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# A Novel Comparison of Artificial Intelligence Methods for Diagnosing Knee Osteoarthritis

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## Computer Simulation

SS-0027

### A NOVEL COMPARISON OF ARTIFICIAL INTELLIGENCE METHODS FOR DIAGNOSING KNEE OSTEOARTHRITIS

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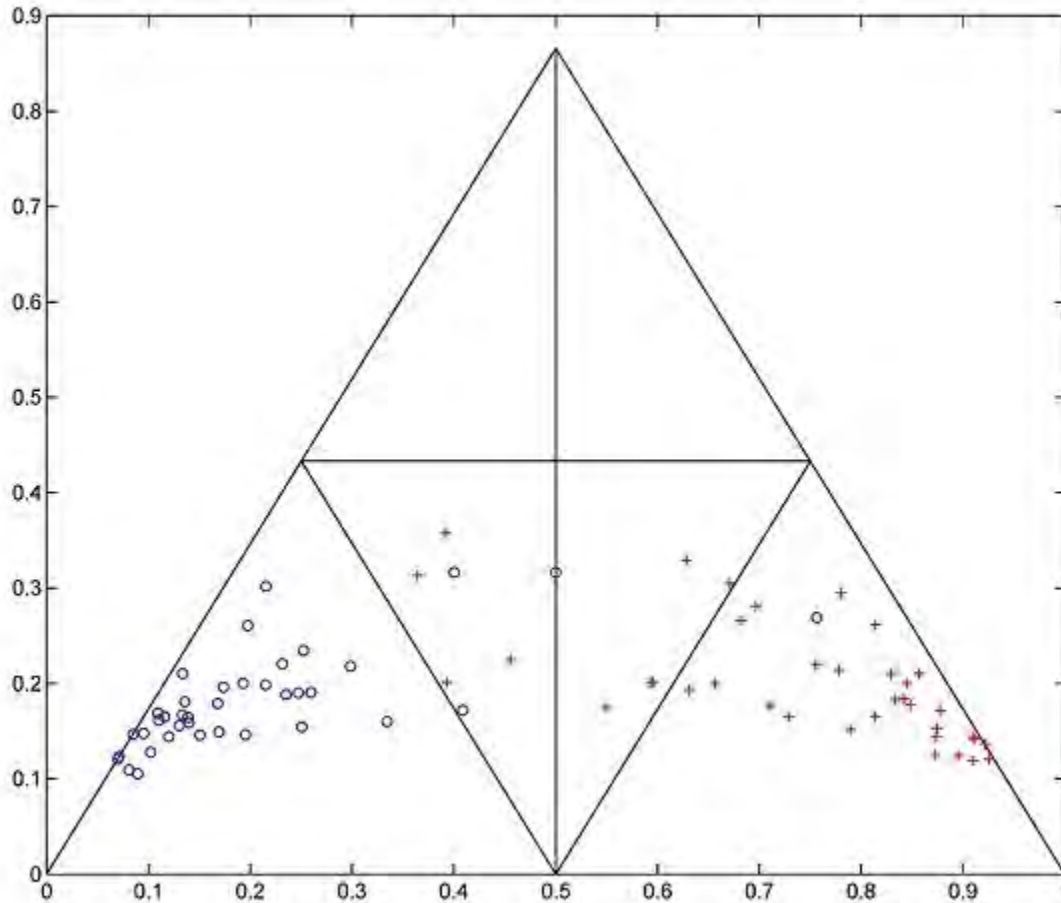
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**Introduction and Objectives:** Three dimensional motion analysis generates a great wealth of information, which has resulted in a range of mathematical techniques aimed at assisting both clinicians and researchers interpret biomechanical data [1]. Jones [2] successfully developed a technique at Cardiff University that facilitates the classification between pathological and non pathological knee function using Dempster-Shafter theory (DST), demonstrating its effectiveness in comparison to Artificial Neural Networks (ANN) and Linear Discriminate Analysis (LDA) in the classification of osteoarthritic gait. Classification techniques have advanced over the last decade with recent studies reporting high accuracies using ANN [3] and Support Vector Machines (SVM) [4]. To the best of our knowledge, this study proposes, for the first time, to compare the performance and suitability of the (i) Cardiff Classifier, (ii) ANN and (iii) SVM in discriminating between healthy and osteoarthritic knee function.

**Methods:** As this study involves dealing with long range data sets, a four-dimensional unsupervised Self-Organising Map (SOM) [5] and a supervised Multi-layer Perceptron (MLP) neural networks with one hidden layer having 20 hidden neurons [6], were built through the MatLab neural network toolboxes respectively named as 'nctool' and 'nprtool' (Mathworks inc., USA). The Lagrangian Support Vector Machines (LSVMs) [7] Machine Learning (ML)-based classification method and the Dempster-Shafter theory (DST)-based classifier ('Cardiff classifier') [2] were selected for pattern recognition tasks and classification purposes. Thirty-eight patients with late stage knee osteoarthritis (OA) and thirty-eight healthy volunteers were instructed to complete walking trials at speeds they deemed to be normal. Spatio-temporal gait data (stride length, cadence, body mass index) and principal components of knee kinematic and ground reaction force waveforms were averaged for five gait cycles. Eighteen selected biomechanical and clinical variables formed the input matrix for the three classifiers. After randomising the data, the physiological knee function of healthy volunteers and pathological function due to knee OA were used as desired outputs for the classifiers. In all neural network models tested for classification accuracy in this study, 70% of the data was used for training, 15% for a ten k-fold cross-validation to prevent over-fitting/overtraining [8], whilst the last 15% of the data was deployed for testing in order to assess the out-of-sample classification accuracy of the neural networks. Instead, in both LSVMs and DST-based classifier the leave-one-out cross (LOO) validation algorithm was adopted, introduced in order to maximise the utilisation of the training cohort.

**Results:** Table 1 below shows the out-of sample classification accuracies associated to each of the four types of classifiers being tested. In Fig. 1 a three-coordinate simplex plot referred to the patient data categorised by the Cardiff classifier is displayed.

Figure:



**Caption:** Fig. 1 Simplex plot showing how the subjects on the left (blue circles) were correctly classified as healthy subjects, whilst those on the right (red crosses) as patients with knee OA.

**Conclusion:** Findings indicate that, for the classified patient dataset, the DST-based classifier proved to be the most suitable method for classifying patients with knee OA (Table 1). This is due to its highest out-of-sample classification accuracy amongst the classifiers tested. This clinically relevant result partially validates the Cardiff classifier as a reliable diagnostic tool to assess the knee joint function of patients affected by knee OA. The DST-based classifier's user-friendly interface (Fig. 1) lends itself to further development into a valuable clinical tool, enabling a clinician to objectively characterise knee function without requiring any assistance from biomechanists. There is also future potential to assist with patient assessment and surgical decision making, aimed at optimising patient outcome. Future work is underway to ascertain whether the Cardiff classifier is a clinically suitable technique for improving the accuracy of the diagnosis and monitoring the effectiveness of the prognosis related to other lower limb pathologies.

**Table:**

Classifier	Out-of-sample classification accuracy
Multi-layer perceptron (MLP) neural network with one hidden layer	81.8%
Four-dimensional self-organising map (SOM)	71.05%
Lagrangian support vector machine (LSVM)	91%
Dempster-Shafer theory-based classifier	93.42%

**Caption:** Table 1. Classifiers tested and relative out-of-sample classification accuracy (on the testing set).

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**Disclosure of Interest:** None Declared