fNIRS Neural Signal Classification of Four Finger Tasks using Ensemble Multitree Genetic Programming

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***Abstract*—Accuracy of classification and recognition in neural signal is the most important issue to evaluate the clinical assessment or extraction of features in brain computer interface. Especially, classification of multitasks by measuring functional Near-Infrared Spectroscopy (fNIRS) is a challenging due to its low spatiotemporal resolution. To improve the classification accuracy of fNIRS neural signals for multitasks, an evolutionary computing method was proposed. Four healthy participants performed four finger tasks which are digit-active, digit-passive, thumb-active and thumb-passive. To classify the four tasks, a multitask classifier was devised by the ensemble multitree genetic programming (EMGP). The experimental results validate the performance of the proposed classifier. The comparison of the conventional and proposed classifiers at the real classification experiment shows the higher accuracy of the proposed method. Moreover, it reveals the improvement of classification accuracy when compared with conventional classifiers in the additional experiment of fifteen dataset in University of California Irvine machine learning repository. The proposed classifier can be effective to classify and recognize the fNIRS neural signals during multitasks. Moreover, the subject dependent learning can be designed for the local brain activation training based on neuro-feedback. After data learning for all classes, the subject tries to make their brain activation of an active task as similar with a passive task by the online motor-imagery with action observation. As a result, the subject is trained to concentrate his brain activation for the essential area of brain. The proposed classifier can be applied well because high classification accuracy is essential to the neuro-training system. Finally, the classification accuracy of the proposed EMGP is 5.48% higher than the average of conventional classifiers.**

Keywords–fNIRS; Classification; Finger Tasks; Neural Signal; Emsemble Learning; Mutitree Genetic Programming

I. Introduction

Paralysis from a stroke or nerve injury has a terrible effect on patients' daily life. Especially, upper limb disorders greatly affect their routine with great inconveniences. Over 30 percent of stroke survivors suffer because their hand motor ability is increasingly turning into disability, even after rehabilitation for a year [1]. The conventional rehabilitation programs only provide passive approaches to patients, but it has limited effect [2]. Currently, there are many researches for promoting the neuroplasticity by brain monitoring or neurofeedback [3]. The patients can perform the interventions more actively by neurofeedback from a brain computer interface (BCI). The first step for the neurofeedback is the neural signal classification and recognition of patients.

Many techniques allow for real-time monitoring of brain activity. Invasive approaches have been successfully employed in human primates. Although such invasive methods have a high performance, non-invasive sensors to monitor brain activity are preferred in order to widely adapt to most of clinical environments, including rehabilitation medicine. Conventional non-invasive brain recording techniques are mainly electroencephalography (EEG), functional magnetic resonance imaging (fMRI) and functional near-infrared spectroscopy (fNIRS).

EEG is the most widely used technique adopted in BCI [3]. EEG provides good time and space resolution, but it has too high sensitivity so that the noisy data requires additional pre-processing for training [4]. fMRI has also been used to interface with the human brain [3]. Although it has advantages such as high temporal and spatial resolution and whole brain coverage including the central, electro-magnetic compatibility constraints, high sensitivity to movement and high costs make it unsuitable in a common therapeutic environment. fNIRS is an optical approach that locally observes cortical activity based on the neurovascular coupling [4]. It is easy to use, safe, affordable, and relatively tolerant to movements. So it can be mobile and operated wirelessly [5]. Compared to EEG, fNIRS allows for the classification of more stable cortical activity and requires less additional processing [4]. There have been many researches of neurofeedback based on fNIRS for various types of classifiers and applications. Classification of hand motor imagery with support vector machines (SVM) and hidden Markov models (HMM) were implemented [6]. An online classification system for BCI was researched in [7]. The classifier was based on a real time difference calculation for both side hand motor imagery. In these studies, the brain activation was induced by motor tasks.

Although many researches have been studied, it is still difficult to design an effective classification system for neuro-monitoring and neurofeedback because the kinds of data have some problems such as vast volume and noises from the human body. For grasping tasks recognition with considerable accuracy, the high-density observation that uses a lot of sensors and frequent measurement is required but it dramatically increases the size of data. To overcome these problems effectively, this study approaches the system with a perspective on machine learning by means of evolutionary computation (EC) inspired by biology that shows outstanding performance to find global optimum model. In this paper, we proposed a classification method based on the ensemble multitree genetic programming (EMGP) for the neural signal recognition for multiple tasks with higher accuracy. The main advantage of the proposed learning algorithm is that the search algorithm based on EC looks for global optimum model in very wide search space effectively, and the sensitivity feature of genetic programming (GP) helps the multi classifiers to ensure their diversity. Consequently, the low spatial resolution problems of fNIRS measurement can be relieved.

The rest of the paper is organized as follows: Section 2 describes the proposed neural signal classification method in detail and in Section 3, the experimental results are depicted. Conclusion is presented in Section 4.

II. Proposed Classification Method

The proposed classification method consists of the data modeling and the EMGP classifier. The neural signal data are collected by fNIRS, noise is reduced by preprocessing, and a data model is built to make the data easier to be handled by the multi-tasks classifier. The proposed EMGP has the major distinction of the multiple classifiers with parallel learning in contrast with [8]. This difference gives the outstanding robustness and search capability to the proposed method. Of course, some modifications are required to compose the effective algorithm with consideration for the structural aspect, characteristics of the data, and medical domain knowledge. All mentioned methods are summarized in the subsections below.

A. fNIRS data modeling for multitask classifier

The fNIRS neural signals are acquired by 24-channels optical brain-function imaging system (FOIRE-3000, Shimadzu Co) at a sampling rate of 7.7 Hz. It uses safe near-infrared light to assess the concentrations of oxygenated hemoglobin (Oxy-Hb) and deoxygenated hemoglobin (Deoxy-Hb) in the cerebral blood at wavelengths of 780 nm, 805 nm, and 830 nm. This study uses Oxy-Hb for analysis and classification, which is found to be more correlated with the regional cerebral blood flow (rCBF) than deoxy-Hb [9]. An increase in rCBF reflects an increase in neural activity [10]. The optical probes are placed on the fronto-parietal regions of the brain cortex to cover an area of 21×12cm. The subjects performed five types of tasks denoted by T_{DA}, T_{DP}, T_{TA}, T_{TP}, and $Rest$ as follows:

- $\{T_{DA}\}$ - Actively grasping four digits except thumb
- $\{T_{DP}\}$ - Passively grasping four digits except thumb by functional electrical stimulation (FES)
- $\{T_{TA}\}$ - Actively grasping thumb except the remains
- $\{T_{TP}\}$ - Passively grasping thumb by FES
- $\{Rest\}$ - Rest without performing any tasks

Each subject performed four types of tasks for three times for a total of 48 sessions for 4 subjects. The task signs are sent to subject at regular intervals like [Rest → Task → Rest] as shown in Figure 1. The signals were collected via 24 optical fibers attached to the pre-frontal cortex for 40 seconds in each session. The dataset contained 14,784 samples and 24 features

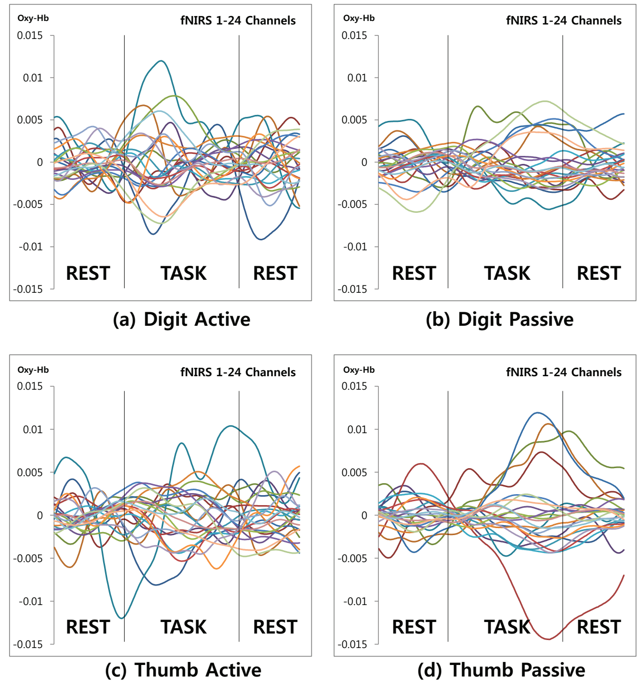

Figure 1. fNIRS data model of four finger tasks.

as described in Figure 1. Noise interference in hemodynamic signals may arise from instrumental, experimental, or physiological sources. Particularly, physiological noises often overlap in frequency with the expected neural signals [11]. In this study, we employ wavelets [12] for noise reduction.

B. Multitree Genetic Programming (MGP)

In the proposed classifier the fitness function, selection strategy, crossover, and mutation of conventional MGP have been modified. The major point is the ensemble in the parallel operation of multiple classifiers. It is robust from noises and can improve the accuracy by the concept of swarm intelligence [13]. If the swarm who has a number of individuals has diversity and active cooperation amongst individuals, the swarm is more intelligent than any individual in the swarm. The system is designed to induce this swarm intelligence. Sufficient numbers of multitrees satisfy the first condition. In addition, the sensitivity of GP and mutation operator help the swarm keep the diversity. Finally, the crossover in parallelized learning of evolutionary groups leads to the cooperation of individuals.

1) Problem formulation: Given a set of pre-processed training data $X := \{x_1, x_2, \ldots, x_m\}$ with corresponding labels $Y := \{y_1, y_2, \ldots, y_m\}$, where $y_i \in \{\pm 1\}$ for $i = 1, i = 2, \ldots, m$, our next goal is to estimate a function $f : X \rightarrow \{\pm 1\}$ to predict whether a new signal observation $z \in X^*$ will belong to class $+1$ or -1. We define classes for the tasks $\{T_{DA}\}$, $\{T_{DP}\}$, $\{T_{TA}\}$, $\{T_{TP}\}$, and $\{Rest\}$.

2) The structure of an individual: An MGP individual consists of independent n trees. The best fitness trees in each group at the final stage of MGP learning become n classifiers. In this study, the internal nodes of tree consist of math operators, i.e. $\{+, -, *, /, exp, log, root\}$. The leaf nodes are selected among R and features. R is random variable from 0 to 1. The decision of each tree is determined by the result of the formula calculation. In other words, if the result is negative, the decision is class A.

3) Ensemble technique for MGP: We utilized and modified the Bagging and Boosting [14] ensemble methods for MGP. At the bagging, different sampled feature sets are allocated to MGP evolving group. Although the different feature sets lead to additional tree validation after the external crossover, it is valuable to reserve the diversity of classifiers. Boosting technique is performed to ensure the diversity between trees in a classifier during the learning time. The details of ensemble for MGP are treated as follows.

Upper nodes of GP individual are decided from early generations as the learning directivity can be kept in the state with a high probability. Therefore, the initial weighting significantly influences the diversity of the ensemble classifiers. To obtain the diversity, each of n groups has different weighting values toward the samples that are separated in n groups by a random sampling algorithm. The detailed process of the ensemble is shown in Figure 2.

The variation of fitness in a group decreases as passing generations. The proposed system sets a new weighting criterion when the fitness variation is less than a lower threshold for the verification of convergence. The weighting criteria for each sample set the number of misclassifications for the individuals in the top k percent. The k is empirically decided as 10 in this paper. The lower threshold is 50 percent of the variation when the weighting criteria are changed.

Algorithm 1 Discrete AdaBoost for EMGP

Samples $x_1, x_2 \ldots, x_n$
Desired outputs $y_1, y_2, \ldots, y_n, y \in \{-1, 1\}$
Initial weight $w_{1,1}, w_{2,1}, \ldots, w_{n,1}$ set to $\frac{1}{n}$
Separate the samples to k groups by random sampling
ith evolving group weight update $w = w \times \alpha$ in ith sample group
Error function $E(f(x), y, i) = e^{-y_i f(x_i)}$
Weak learners $h : x \rightarrow [-1, 1]$
for t in $1, 2, \ldots, T$ **do**
    Choose $f_t(x)$:
    Find weak learner $h_t(x)$ that minimizes ϵ_t, the weighted sum error for misclassified points $\epsilon_t = \sum_i w_{i,t} E(h_t(x), y, i)$
    Choose $\alpha_t = \frac{1}{2} \ln \left(\frac{1-\epsilon_t}{\epsilon_t} \right)$
    Add to ensemble:
    $F_t(x) = F_{t-1}(x) + \alpha_t h_t(x)$
    Update weights:
    $w_{i,t+1} = w_{i,t} e^{-y_i \alpha_t h_t(x_i)}$ for all i
    Renormalize $w_{i,t+1}$ such that $\sum_i w_{i,t+1} = 1$
end for

Figure 2. The Algorithm Specification of Discrete AdaBoost for EMGP

4) Final decision: Instead of training a single classifier, we train multiple GP groups which mean the number of tree in each individual for the purpose of further improvment in the overall accuracy as described in Figure 1. We consider a multiple n - classifier functions $\{f_1, f_2, \ldots, f_n\}$ and a data set $\{(x_i, y_i)_{i=1}^m\}, x_i \in X, y \in Y$. The tree groups are trained in parallel to predict $f_{i=1}^n : x \rightarrow \{\pm 1\}^n$. The outputs from all classifier functions are then defined as an m-dimensional binary vector $y = [y_{1,i}, y_{2,i}, \ldots, y_{m,i}]$, such that $y_{j,i} = 1$ if f_i recognizes x_j and 0 otherwise for $i = 1, 2, \ldots, n$. The number of correct assignments is $N_1(f_i) = \sum_{j=1}^m y_{j,i}$ and the number of mistakes is $N_0(f_i) = m - \sum_{j=1}^m y_{j,i}$. In order to make the final decision from the set of functions $\{f_i, \ldots, f_n\}$, we define the following majority voting rule:

$$\begin{cases} +1 & if \quad \sum_i^n f_i(z) \geq k \\ -1 & else \quad \sum_i^n f_i(z) \leq n - k \end{cases} \tag{1}$$

where $k < n$ and $i = 1, 2, \ldots, k$ making similar predictions defined by the $k - of - n$ majority classifier for $k \geq \frac{n}{2}$. Thus, we have two possible outcomes from all classifiers $F : X \rightarrow \{+1, -1\}$. Machine learning consists of training and testing phases. In both phases, we train and test five different groups of multiple classifiers $E_1, E_2, \ldots, E_5$.

Group E_1 is trained by taking samples from the digit-active task $\{T_{DA}\}$ as positive and samples from the remaining tasks as negative. Likewise, group E_2 is trained by taking samples from digit-passive task $\{T_{DP}\}$ as positive and samples from the remaining tasks as negative.

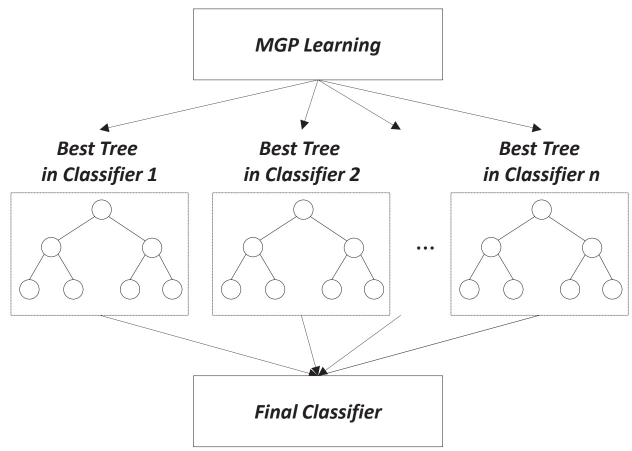

Figure 3. Combining decisions from the best tree in each classifier

In the training phase, each individual base MGP is separately trained using the same input data from the 10-fold cross validation. During the testing phase, unseen examples are applied to all base functions simultaneously in real time. Further, a collective decision is obtained on the basis of the majority voting scheme using Equation (1). In other words, once each of the n base classifiers from the MGP evolving group has cast its vote as shown in Figure 3. The majority voting strategy assigns the test patterns to the class with the largest number of votes and outputs are provided as the final prediction.

III. EXPERIMENTAL RESULTS

The simulation environment of the proposed EMGP is constructed in C++. Parameters such as population size, depth limitation, iteration number, probability of internal crossover, external crossover, and mutation are set 10000 individuals, 10 depths, 1000 generation, 0.7, 0.05, and 0.1, respectively. The parameters of the conventional classifiers are set as default value of WEKA [15]. All accuracy results in this paper were obtained by 10-fold cross validation.

TABLE I. ACCURACIES AND ROOT RELATIVE SQUARED ERROR (RRSE) (%) OF THE CONVENTIONS AND PROPOSED EMGP FOR OVERALL BRAIN DATA

Classifier	Accuracies	RRSE
PART	97.78	25.20
Jrip	96.59	31.27
Naive Bayes	57.01	96.98
Bayes Net	74.20	75.36
J48	98.13	22.83
BFTree	97.44	26.73
FT	97.88	24.24
NBTree	97.59	25.77
RBFNetwork	62.48	86.47
Max. of Conv.	98.13	22.83
Proposed GP	99.39	15.03

TABLE II. CLASSIFICATION ACCURACIES (%) OF CONVENTIONAL CLASSIFIERS AND PROPOSED EMGP FOR SUBJECT DEPENDENT LEARNING

Classifier	S_1	S_2	S_3	S_4
PART	98.64	98.53	98.26	98.97
Jrip	98.32	97.51	96.78	97.83
Naive Bayes	76.81	72.67	73.05	71.42
Bayes Net	92.47	95.34	90.71	88.90
J48	98.43	98.62	98.34	98.91
BFTree	97.94	97.47	98.13	98.45
FT	98.56	98.86	98.86	98.62
NBTree	97.59	98.02	97.72	98.29
RBFNetwork	83.90	84.03	85.44	80.76
Max. of Conv.	98.64	98.86	98.86	98.97
Proposed GP	99.43	99.10	99.02	99.24

Table 1 shows the classification results for conventional classifiers which are implemented in WEKA and the proposed EMGP. The conventional algorithms used in the experiment are Pruning rule based classification tree (PART), Jrip, naive Bayesian, Bayesian Network, J48, Best First Decision Tree (BFTree), Functional trees (FT), Naive-Bayes tree (NBTree), and radial basisbasis function network (RBFNetwork). In consideration of the structure of the tree based GP, the tree-based learning algorithms such as PART, Jrip, J48, BFTree, FT, and NBTree were selected as the target of comparison tests. Probability based algorithms such as naive Bayesian and Bayesian Network; and RBFNetwrok that is a universal learning technique are used. In this experiment, the full data obtained by the previous description is compared based on the accuracy. By referring to the results of Table 1, it can be seen that the proposed classification method has the best accuracy with the minimum RRSE when compared with conventional classifiers.

In the subject dependent test as shown in Table 2, EMGP classified the four finger-grasping tasks with the best accuracy. Here we compared the performance of the training and testing for single subject data. Other signal patterns may come on the same motion according to individual differences. Thus, this experiment was performed to exclude the uncertainty. As expected, it was able to confirm that the learning accuracy is improved overall.

To show the appropriateness of the proposed method, fifteen UCI datasets [16] are used as benchmark dataset. Table 3 shows specifications of each dataset. The data set for the biological signals were chosen as a test candidate. If the learning ability is good in this result, the proposed algorithm is to be used universally in bio-signal data. Table 3 shows the classification results for conventional classifiers and the proposed EMGP. The classification accuracy of EMGP is

TABLE III. NUMBER OF SAMPLES (S) AND FEATURES (F) ALONG WITH MODEL SIZE FOR UCI DATASET, AND CLASSIFICATION ACCURACIES (%)

	Specifications			Results	
Dataset	S	F	ModelSize	Conv.	EMGP
Blood Transfusion	748	4	2992	77.20	79.54
Breast Cancer	683	9	6147	96.18	97.21
Breast Tissue	106	9	954	66.46	68.87
Cleveland	297	13	3861	50.13	44.78
Glass	214	9	1926	61.89	69.62
Heart	270	13	3510	79.55	78.51
Ionosphere	351	33	11583	89.68	95.15
Lung Cancer	27	56	1512	55.56	59.25
Olitos	120	25	3000	69.81	84.16
Parkinson	195	22	4290	82.34	90.76
Pima Indian Diabetes	768	8	6144	75.00	76.56
Sonar	208	60	12480	67.47	88.46
Soybean	47	35	1645	98.58	100.00
SPECTF Heart	80	44	3520	73.06	80.00
Wine	178	13	2314	85.52	97.75
Mean	286.13	23.53	4391.86	75.22	80.70

5.48% higher than the average of conventional classifiers.

IV. CONCLUSION

The classification of four finger-grasping tasks, based on neural signal data, isf challenging task in non-invasive neuro-monitoring due to the difficulty of recognition for activation near different cortical areas. Many machine-learning techniques have been developed to obtain highly accurate classification performance. This paper also targets the improvement of the neural signal recognition and proposes a new classification method for neural signal recognition during multitasks which is based on EMGP with considerations of the signal characteristics. The high sensitivity of GP is known as a disadvantage to handle signal data. The proposed GP tried to solve the problem by using multiple classifiers consisting of several trained GP trees with majority voting. Also, the system performs the parallel learning with several evolutionary groups. According to the experimental results, we validated the relevance of the proposed method.

In the future work, approaches based on probability theory regarding the margin to solve such problems would develop GP classifiers. The current decision which combines method with the majority voting can be improved by theoretical approaches or advanced ensemble combiners such as weighted voting and stacking. This study can be applied to activate the brain training for enhancing brain plasticity. For the applications, the subject dependent learning in this paper can be designed for the local brain activation training based on neuro-feedback. In other words, the learning models] collected through a pre-experiment can systematically help the user in a specific area immersion. Future research will continue to focus on the application of EMGP.

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REFERENCES

[1] E. Buch, et al., “Think to move: a neuromagnetic brain-computer interface system for chronic stroke.” Stroke, vol. 39, no. 3, 2008, pp. 910-917.

[2] N. Hogan, H. I. Krebs, B. Rohrer and J. J. Palazzolo, "Motions or muscles? Some behavioral factors underlying robotic assistance of motor recovery." Journal of rehabilitation research and development, vol. 43, no. 5, 2006, pp. 605.

[3] W. Wang, et al., "Neural interface technology for rehabilitation: exploiting and promoting neuroplasticity." Physical medicine and rehabilitation clinics of North America, vol. 21 no. 1, 2010, pp. 157-178.

[4] N. Birbaumer, "Breaking the silence: brain-computer interfaces (BCI) for communication and motor control." Psychophysiology, vol. 43, no. 6, 2006, pp. 517-532.

[5] M. Ferrari and Q. Valentina, "A brief review on the history of human functional near-infrared spectroscopy (fNIRS) development and fields of application." Neuroimage, vol. 63, no. 2, 2012, pp. 921-935.

[6] N. Birbaumer and G. C. Leonardo, "Brain-computer interfaces: communication and restoration of movement in paralysis." The Journal of physiology, vol. 579, no. 3, 2007, pp. 621-636.

[7] G. Pfurtscheller, et al., "The hybrid BCI." Frontiers in neuroscience, vol. 4, 2010.

[8] D. P. Muni, R. P. Nikhil and D. Jyotirmoy, "A novel approach to design classifiers using genetic programming." Evolutionary Computation, IEEE Transactions on, vol. 8, no. 2, 2004, pp. 183-196.

[9] E. Gratton, et al., "Measurement of brain activity by near-infrared light." Journal of Biomedical Optics, vol. 10, no. 1, 2005, pp. 011008-01100813.

[10] M. Jueptner and C. Weiller, "Review: does measurement of regional cerebral blood flow reflect synaptic activity?-Implications for PET and fMRI." Neuroimage, vol. 2, no. 2PA, 1995, pp. 148-156.

[11] S. Coyle, et al., "On the suitability of near-infrared (NIR) systems for next-generation brain-computer interfaces." Physiological measurement, vol. 25, no. 4, 2004, pp. 815.

[12] B. Abibullaev and J. An, "Classification of frontal cortex haemodynamic responses during cognitive tasks using wavelet transforms and machine learning algorithms." Medical engineering & physics, vol. 34, no. 10, 2012, pp. 1394-1410.

[13] E. Bonabeau and M. Christopher, "Swarm intelligence: A whole new way to think about business." Harvard business review, vol. 79, no. 5, 2001, pp. 106-115.

[14] T. G. Dietterich, "Ensemble methods in machine learning." Multiple classifier systems, Springer Berlin Heidelberg, 2000, pp. 1-15.

[15] M. Hall, et al., "The WEKA data mining software: an update." ACM SIGKDD explorations newsletter, vol. 11, no. 1, 2009, pp. 10-18.

[16] A. Asuncion and N. David, "UCI machine learning repository." [http://archive. ics. uci. edu/ml] (2007).

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