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ORTHOPEDIC DIAGNOSTICS WITH ENSEMBLES OF LEARNING SYSTEMS

1. INTRODUCTION

The demand for a variety of prostheses, resulting from increasingly higher number of injuries and osteoarticular pathologies which are a consequence of ageing society, stimulates the necessity for improvement of materials used for implants [1]. Reconstruction surgery allows for repairing the tissues damaged as a result of an injury or pathological changes, which makes it possible to regain the lost functions [2]. An essential problem is proper diagnosing of tissue structure and identification of functional deficiency. Achievement of these aims necessitates the use of proper diagnostic methods, precision and experience of the surgeons [7].

Due to its functions, hip joint is one of the most frequently used load--bearing joint, which leads to occurrence of degenerative changes. Human race has always sought methods of reconstruction of damaged tissues and organs and the scientists have focused on these activities for over a hundred years. The only method of treatment in the case of serious problems was to remove the damaged organ. However, it improved life comfort only to an insignificant degree. The situation changed when progress in both medical science and material engineering allowed for collection and transplantation of living tissues and implantation of synthetic or natural biomaterials in order to restore the functions of defected or even removed organs.

In the paper, we classify and assess orthopaedic data by neuro-fuzzy classifiers. Classifiers can be combined to improve accuracy [6]. By combining intelligent learning systems, the model robustness and accuracy is nearly always improved, comparing to single-model solutions. Popular methods are bagging and boosting which are meta-algorithms for learning different classifiers. They assign weights to learning samples according to their performance on earlier classifiers in the ensemble. Thus subsystems are trained with different datasets created from the base dataset. We use another method called negative correlation learning to create an ensemble of classifiers.

Learning the ensemble of classifiers correctly diagnosing hip joint pathology and choosing suitable cure methodology required selecting a group of patients with hip joint dysfunction.

We used 150 patients' histories from Orthopedics and Traumatic Surgery Department of NMP Voivodship Specialist Hospital in Częstochowa. Data were divided into the following groups:

- Clinical trials, which assessed the reasons for the pathology, patient age, anthropometric and goniometric measurements, coexisting diseases and the involvement of the patient during the postoperative rehabilitation and intensity of use of an artificial hip joint (motility).
- Radiological examinations, where X-ray images allowed us to determine changes in bone in Gruen zones and areas of heterotopic ossification (Brook's classification). On the basis of X-ray images the size of the femur was determined (including the shape and size of the femur and the marrow cavity to determine the mechanical axis of the bone, angle of neck-molar, the existence of the femoral head, the steepness of the acetabulum) pathologically changed hip joint functionality and functionality of the knee.
- Experimental studies which consisted in the determining of the impact of selected types of commercial implants to maps of the stress of the femur using human hip joint simulator, see Figure 1.

Fig 1. Femur bone placed on human hip joint simulator and connected to the measuring and recording device.

- Experimental examinations involving the assessment of the size and degree of wear of the head - acetabulum made of various materials and to adapt these parameters to individual patient needs was conducted on the wear simulator of endoprostheses, shown in Figure 2.

Fig. 2 Simulator to examine friction and wear of artificial joints

- Tribological tests, which were conducted on commercial heads and acetabulum of leading manufacturers, including different types of friction couples commonly used in orthopedics. The nature of the simulator allows loading the examined system in accordance with the load of the limb during the gait and movement kinematics allows performing friction-wear test with analysis of both mating surfaces, as well as wear products. Wear processes of the hip join components on the simulator has been compared with the course of wear dentures with a given history in the human body - removed for aseptic loosening.

2. RESEARCH METHODS

Combining classifiers to improve accuracy gains a lot of attention nowadays. Various known classifiers [9, 10, 11] and other learning systems [8] can be combined in ensembles to improve accuracy [4, 5, 6]. By combining intelligent learning systems, the model robustness and accuracy is nearly always improved, comparing to single-model solutions. Combined systems are developed under different names: blending, combining models, bundling, ensemble of classifiers, committee of experts. Classifiers can be combined at the level of features, data subsets, using different classifiers or different combiners, see Figure 1. Popular methods are bagging and boosting [12] which are meta-algorithms for learning different classifiers. They assign weights to learning samples according to their performance on earlier classifiers in the ensemble. Thus subsystems are trained with different datasets.

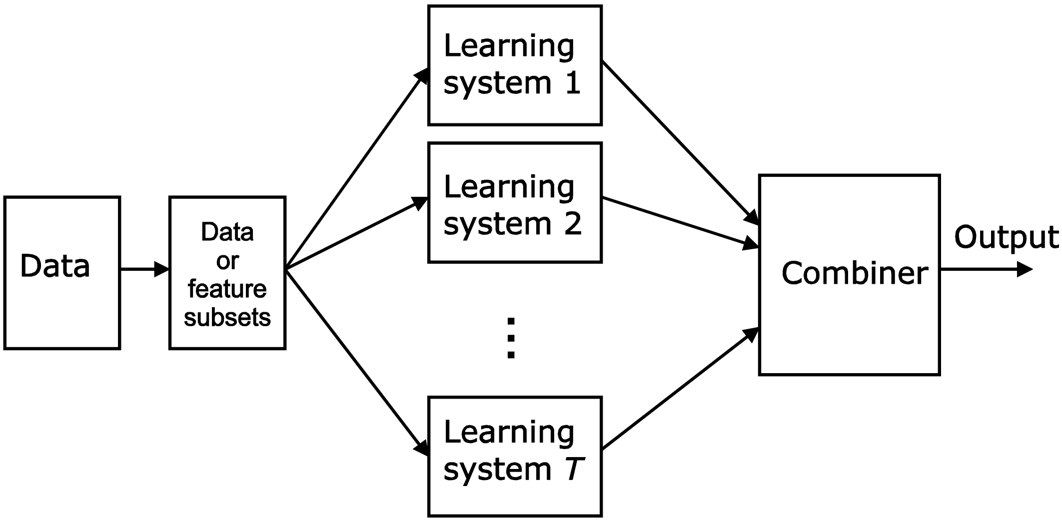

Fig. 3. Various levels of creating learning system ensembles [8].

Negative correlation learning [4,5] is another meta-learning algorithm for creating negatively correlated ensembles. Let us denote the l-th learning vector by $\mathbf{z}^l = [x_1^l, ..., x_n^l, y^l]$, $l = 1...m$, is the number of a vector in the learning sequence, n is the dimension of input vector $\mathbf{x}^l$, and y^l is the learning class label. The overall output of the ensemble of classifiers is computed by averaging outputs of all hypothesis

$$f(\mathbf{x}) = \frac{1}{T}\sum_{t=1}^{T} h_t(\mathbf{x}), \tag{1}$$

where $h_t(\mathbf{x})$ is the response of the hypothesis t on the basis of feature vector $\mathbf{x} = [x_1, ..., x_n]$. All neuro-fuzzy parameters, i.e. antecedent and consequent fuzzy sets parameters, are tuned by the backpropagation algorithm. Having given learning data set of pair $(\mathbf{x}^l, y^l)$, where y^l is the desired response of the system we can use the following error measure

$$E\left(\mathbf{x}^l, y^l\right) = \frac{1}{2}\left[h_t(\mathbf{x}) - y^l\right]^2 \tag{2}$$

Every neuro-fuzzy system parameter, denoted for simplicity as w, can be determined by minimizing the error measure in the iterative procedure. For every iteration t, the parameter value is computed by

$$w(t+1) = w(t) - \eta \frac{\partial E\left(\mathbf{x}^l, y^l; t\right)}{\partial w(t)} \tag{3}$$

where η is a learning coefficient. This is a standard gradient learning procedure. As we build an ensemble of negatively correlated neuro-fuzzy systems, the error measure is modified by introducing a penalty term $p_t(l)$ and determining error after the whole epoch

$$E_t = \frac{1}{m}\sum_{l=1}^{m} E_t(l) = \frac{1}{m}\sum_{l=1}^{m}\frac{1}{2}\left(h_t(l) - y^l\right)^2 + \frac{1}{m}\sum_{l=1}^{m}\lambda p_t(l), \tag{2}$$

where λ is a coefficient responsible for the strength of decorrelation. The penalty term is defined

$$p_t(l) = \left(h_t(l) - f(\mathbf{x})\right)\sum_{k \neq l}\left(h_t(k) - f(\mathbf{x})\right). \tag{3}$$

The NCL metalearning tries to keep responses of the member neuro-fuzzy systems as different as possible, retaining at the same time classification accuracy. In other words, each of the neuro-fuzzy classifiers tries to learn its own part of the knowledge comprised in the data set.

3. SIMULATION RESULTS

Our negative correlation learning ensemble of neuro-fuzzy systems forecast and assessed changes in bone around the implant based on several hundred patients' histories from Orthopedics and Traumatic Surgery Department of NMP Voivodship Specialist Hospital in Częstochowa were used. We obtained 100% accuracy. The ensemble of four neuro-fuzzy systems, each with three fuzzy rules, was able to reflect accurately the assessment made by orthopaedists. The systems were initialized randomly by the fuzzy *c*-means clustering and then trained by the backpropagation algorithm with the negative correlation learning. The learning of each subsystem took 3000 iterations.

4. CONCLUSIONS

The paper introduces a new method for assessing orthopaedic data based on so called negative correlation learning. We assessed changes around changes around implant after total hip arthroplasty. We used several dozen inputs and one output to numerically determine level of changes in femur. The neural network was trained by the backpropagation algorithm. The algorithm is able to find a local minimum of a nonlinear function over a space of parameters of the function. In the case of neuro-fuzzy systems the parameters are fuzzy sets membership functions which store the knowledge obtained during learning.

During learning the parameters are changed to fit the network to the learning data. Using the negative correlation ensemble we achieved maximal accuracy, thus the ensemble of classifiers was able to imitate the assessments made by orthopaedists.

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