OR-ensemble designed for interpretable predictions of rotator cuff injuries

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Abstract

When diagnosing a rotator cuff injury, time and money can be saved by using a machine learning model in the process of diagnosing. The objective of this paper is to create a classifier that distinguishes patients from non-patients and whether these patients have a rotator cuff tear. It is key to build a model that is transparent to a physician. One-sided classifiers are combined using a Boolean OR-operator resulting in an OR-ensemble. A physician can easily retrace which feature(s) defined the classification. State-of-the-art ensemble methods, that have previously been adopted by medical studies where a machine learning algorithm is used, are compared to the OR-ensemble. Conclusively, this study demonstrates that the OR-ensemble often scores higher, in addition to having more transparent results.

Keywords: Ensemble method, Flock of Birds, Rotator cuff injury, OR-ensemble

1. Introduction

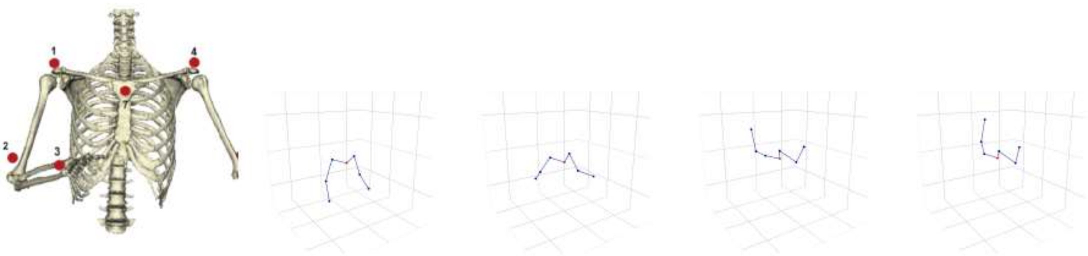
Rotator cuff injuries are common among people over sixty years old and people who tend to overload their shoulder during exercise [1]. Medical diagnosis usually involves the use of expensive and time-consuming imaging techniques such as X-rays, ultrasounds, or MRI. This project, OrthoEyes, could be a novel solution by having machine learning algorithms classify the degree of a patient's shoulder injury. This alternative approach could provide both financial and procedural benefits to the medical diagnosis methods stated above.

This study aims to improve the earlier established OR-ensemble by Vuurens, Andrioli, and de Vlugt [2]. This OR-ensemble consists of single one-sided classifiers which each act as standalone deciding factors. The results of the classifiers are combined using a Boolean OR-operator. Therefore, one deviating classifier in the OR-ensemble can decide the outcome. It is important that the OR-ensemble is highly interpretable, and the selected features are of substantial clinical quality. Even though machine learning models have contributed to contemporary technology, it is difficult to properly apply to the medical field due to its lack of medical accountability. The adjustments to the OR-ensemble found in this study aim to tackle the issues stated above. This concept is applied on two experiments. One to distinguish patients from non-patients and the other to distinguish between individuals with or without rotator cuff tears. In conclusion, the purpose of this research is to assess in which ways the OR-ensemble can be improved.

The remainder of this paper is structured as follows: Section 2 describes the background and preparation of the dataset. Section 3 provides an analysis of interpretability and the feature selection. Section 4 will discuss the OR-ensemble in general. In successive order, Section 5 will examine the results of this study and provide a comparison to other models. Section 6 is dedicated to discussion points and future research on kinematic analysis of the shoulder and finally, Section 7 describes the conclusion.

2. Data

The dataset consists of positional and rotational data of different exercises, performed by four patient groups. The data has been anonymized. The majority of exercises lack a uniform protocol between each patient group. In order to cut out noise during movements, data cleaning has been applied to all patient groups.



(a) (b)

Figure 1: Illustration of (a) how sensors are placed on the body, and (b) a sequence of sensor recordings for an abduction exercise, frontal view.

2.1 Sensor recordings

The dataset of this study was collected by the LUMC using a Flock of Birds system (FoB). FoB is an electromagnetic motion capture system, which is a useful tool for kinematic shoulder studies [3]. A total of seven sensors were placed on the wrists, elbows, shoulders, and sternum [figure 1].

Participants were asked to perform certain exercises that could be examined from a medical viewpoint: Abduction (AB), Anteflexion (AF), Retroflexion (RF) and Exo- and Endo-rotation Low (EL). During the AB-exercise, participants were asked to raise their arms in an arch to the highest point and then slowly return to the original position. During the AF-exercise participants were instructed to extend their arms forwards and lift them up to the highest point. After raising their arms to 180 degrees, the arms would return to their starting position. The RF-exercise is performed by pointing the arms backwards as far as possible and then returning to the original position. Lastly, the EL-exercise is performed by having each participant arch their upper arm along their upper body and moving the wrist back and forth, along the opposite plane.

The positional data of each sensor is recorded during these movements, by the FoB-system. these datapoints are in an XYZ-cartesian space. The XY-plane represents the transverse view, the YZ-plane represents the frontal view and the XZ-plane the sagittal view.

2.2 Labels

The dataset consists of four categories in which participants from Category 1 (n=30) have no injury. The participants in Category 2 (n=39), Category 3 (n=37), and Category 4 (n=28) have increasing severities of shoulder injuries. Patients from Category 3 and Category 4 are diagnosed with a rotator cuff tear. Since there are no labels for the specifications of the individual injuries, it is unknown whether the right or left shoulder has been injured. In addition to this, there are no labels that indicate what kind of rotator cuff injury the participant has.

2.3 Cleaning

Two participants were excluded, after the data was inspected, because they did not perform all four exercises (AB, AF, RF and EL). Three other participants were excluded because the sensor, which was supposed to be placed on their sternum, was instead placed on their back between both scapulae.

The data was cleaned after discovering noise before and after an exercise. Additionally, some participants performed an exercise twice in one recording, while others performed an exercise only once. The execution of an exercise was sliced, and the noise was deleted. These frames mostly contained either random movements or no movement at all, which were not a part of the exercise. If a participant executed an exercise twice in one recording, the second execution was stored in a new recording.

The range of the coordinates was not uniform among categories. For example, the X-coordinates from Category 1 ranged between 700 and 1300, while the X-coordinates from Category 4 ranged between 30 and 50. This was solved by calibrating all categories. For each participant, the calibration consisted of two parts: translation and scaling. Firstly, the positional data from all sensors was translated, so that for every frame the coordinate for the sensor on the sternum (sensor 3 in figure 1) was placed on the coordinate (0, 0, 0). Secondly, scaling was applied to ensure that the positional data from all categories fell in the same range. The average length of both upper arms was calculated by taking the length of the 3D-vector between the sensor on the shoulder and the sensor on the elbow. Then the average length of the two upper arms was calculated and scaled down to a length of 1. Based on this scaling, the rest of the positional data was scaled as well.

2.4 Test set

For the final validation of the model, twenty percent of the participants from each category was randomly selected and isolated.

3. Analysis

The features which are used as input for the model need to be interpretable. These features will be analysed and justified in the upcoming chapter. Additionally, calculations need to be performed on the data to be used as input for features.

3.1 Interpretability

From a medical standpoint it is of high importance that the results are interpretable, considering a physician will not make conclusions based on results without supporting evidence. Therefore, the selected features which indicate the decision should be retraceable for each participant.

3.2 Feature selection

Features are selected on their data-scientific significance, as they are required have a certain contribution to the system. Additionally, the features used in this study need to be medically justifiable. Therefore, a patient must be classified based on a perspective which reflects medical classification methodology. In the following subsections the medical justification of the features used in this study will be described and the calculations for these features will be explained.

3.2.1 Medical justification

Shoulder angles and compensation behaviour

An individual without a shoulder injury will have no trouble performing movements. This means that the angle of the shoulder will approach 180° during the abduction and anteflexion movement. If a participant is unable to approach this angle, it increases the likelihood of this person having a rotator cuff injury. Same goes for the maximum height of the wrist during these movements [4]. Besides not being able to reach the optimal angle of the shoulder and height of the wrist, patients with a rotator cuff injury are likely to compensate their lack of height during the movement by extensively raising their injured shoulder [10].

Velocity and acceleration of the movement

Rotator cuff injuries are associated with loss of shoulder stability [5]. Having a decent shoulder stability implies one is able to execute the movement fluently. Similarly, the speed in which the movement is executed could be an indicator of possible injuries of the rotator cuff.

Symmetry of the movement
Loss of strength in the shoulder is, in many cases, a consequence of a rotator cuff injury [6]. To measure loss of strength, the injured arm was compared to the not-injured arm [7]. This is done by comparing the difference in height, speed, and acceleration of the wrists and elbows for both sides. A large difference between the left and right arm during an exercise indicates a higher probability of the participant having a rotator cuff injury.

Deviation in an exercise
Given that injured people will avoid painful movements as much as possible [8], it is feasible to recognise a rotator cuff injury by identifying deviation in an exercise. Conclusively, this means that participants who experience pain 'move around' a painful part of the exercise to avoid feeling pain.

3.2.2 Calculations

Each of the named indicators, along with some others, can be combined with one or multiple meaningful mathematical operations forming features.
Shoulder angle

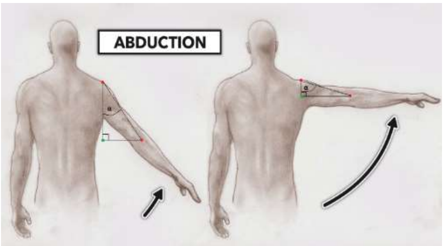


Figure 2: Calculation shoulder angle

The maximum shoulder angle appears insightful when diagnosing people with rotator cuff injuries. In the AF and RF exercises, the Y-axis is irrelevant to observe the main motion. Therefore, the shoulder angle is calculated using the location of the elbow- and shoulder-sensor in the XZ-plane. This is accomplished by creating a right-angled triangle using the shoulder and elbow point and adding a third point at the height of the elbow and the width of the shoulder. For every frame of the exercise, the angle is calculated and the maximum shoulder angle is determined. This results in features 1 and 2 [A].

The same approach is used to calculate the shoulder angle for the AB exercise. Only during this exercise, the participant moves in a different plane, as explained in section 2.1. In this case the YZ-plane shows the majority of the action and therefore, the X-axis can be discarded. The rest of the calculations remain the same as explained in the previous paragraph. This results in features 3 and 4 [A].

Symmetry in position
Continuing, the following features are based on the difference in position between the left and right side of the body. As well as the previous features, the meaningful axes differ per exercise [A]. The positions of the wrist, elbow and shoulder are retrieved and the variation between the right and left side is calculated by taking the difference. These values are calculated for each frame in the movement. The mathematical operation that is enforced on the feature bases is the standard deviation, resulting in features 5 through 12 [A].

Furthermore, the positional data of the elbows and wrists along the Z-axis during exercises AB, AF and RF give insight into how well the exercise was performed, leading to feature 13 and 14 [A]. Regarding the EL movement, only the maximum heights of the wrists along the X-axis are useful to consider for classification, resulting in feature 15 [A]. The elbows are moved throughout the movement EL, which is a flaw in the protocol. This has to be taken to account while examining the wrist positioning during the movement. Due to this, the difference in position of the wrist is not taken to account for movement EL.

Velocity and acceleration
The smoothness of a motion is measured by determining the standard deviation of the velocity and acceleration during that exercise. A large difference in acceleration within an exercise, implies there is little stability in the shoulder. Therefore, large fluctuations in acceleration are an indicator for having a shoulder injury. This provides features 16 through 23 [A].

Angular velocity and acceleration
The angular velocities and accelerations of a movement can likewise give a good indication of the shoulder quality of the participant. These are calculated by retrieving the velocity of the right and left elbow in the desired plane for every exercise. By dividing the velocity by the length of the arm, the angular velocity remains. The same is done for the acceleration, only the differential of the angular velocity is taken after the previous calculations. The standard deviation is used on the angular velocity, because this gives insight into the degree of variation in the speed whilst not measuring protocol, since participants were instructed to perform
the exercise at different speeds. As for the angular acceleration both the standard deviation and mean can be used to generate a feature, since the protocol will not be measured by this operation. Thus, introducing feature 24 through 31 [A].

4. Model

The OR-ensemble brought forward by this study is based on the combination of multiple one-sided logistic regression models, using a Boolean OR-operator. This results in the option to combine only the features that possess a training result with a perfect precision. In this section the hyperparameter *f*, further on referred to as the 'factor', is introduced and the essence is elaborated on using a feature distribution example. The process of establishing the factor is discussed briefly.

4.1 One-Sided logistic regression

The trained models for each feature assign identifiable patients to their designated categories. Leave-One-Out cross-validation is applied to optimize the use of the small data set. The model searches for participants who are identifiable. Only certain values that are distinctly lower or higher, which depends on the polarity of the feature, will be selected as those patients are easily identifiable.

To achieve a perfect precision score, the model introduces a hyperparameter *f*. This parameter creates a threshold applied for all the different features. The hyperparameter *f* is used to change the value of the threshold. The following formula is used to determine the threshold.

$$\begin{cases} t = \overline{x_0} - f \cdot x_{0,\text{low}} \text{ for } x_{1me} < x_{0me} \\ t = \overline{x_0} + f \cdot x_{0,\text{high}} \text{ for } x_{1mean} \geq x_{0mean} \end{cases}$$

The green dots represent the patients in Category 2, 3 and 4. The control group, Category 1, is represented by red dots (y=0). Figure 4 shows that some values of the patient (y=1) group are in range of the values of the control group. This results in patients being incorrectly identified to a category. If the value of *f* is increased, the threshold boundary moves as seen in [figure 5].

Depending on the value of *f*, certain participants labelled as y=1 are excluded from the training data. This means the training data only consists of two distinct groups of participants.

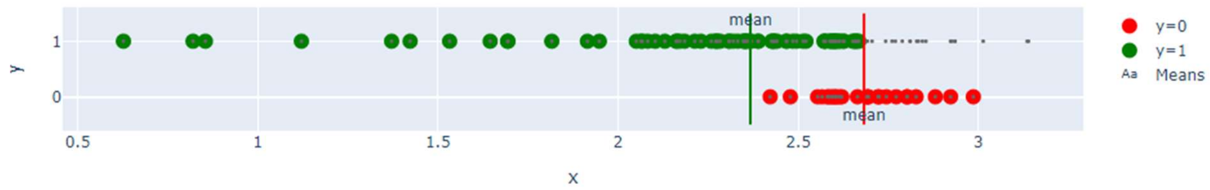


Figure 3:The hyperparameter f is set to 0. Consequently, the threshold lays at the mean of y = 0. Overlap of two groups causes wrong identification in the range between the mean values.

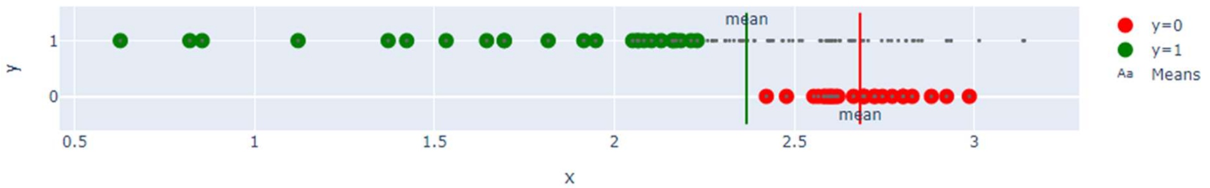


Figure 4: The hyperparameter f is set to 1.7. There is no overlap of green and red dots, which means few false identifications will be made.

4.2 OR-ensemble

Each one-sided classifier predicts a subset of patients with high precision. The classifiers with a precision of exactly 1.0 are combined through a Boolean OR-operator. If at least one of the classifiers predicted a participant to be a patient, the ensemble foresees the participant to be a patient as well. The features on which a patient was classified can always be retraced from the model. Therefore, the OR-ensemble created by this method is straightforward to interpret.

For all one-sided classifiers within the OR-ensemble the hyperparameter *f* was set to the same value. This value was manually picked. Firstly, the results for different values between 1.0 and 2.0 are examined. Secondly, the value with the optimal results was picked.

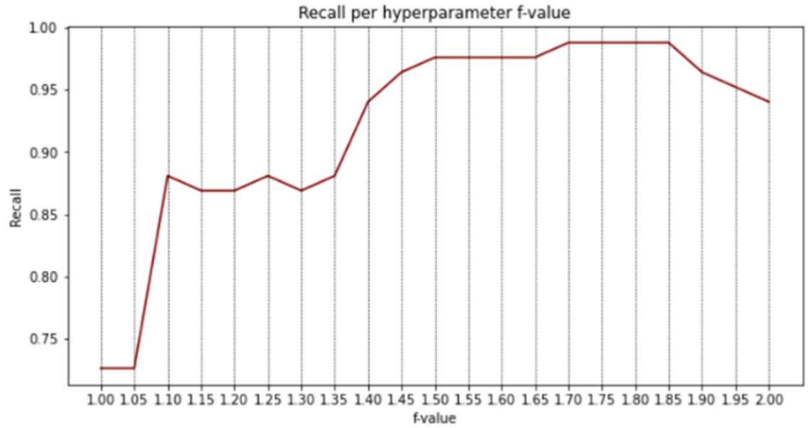


Figure 5: hyperparameter tuning for classifying patients from non-patients

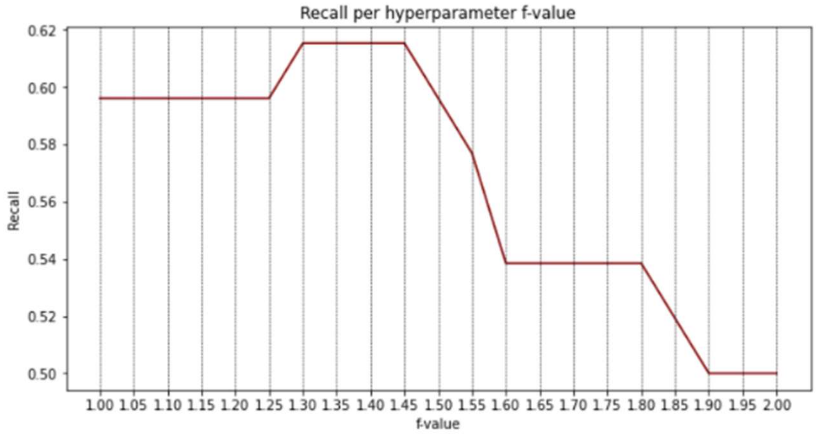


Figure 6: hyperparameter tuning. classifying rotator cuff tears from shoulder pain

5. Results

In the following section the results of the two experiments are shown. Both sections contain the results from the OR-ensemble and other ensemble methods. Section 5.1 shows the validating and test results for distinguishing patients from non-patients. Section 5.2 shows the validating and test results for distinguishing patients with rotator cuff tears from patients with regular shoulder pain. The final paragraph, section 5.3, explains how the different ensemble methods have been executed and tuned.

5.1 Classifying patients from non-patients

The following tables show the validation results (table 1) and the test results (table 2) for distinguishing non-patients from patients. By hyper parameter tuning, shown in figure 6, the factor for the OR-ensemble is set on 1.7. For the validation set, the OR-ensemble gives near perfect results. The test set results are somewhat lower than the validation results.

	OR-ensemble f=1.7	AdaBoost	Random Forest	Bagging	SVC
Precision	1.00	0.92	0.95	0.90	0.93
Recall	0.98	0.90	0.95	0.89	0.92
Accuracy	0.99	0.90	0.95	0.89	0.92

Table 1: Validation results for classifying patients from non-patients

	OR-ensemble f=1.7	AdaBoost	Random Forest	Bagging	SVC
Precision	0.9	0.74	0.93	0.8	0.87
Recall	0.95	0.76	0.92	0.88	0.88
Accuracy	0.88	0.76	0.91	0.88	0.88

Table 2: Test results for classifying patients from non-patients

5.2 Classifying patients with rotator cuff tears from patients with regular shoulder pain

The tables below show the validation results (table 3) and the test results (table 4) for distinguishing patients with and without rotator cuff tears. By hyper parameter tuning, shown in figure 7, the factor for the OR-ensemble is set to 1.45. For the validation set, the OR-ensemble remains to have precision of 1.0, whilst the recall and accuracy have significantly declined. The test set returns a precision that is not equal to 1.0.

	OR-ensemble f=1.45	AdaBoost	Random Forest	Bagging	SVC
Precision	1.00	0.59	0.65	0.60	0.61
Recall	0.61	0.59	0.65	0.59	0.61
Accuracy	0.76	0.59	0.65	0.59	0.61

Table 3: Validation results for classifying patients with rotator cuff tears from patients without tears

	OR-ensemble f=1.45	AdaBoost	Random Forest	Bagging	SVC
Precision	0.78	0.40	0.47	0.73	0.73
Recall	0.58	0.63	0.52	0.75	0.73
Accuracy	0.63	0.63	0.49	0.75	0.73

Table 4: Test results for classifying patients with rotator cuff tears from patients without tears

5.3 Comparing ensemble methods

Machine learning has become one of the most prominent new technologies of the decade. However, numerous machine learning models lack interpretability and transparency, especially when used within the medical domain [9]. This study examines a small medical dataset and classifies patients using the OR-ensemble method. To ensure that the OR-ensemble is the best possible model for this study, it will be compared to state-of-the-art ensemble methods, which have been used successfully in medical studies [10][11][12][13][14].

5.3.1 Random forest

A Random Forest model uses multiple decision trees to make a final decision. The Random Forest model was applied to the cleaned and calibrated dataset. By automatically optimizing the hyperparameters of the Random Forest model, the score reached its optimum value. However, the precision score never reached 1.0. This means there will be false positives using the Random Forest. For medical purposes false positives are undesirable since these will result in unnecessary costs.

5.3.2 AdaBoost

AdaBoost is an ensemble learning method that can be applied to regression problems. The AdaBoost algorithm improves the model by building a strong learner from the mistakes of several weaker models [15]. The hyperparameters have been tuned to generate the optimal results. When comparing AdaBoost to the OR-ensemble, it can be concluded that the AdaBoost scores notably worse than the OR-ensemble. An important difference between these two ensemble methods, is that the precision in the AdaBoost method will not reach 1.0. This means the model will ultimately consist of false positives. False positives are generally unfavourable, therefore AdaBoost can be seen as a worse alternative compared to the OR-ensemble.

5.3.3 Bagging

Bagging is an ensemble-based algorithm that uses bootstrapping and aggregating techniques. A Bagging Regressor was used to compare the Bagging ensemble against the OR-ensemble. Hyperparameters were tuned by using the same methodology as previous methods. The amount of decision trees will not cause overfitting due to the stochastic nature of Bagging itself. Even though Bagging is best suited for small training data sets [15], the results of Bagging were lower than the OR-ensemble during the first experiment. However, in the second experiment Bagging scored better regarding recall and accuracy. This can be attributed to coincidence. Like other ensemble learning methods, the Bagging ensemble could not uphold a precision of 1.0 while training.

5.3.4 Linear Support Vector Classification

As for the SVC, the results regarding the optimized hyperparameters were quite reasonable. The results are calculated and plotted for a c-parameter in the range of 10^{-4} to 10^{4}. The OR-ensemble scores better when differentiating patients from non-patients. Seen in table 1 and 2, the results of SVC are better concerning the recall and accuracy compared to the OR-ensemble. Yet the OR-ensemble still is the best choice when trying to classify regarding the medical field seeing the precision of 1.0 is reached. This ensures that non-patients are never classified as a patient.

6. Discussion

The most important finding of this study is that the OR-ensemble can distinguish patients from non-patients, in addition to whether they have a rotator cuff injury or not. The precision score of the OR-ensemble will always be 1.0, when testing with the validation set. Therefore, the number of false positives will be zero.

The models that were combined into the OR-ensembles are based on medical tests, which are associated with the identification of shoulder injuries and rotator cuff tears. Those logistic regression models represent features based on active movements. In the process of diagnosing a rotator cuff injury, medical specialists look at the passive movements as well [4]. This has not been considered in this research. Important to state is that dataset for this research is relatively small (n=134). Besides the small dataset, the individual logistic regression models have only been trained on the identifiable members of the dataset. Consequently, the model may be trained on insufficient data.

As the data has been collected from different studies, there may be some differences in protocol. To make sure that these differences do not interfere with the quality of the results, it may be beneficial to use the method of the OR-ensemble on new data, which has been generated using one protocol. A last caveat in this research is the lack of background information on the participants. There is no information of the age, gender, and previous injuries of the patients. This information might contribute to indicating whether the subject has a rotator cuff injury or not.

The features were manually picked during the feature selection. Determining the added value for each feature gives insight on the importance of the features. With more information about the importance of a feature, the number of features can be narrowed down.

In this paper, a global factor for separating in- or outliers in the dataset is chosen for all features at once. This might not be a good approach when looking at some of the regression lines for each feature and the equation describing the separation of individuals. Based on the multiplication of the mean values, outliers are filtered out of the dataset. Getting a set on which a logistic regressor can be fitted properly is strongly dependent on the distribution of datapoints for a feature. When means are close to each other, the factor needs to be very high to get any meaningful results for a feature. Vice versa, when the difference in means is large, the factor does not need to be that high at all. Therefore, it might be a better approach to automate the selection of the value for the factor parameter for each feature in some way.

Future research

In addition to the completed research brought forward in this paper, there are some particularly interesting subjects to consider looking into for future research. The final goal of OrthoEyes is to classify a rotator cuff injury of a patient by using a camera in a waiting room of the doctor's office. By providing the doctor with a first indication of the degree of the shoulder injury, a few steps during the research cycle can be skipped.

To accomplish the final goal of this project, it is necessary to dive into the world of cameras and how to position them accordingly. Considering it is relatively easy for cameras to obtain positional data, compared to taking measurements with the FoB-system which takes longer to prepare. Doing research on the optimal camera type and the most favourable position of this camera is essential to build forward on the completed work.

Due to the fact that it is hard to obtain rotational data using cameras, it seems unnecessary to continue looking into the rotation matrices and features which are based on this data. In addition to this, the researchers at the LUMC used specific calculations to transfer the placing of the sensors to the bony landmarks of the individual, before starting actual calculations using rotation matrices. The functions used by the LUMC researchers are unavailable for groups working on this project and without these functions it is impossible to use the rotation matrices accurately. Analysing the rotation matrix data can lead to a promising feature but will not lead to a useful contribution to the long-term goal of this project. Seeing the missing information is essential to grasp a full understanding of the matrix data, it seems best to leave the matrices out of further research.

7. Conclusion

The main objective of this study was to create a model that would distinguish patients from non-patients and patients with or without a rotator cuff tear. When creating this model, it was crucial to make it relatively transparent to the physician. Besides high transparency of the model, generating few false positives is key. To accomplish this, the OR-ensemble was created. The OR-ensemble consists of several one-sided logistic regression models, that each represent a chosen feature. Comparing the OR-ensemble to conventional ensemble methods showed that the OR-ensemble is not necessarily the best ensemble method to use on this dataset. Nevertheless, the OR-ensemble is easier to interpret than the other ensemble methods.

Appendix
[A]

	Feature basis	Mathematical operation	Axis / plane	AB	AF	RF	EL
1	angle_left_shoulder_xz	Max	XZ		✔	✔	
2	angle_right_shoulder_xz	Max	XZ		✔	✔	
3	angle_left_shoulder_yz	Max	YZ	✔			
4	angle_right_shoulder_yz	Max	YZ	✔			
5	diff_x_wrist	Std	X		✔	✔	✔
6	diff_x_elbow	Std	X		✔	✔	✔
7	diff_x_shoulder	Std	X		✔	✔	✔
8	diff_y_wrist	Std	Y	✔	✔	✔	✔
9	diff_y_elbow	Std	Y	✔			
10	diff_z_wrist	Std	Z	✔	✔	✔	
11	diff_z_elbow	Std	Z	✔	✔	✔	
12	diff_z_shoulder	Std	Z	✔	✔	✔	
13	z_elbow	Max	Z	✔	✔	✔	
14	z_wrist	Max	Z	✔	✔	✔	
15	x_wrist	Max	X				✔
16	vel_wrists_x_l	Std	X				✔
17	vel_wrists_x_r	Std	X				✔
18	vel_elbows_z_l	Std	Z	✔	✔	✔	
19	vel_elbows_z_r	Std	Z	✔	✔	✔	
20	acc_wrists_x_l	Mean, std	X				✔
21	acc_wrists_x_r	Mean, std	X				✔
22	acc_elbows_z_l	Mean, std	Z	✔	✔	✔	
23	acc_elbows_z_r	Mean, std	Z	✔	✔	✔	
24	angular_vel_xz_elbow_l	Std	XZ		✔	✔	
25	angular_vel_xz_elbow_r	Std	XZ		✔	✔	
26	angular_acc_xz_elbow_l	Mean, std	XZ		✔	✔	
27	angular_acc_xz_elbow_r	Mean, std	XZ		✔	✔	
28	angular_vel_yz_elbow_l	Std	YZ	✔			
29	angular_vel_yz_elbow_r	Std	YZ	✔			
30	angular_acc_yz_elbow_l	Mean, std	YZ	✔			
31	angular_acc_yz_elbow_r	Mean, std	YZ	✔			

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