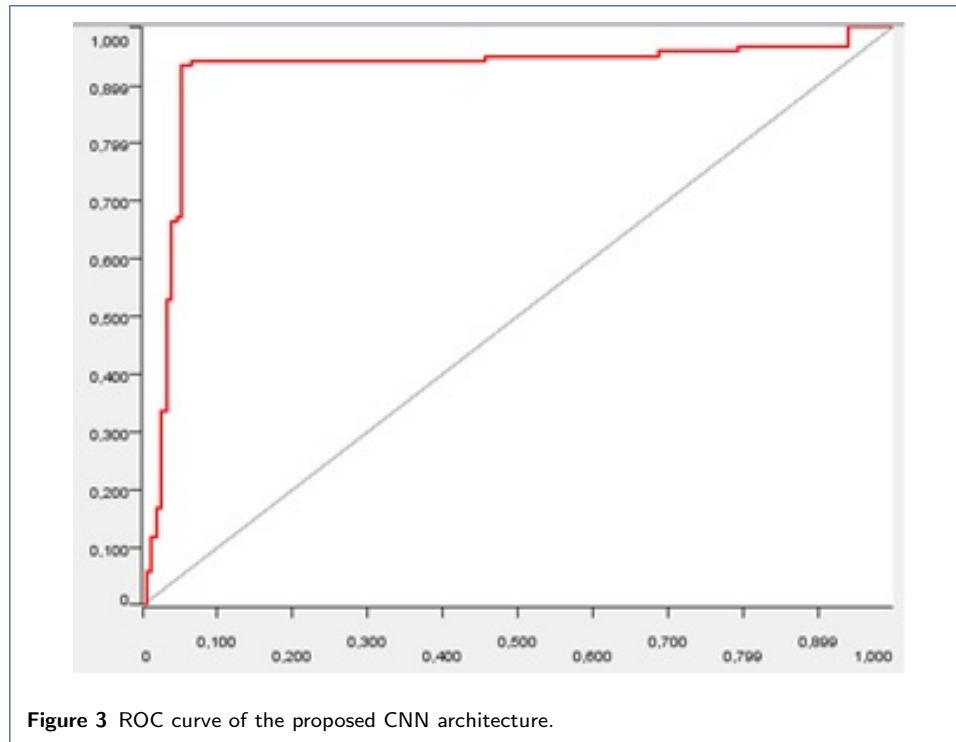
The proposed CNN method obtained better results in terms of accuracy than both the feed forward deep reinforced learning architecture and the ANFIS architecture. However, the temporal performance during model estimation in both training and live systems are lower than other architectures applied in this study (Table 4). Both the performance criterion results presented in Table 3 and the processing time of the architectures given in Table 4 indicate that the proposed architecture is applicable according to the temporal criticality of the problem to be applied.

Table 3 Comparision of architectures.

	Proposed CNN	Deep Reinforced Network	ANFIS
Training time (min./sec.)	19/26	15/17	11/26
Test time (sec.)	32.12	28.11	16.15

Discussion

In this study, the predictability before the cardiac arrest of the risk of heart attack, which ranks top of the list among the death rates all over the world, with the deep

Figure 3 ROC curve of the proposed CNN architecture.

learning method was shown. The proposed model, the applicability of which has been demonstrated as a result of the findings obtained, can be integrated into the system which is in a wearable technology and the risks of heart attacks can be continuously controlled by obtaining the instantaneous information of the people.

Conclusions: In the study, the applicability of proposed CNN method with images obtained from numerical data has been demonstrated. With the early prediction system proposed, it is now possible to take precautionary measures against possible cardiac arrest. In this study; a new method based on CNN is proposed for early detection of possible heart attack, which is a great risk for human life. Different from studies in the literature, it was used in the proposed CNN method by converting all numerical data from dataset into 2D images. Afterwards, to show whether this the proposed method is applicable or not, the dataset which is numerical form was applied to other methods and compared.

Abbreviations
- ANFIS: Adaptive Neural-Fuzzy Inference System
- CNN: Convolutional Neural Network
- GPU:Graphics Processing Unit
- ROC: Receiver Operating Characteristic
- UCI: University of California Irvine
- WHO: World Health Organization

Ethics approval and consent to participate
The dataset used in this study is the heart attack dataset in the UCI machine learning database which is open shared and has no personal information in the data. Therefore, there are no ethical problems.

Consent for publication
I understand that the text and any pictures or videos published in the article will be freely available on the internet and may be seen by the general public.

Availability of data and material
The datasets analysed during the current study are available in the UCI repository,
[https://archive.ics.uci.edu/ml/datasets.php]

Competing interests
The authors declare that they have no competing interests.

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