

# A Deep Learning Approach to Prevent Problematic Movements of Industrial Workers Based on Inertial Sensors

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**Abstract**—Nowadays, manufacturing industries still face difficulties applying traditional Work-related MusculoSkeletal Disorders (WMSDs) risk assessment methods due to the high effort required by a continuous data collection when using observational methods. An interesting solution is to adopt Inertial Measurement Units (IMUs) to automate the data collection, thus supporting occupational health professionals. In this paper, we propose a deep learning approach to predict human motion based on IMU data with the goal of preventing industrial worker problematic movements that can arise during repetitive actions. The proposed system includes an initial Madgwick filter to merge the raw inertial tri-axis sensor data into a single angle orientation time series. Then, a Machine Learning (ML) algorithm is trained with the obtained time series, allowing to build a forecasting model. The effectiveness of the developed system was validated by using an open-source dataset composed of different motions for the upper body collected in a laboratory environment, aiming to monitor the abduction/adduction angle of the arm. Firstly, distinct ML algorithms were compared for a single angle orientation time series prediction, including: three Long Short-Term Memory (LSTM) methods – a one layer, a stacked layer and a Sequence to Sequence (Seq2Seq) model; and three non deep learning methods – a Multiple Linear Regression, a Random Forest and a Support Vector Machine. The best results were provided by the Seq2Seq LSTM model, which was further evaluated for WMSD prevention by considering 11 human subject datasets and two evaluation procedures (single person and multiple person training and testing). Overall, interesting results were achieved, particularly for multiple person evaluation, where the proposed Seq2Seq LSTM has shown an excellent capability to anticipate problematic movements.

**Index Terms**—Musculoskeletal Disorders, Sensor Fusion,

Forecasting, Deep Learning, Long Short-Term Memory (LSTM).

## I. INTRODUCTION

In diverse manufacturing sectors (e.g., textile, garment, automotive), the production processes typically require a cooperation between human operators and machines. Often, the actions carried out by the workers are repetitive, which is a risk factor for developing Work-related MusculoSkeletal Disorders (WMSDs) [1]. In effect, WMSDs represent one of the biggest concerns for the workers' health and safety, producing a significant impact on productivity and product quality, while also leading to absenteeism and early retirement [2]. For instance, in Portugal, where the automotive industry represents a substantial part of the exportation sector, the WMSDs have a massive impact on the operators' lives. Indeed, a study made in an assembly line of a Portuguese automotive industry showed that 56.7% of the analyzed 400 workers had suffered from these injuries [3]. In particular, upper limbs (mainly shoulder, wrist, and hand), cervical/neck, and lumbar spine were the body parts mostly reported for discomfort and pain.

Ergonomics departments at large industrial manufacturing systems often conduct systematic analysis of processes and workplaces towards the prevention of WMSDs. These ergonomic professionals often rely on observational methods for data acquisition, which involve analyzing in-place or video

recording data from operators at work and manually filling ergonomic worksheets (e.g., RULA and EAWS) according to ISO norms of WMSD risk. A promising alternative for WMSD prevention is based on inertial motion capture systems. Inertial Measurement Units (IMUs) are the base component of such systems and usually measure acceleration, angular velocity and the magnetic field. These data can be combined by using sensor fusion techniques to obtain a more accurate and reliable attitude representation [4]. In particular, the data from human movement is often converted into postural angles, which can directly be used to measure WMSD risk.

In this paper, we propose a Long Short-Term Memory (LSTM) deep learning model approach for motion prediction using inertial sensors. The proposed Machine Learning (ML) pipeline consists of four steps: 1 – IMU data collection (tri-axis accelerometer, magnetometer and gyroscope data); 2 – a sensor fusion using the Madgwick orientation filter to obtain a single time series with the angular construction of the movement; 3 – a time series forecasting approach to predict upcoming angular postures based on current poses (via the LSTM model); and 4 – an assessment of the LSTM predicted motion according to the ISO 11226 norm, which focuses on evaluating high risk working postures. The final goal (not studied in this work) is to automatically feed an exoskeleton suit with the LSTM high risk alarm signals, such that it would trigger a muscle blocking response, thus preventing the risky movements in advance. The proposed ML pipeline is validated by using an open-source dataset related with different worker motions for the upper body collected in a controlled laboratory environment. In step 3, we initially assume one angular posture time series, in order to compare distinct ML algorithms: three different LSTM prediction models – single layer, stacked layer and Sequential to Sequential (Seq2Seq) model; and three non deep learning methods – Multiple Linear Regression (MLR), Support Vector Machine (SVM) and Random Forest (RF). The best results were obtained by the Seq2Seq LSTM, which was then evaluated in terms of its value to perform the fourth step of the pipeline, by considering data from 11 human subjects and two evaluation training and testing procedures (single and multiple person).

The paper is structured as follows. Section 2 introduces the related work on ergonomic evaluation based on IMUs. Next, Section 3 describes the IMU data, the proposed WMSD prevention approach and evaluation methodology. Then, Section 4 discusses the obtained results. Finally, Section 5 presents the main conclusions.

## II. RELATED WORK

Although the manual methods still are the most common used, IMUs are becoming a popular method for human motion capture. In recent years, some studies have proposed a inertial motion tracking system for industrial applications, aiming to analyze and evaluate the human motion of the workers. In [5], IMUs were used with the European Assembly Work-Sheet (EAWS) ergonomic tool in an automotive industry, where the goal was to evaluate working postures. In the same

industry, the study of [6] proposed a method for inertial data anomaly detection using human working movements. Some ML studies adopt a classification approach to identify postures from IMU data. For instance, in [7] several ML algorithms were used to classify nine different human exercises, with a RF model obtaining the highest accuracy results. In [8], a deep Convolutional Neural Network (CNN) was proposed for gait phase recognition, reaching an 97% of accuracy. In the same work, the authors argued about the advantage of exoskeletons to provide support and assistance to the working movements. Regarding gait kinematics and kinetics prediction, three Artificial Neural Networks (ANN) were compared in [9]: Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM) and CNN. The experiments revealed that CNNs provided the best predictions for joint angles, MLPs for joint moments and LSTMs for real-time joint angle and joint moment prediction. LSTMs were also used in [10] to predict human gait stability of the elderly users based on data from real patients walking with a robotic rollator. The main goal was to perform a real-time classification of the type of walking movement (safe or risk) by adopting a Seq2Seq LSTM model. In another study [11], the same Seq2Seq LSTM architecture was proposed for the detection of suspicious human behaviors based on abnormal pedestrian trajectories.

While interesting results have been achieved by the related works, there is still a lack of IMU data studies that address the full ML cycle, from IMU data to the final WMSD prevention. This is precisely the research gap addressed in this paper, where we propose a complete ML pipeline to prevent WMSD based on IMU data. The ML pipeline includes a sensor fusion based on the Madgwick filter, generating an angular time series that is forecasted using ML algorithms. Several of the related works assume a classification approach when tracking human motion (e.g., [7], [8]). In contrast, we assume a more flexible time series (regression) approach, where the same trained ML models can be applied to anticipate different WMSD risk levels (e.g., by considering distinct angle risk thresholds). Moreover, we compare six different ML methods for angular motion time series prediction, including three LSTM deep learning models. And the best method (Seq2Seq LSTM) is further evaluated to prevent WMSD by considering two procedures (single and multiple data), using real-world data related with 11 human subjects.

## III. MATERIALS AND METHODS

### A. Industrial Worker Data

The “Upper-body movements: precise tracking of human motion using inertial sensors” is an open-source dataset available at Zenodo platform [12]. The data contains different motions for the upper-body of 11 participants (five women and six men) using a total of four IMUs. We note that the IMU devices need less processing power and are more economic when compared with other human motion capture systems [13]. Each set of movements contains the collection time acquired at 100 Hz and tri-axis data from the accelerometers, gyroscopes and magnetometers. In this paper, we assume a

movement that was collected from a single IMU placed on the right arm, which represents the static evaluation of the shoulder joint. Fig. 1 exemplifies the placement of the IMU units (left side) and the data that can be generated using the shoulder joint sensor IMU (right side).

### B. Data Preprocessing

As we focus on the evaluation of the abduction/adduction of the right shoulder, we use the data collected by the IMU 3 placed on the right arm for the 11 participants. To merge the raw data (total of 9 variables) into a single angular movement time series, we employ the Madgwick orientation filter [15], as implemented by the Attitude and Heading Reference System (AHRS), which is an open-source Python toolbox for attitude estimation (<https://ahrs.readthedocs.io/en/latest/>). The orientation filter was proposed by Madgwick [16]. It is an algorithm commonly used due to it is high accuracy and good performance at low-power real-time applications. Also, it needs less time-consuming calculations when compared to the known Kalman filter for orientation sensors [17]. In particular, Madgwick showed that this filter it is a very good option to overcome the difficulty of implementing the Kalman technique since the obtained results indicates a matching accuracy between these two approaches [16].

The Madgwick filter uses accelerometer and magnetometer readings to handle the gyroscope signal drift, which corresponds to the sensor’s low frequency bias, an instability that grows unbounded over time [18]. With the filter, it is possible to obtain a quaternion, which represents an orientation that can be converted into Euler angles (pitch,  $\phi$ , roll,  $\theta$ , and yaw,  $\psi$ ). Considering the Earth frame as reference, as shown in the left of Fig. 1, the  $\theta$  angle corresponds to the arm’s abduction/adduction. An example of the attitude representation of the studied movement (in angles) is presented in Fig. 2. We further inspected the graphical application of the Madgwick filter on the analyzed dataset, thus obtaining a manual visual confirmation that the generated time series is well aligned with the annotated data.

### C. Modeling

We assume Time Series Forecasting (TSF) approach to model the generated angular data  $\theta_t = y_t = (y_1, y_2, \dots, y_m)$ , where  $t$  denotes the time period, measured in centiseconds (cs), and  $m$  represents the length of the series. The goal is to estimate the next angular movements at the current time  $T$  by using a forecasting model ( $f$ , previously trained with historical data) that is fed with  $K$  time lags, allowing to compute an  $h$ -ahead prediction:  $\hat{y}_{T+h} = f(h, y_T, y_{T-1}, \dots, y_{T-K+1})$ .

By adopting an TSF approach, the same trained models can be applied to anticipate distinct WMSD risks. Let  $R_l$  and  $R_u$  denote a particular lower and upper angle WMSD risk level. The future angular estimates can be computed at time  $T$  and thus an alarm signal can be triggered if any of the obtained ahead forecasts is set outside the  $[R_l, R_u]$  range. To increase the sensibility of the WMSD alarm system, we define a  $\tau$  tolerance value and thus we predict a problematic movement

if  $\hat{y}_{T+h} + \tau > R_u$  or  $\hat{y}_{T+h} - \tau < R_l$ , where  $h \in \{1, \dots, H\}$  and  $H$  denotes the maximum forecasting horizon (or anticipation time).

The LSTM is a special type of deep Recurrent Neural Network (RNN) that solves the “short-term memory” problem through a mechanism of gates that manage to regulate the flow of information [19], [20]. These recurrent neural networks are also capable of learning order dependence in sequence prediction problems, which is the case of time series prediction. Each LSTM is a set of cells, where each cell includes three control gates: the “forget gate” that defines whether the information is relevant (1) or not (0); the “memory gate” that decides the new data that should be stored and/or modified in the cell; and the “output gate” that controls what is produced in each cell [21].

In this work, we assume a base LSTM that is fed just with one time lag ( $K = 1$ ) and that is capable of predicting up to  $H$ -ahead predictions (e.g.,  $\hat{y}_{T+5} = f(5, y_T)$ ). In this work, we fix the maximum horizon to  $H = 25$ , which corresponds to one quarter of a second. We explore three LSTM models, all trained with the Adam optimizer, using the Mean Squared Error (MSE) loss function. The simpler LSTM includes one input node (fed sequentially during the training phase) that is linked to a LSTM layer composed of  $L$  cells (hidden units), each assuming the Leaky ReLU activation function. This function was adopted since it allows to output negative values, which often occur in our angular series (Fig. 2). Then, the hidden LSTM layer is connected to an output dense layer, with  $H$  nodes and linear activation functions (since we do not normalize the original angular series). Under this setup, when  $y_t = (1, 2, \dots, 10)$  and  $H = 5$ , a total of 5 training examples are generated. The first example is  $1 \rightarrow (2,3,4,5,6)$  and the last training instance is  $5 \rightarrow (6,7,8,9,10)$ . Preliminary experiments were held by considering the first 70% observations of a single time series (from person A, which contains a total of 7,069 observations), allowing to fix the number of LSTM layer cells (by inspecting the best MSE value when using a simple grid search  $L \in \{25, 50, 100, 200\}$ ) to  $L = 100$ . Stacked LSTMs allow a more complex feature representation of the current input and have been shown to improve time series forecasting results [22]. Thus, in this work we also test a stacked LSTM that includes two LSTM hidden layers, each with  $L = 100$  cells. The third Seq2Seq LSTM model assumes a encoder-decoder or sequence to sequence architecture, which contains one model for reading and encoding the input sequence and a second model to decoding and predict, such as presented in [23]. As shown in Fig. 3, the model includes two LSTM layers ( $L = 100$ ), one repeat vector layer with  $H$  nodes, to repeat the incoming inputs for up to  $H$  times, and one time distributed layer, to process the output from the LSTM hidden layer and generate the  $H$  sequential output values.

For benchmarking purposes, we explore three additional ML algorithms: MLR, RF and SVM (with a Gaussian kernel). Since these models to not contain an internal temporal memory, we adopt a sliding time window to generate the training examples, assuming a total of  $K = H$  time lags:

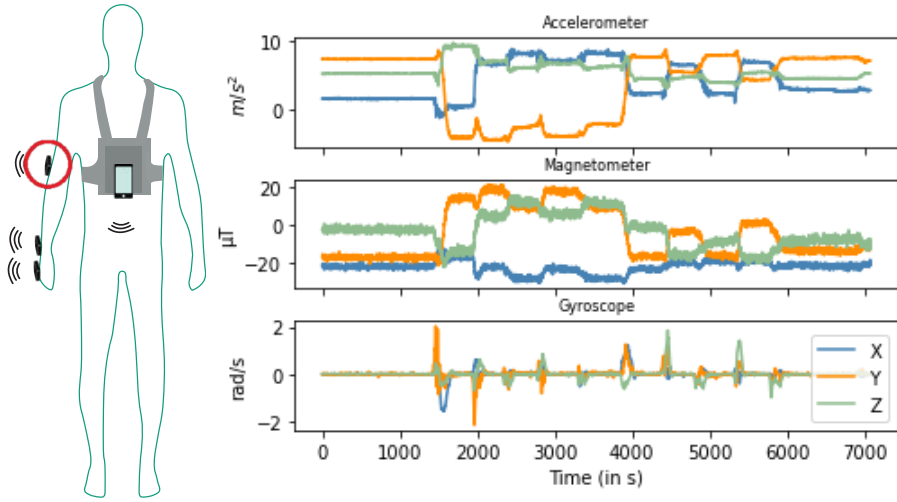


Fig. 1: Placement of the sensors and the Earth reference frame (left image, adapted from [14], the third IMU sensor is signaled by a red circle) and an example of the data collected from the shoulder joint sensor (third IMU, right plot)

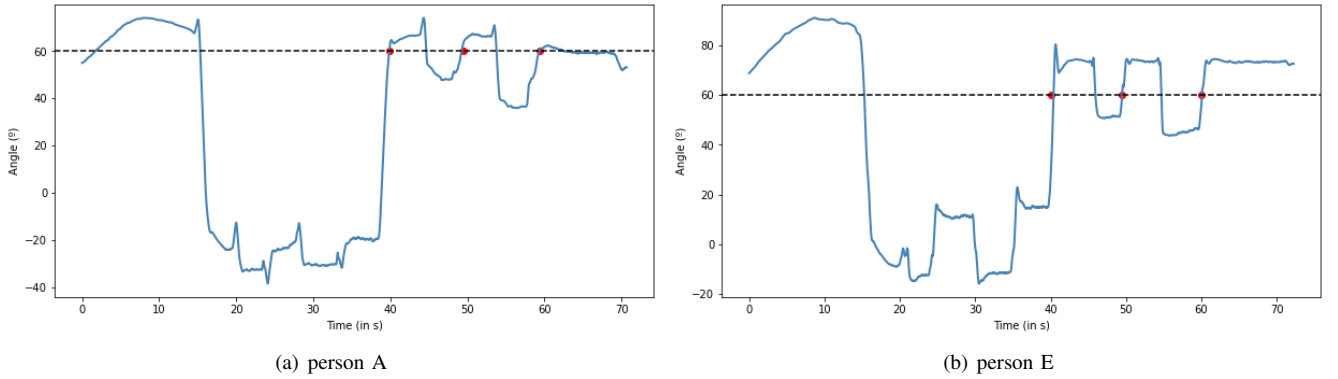


Fig. 2: Example of an angular reconstruction of the abduction/adduction of the arm for two human subjects (A and E) when using the Madgwick filter (dashed horizontal line denotes the ISO 11226 WMSD risk level; red circle represents the target time period when evaluating the WMSD anticipation capability of the proposed approach).

$\hat{y}_{T+h} = f(h, y_T, y_{T-1}, \dots, y_{T-H+1})$ . Moreover, since each algorithm can only output one value (the next forecast), multi-step ahead forecasts can be obtained by assuming an iterative feedback of previous forecasts [24]. For instance,  $\hat{y}_{T+2} = f(2, \hat{y}_{T+1}, y_T, \dots)$ , and so on.

All the ML experiments were executed by using an Intel i7 processor with 1.80 GHz and 16.0 GB of RAM. The data processing and modeling was implemented by using the Python programming language. In particular, we adopted the following Python libraries: `scikit-learn` – for MLR, SVR and RF and `TensorFlow` – for LSTM. To generate the training examples for the non deep learning methods (MLR, RF and SVM), we adopted the `CasesSeries` function from the `rminer` R package [25]. The MLR, RF and SVM methods were set with their default implementation values.

#### D. Evaluation

In this work, we assume three evaluation procedures. Firstly, we adopt a pure TSF evaluation by considering a single time

series (person A) to compare the six forecasting methods from Section III-C. We assume a time ordered holdout split, in which 70% of the oldest observations are used for training and the more recent 30% of the values are used for testing purposes. Four popular TSF measures are adopted, namely the coefficient of determination ( $R^2$ ), the Mean Absolute Error (MAE), MSE and Root MSE (RMSE):

$$R^2 = 1 - \frac{\sum_{i \in \mathcal{T}} (y_i - \hat{y}_i)^2}{\sum_{i \in \mathcal{T}} (y_i - \bar{y})^2} \quad (1)$$

$$MAE = \frac{1}{n} \sum_{i \in \mathcal{T}} |y_i - \hat{y}_i| \quad (2)$$

$$MSE = \frac{1}{n} \sum_{i \in \mathcal{T}} (y_i - \hat{y}_i)^2 \quad (3)$$

$$RMSE = \sqrt{MSE} \quad (4)$$

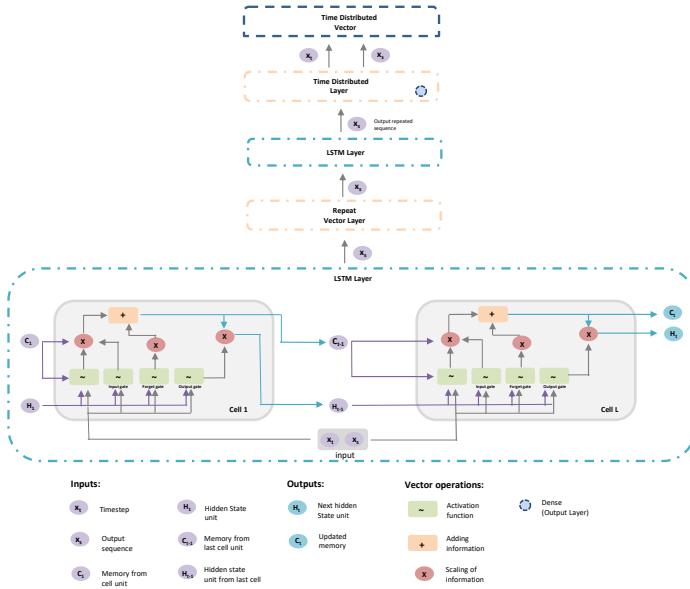


Fig. 3: Diagram of the proposed LSTM Seq2Seq network.

where  $\mathcal{T}$  denotes the testing period when assuming a fixed  $h$  value. For instance, the person A series contains a total of 7,079 observations, with the oldest 4,948 elements being used to train the forecasting model, which is tested on the remainder 2,131 values. For  $h = 1$  (one-ahead predictions),  $\mathcal{T} = \{49.48+h, 49.49+h, \dots, 70.78+h\}$ . Similarly, for  $h = 5$ ,  $\mathcal{T} = \{49.48 + h, 49.49 + h, \dots, 70.74 + h\}$ , and so on. For  $R^2 \in [0, 1]$ , the higher the values, the better are the predictions. As for the other measures (MAE, MSE and RMSE), better forecasts correspond to lower values.

Once the best forecasting method is selected, we perform a WMSD anticipation evaluation. For the analyzed shoulder movement, the ISO 11226 norm (“Ergonomics – Evaluation of static working postures tool”) only defines a risk for a positive angle ( $R_u = 60$  degrees), thus we assume an allowed angular range of  $[-\infty, 60]$ . As shown in Fig. 2, the  $R_u = 60$  risk level was applied to all 11 angular movement time series. In particular, we test the WMSD anticipation capability on the second half of each time series and thus we store the all initial time periods in terms of  $t$  values of risky shoulder movements (denoted here as  $t_r = \{t_{r_1}, t_{r_2}, \dots, t_{r_n}\}$ ) that occur within such second half time period. In Fig. 2, these time periods are signaled by using red colored points. For instance, there are 3 WMSD testing points for persons A and E. The total number of tested periods ( $t_{r_n}$ ) for each series is presented in Table III. For different anticipation times ( $h \in \{1, 2, \dots, H\}$ ), we execute two WMSD training and testing evaluation procedures, which work as follows:

**Single Person** – A growing window scheme [26], [27] is applied such that there are  $t_{r_n}$  model training and testing updates. For the first  $t_r$  value ( $t_{r_1}$ ), all the oldest observations up to  $t_{r_1} - H$  are used to train the TSF model. Then, for  $\max(h) = H$  and  $T = t_{r_1} - H$ , up to  $h$  ahead forecasts are

computed and the procedure detailed in Section III-C is applied, namely a correct WMSD is detected as:  $w(T, \max(h)) = 1$  if  $\hat{y}_{T+h} + \tau > R_u$ , else  $w(T, \max(h)) = 0$ . After this, we increase the current time ( $T$ ) and decrease the maximum horizon  $H$ , namely  $T = t_{r_1} - H + 1$  and  $\max(h) = H - 1$ , and so on until a one step ahead prediction is executed ( $T = t_{r_1} - 1$  and  $\max(h) = 1$ ). Then, we consider the next  $t_r$  value ( $t_{r_2}$ ), retraining the forecasting model with all observations up to  $t_{r_2} - H$ , repeating the previously described steps, until all  $t_{r_n}$  points are analyzed. For a fixed  $\max(h)$  value, the overall WMSD score (in %) is computed as the sum of all  $w(T, \max(h))$  computations divided by the total number of risky points ( $t_{r_n}$ ). This procedure is applied separately to all 11 human subject data from the analyzed dataset.

**Multiple Person** – More similar to other ML applications, the forecasting model is now trained with the full angular time series (pure TSF learning) of several persons (7 persons selected from the 11 time series, namely the set  $\{A, B, E, G, H, J, K\}$  that corresponds to the series that have  $t_{r_n} = 3$ ), which consists in the training set. Then, the trained and fixed forecasting model is tested on the WMSD risky points ( $t_r$ ) of the remainder 4 time series ( $\{C, D, F, I\}$ ), allowing to compute individual and overall WMSD scores.

#### IV. RESULTS

Table I summarizes the TSF results obtained for the first evaluation phase ( $h = 1$ , one-step ahead predictions). When analyzing the table, it becomes clear that the LSTM based methods perform much better than the non deep learning methods (MLR, RF and SVM). Overall, the best predictive results was obtained by the Seq2Seq LSTM, since it provides lower MAE, MSE and RMSE values when compared with the one layer and stacked LSTM, while obtaining the same  $R^2$  level. Following these results, the Seq2Seq LSTM is selected as the TSF algorithm for the remainder experiments presented in this paper.

TABLE I: TSF results for each model (person A series,  $h = 1$ , best values are in **bold**).

Model	$R^2$	MAE	MSE	RMSE
MLR	0.66	15.62	304.12	15.65
RF	0.09	10.68	210.06	10.70
SVM	0.60	15.14	336.52	15.16
One layer LSTM	<b>0.88</b>	0.40	0.19	0.40
Stacked LSTM	<b>0.88</b>	0.38	0.16	0.38
Seq2Seq LSTM	<b>0.88</b>	<b>0.11</b>	<b>0.02</b>	<b>0.12</b>

For TSF quality demonstration purposes, we consider the same person A series and its three risky shoulder time periods ( $t_r$ ). Table II presents the forecasting measures when performing  $H = 25$  predictions under a  $h = 1$  or  $h = 25$

forecasting horizon. For the first target point ( $t_{r_1}$ ) and  $h = 1$ ,  $\mathcal{T} = \{t_{r_1} - 25 + h, \dots, t_{r_1} - 1 + h\}$ . Similarly, for the same point and  $h = 25$ ,  $\mathcal{T} = \{t_{r_1} - 50 + h, \dots, t_{r_1} - 25 + h\}$ . As expected, the forecasting results degrade when the anticipation range is increased ( $h = 25$ ), in an effect that is noted more on the MAE, MSE and RMSE measures. To complement the TSF demonstration results, Fig. 4 presents the Seq2Seq LSTM forecasts for the first phase test data (for a time period related with  $t_{r_3}$ ). In particular, the one-ahead ( $T + 1$  or  $h = 1$ , blue line) and 25-ahead ( $T + 25$ , green line) forecasts are plotted against the ground truth values (black line). For baseline comparison purposes, the figure also includes the  $T + 25$  ahead naive forecasts (red line), which correspond to the previous ground truth angular values (known at time  $T$ ). As expected, the  $h = 1$  forecasts are better than the  $h = 25$  ahead predictions. Moreover, both Seq2Seq LSTM forecasts anticipate the rising angular motion of the ground truth and naive 25-ahead forecasts, which is valuable to prevent a WMSD movement (angular values close to  $R_u - \tau$ ). In the next WMSD evaluation phases (single and multiple person), we further evaluate the Seq2Seq LSTM capability to anticipate shoulder risky movements.

TABLE II: Seq2Seq LSTM prediction results for person A,  $H = 25$  and three risky periods ( $t_r$ ).

$h$	$t_r$	$R^2$	MAE	MSE	RMSE
1	$t_{r_1} = 39.87$	0.99	0.50	0.26	0.51
	$t_{r_2} = 49.51$	0.99	0.35	0.12	0.35
	$t_{r_3} = 59.34$	0.99	0.69	0.48	0.69
25	$t_{r_1} = 39.87$	0.98	8.08	70.73	8.41
	$t_{r_2} = 49.51$	0.98	2.53	6.69	2.59
	$t_{r_3} = 59.34$	0.89	1.65	2.99	1.73

Turning to the WMSD anticipation evaluation, and after consulting occupational health experts, we assumed a very small tolerance value of  $\tau = 1$  degree. Table III shows the single person evaluation results, where each cell contains in the numerator the total  $w()$  score (number of correct anticipations) and in the denominator the number of considered risky points ( $t_{r_n}$ ). To simplify the visualization, the table only shows a subset of the tested anticipation time periods ( $\max(h)$ ). The average anticipation score, computed for a fixed  $\max(h)$  value and for all 11 time series (horizontal analysis), is presented at the last column of the table. The analysis of this score confirms a trade-off between the anticipation time and the WMSD detection capability. The highest predictive score is obtained when the risk detection is performed just 1 cs in advance (86%). The performance decreases significantly (54%) then the anticipation time is 2 cs. Afterwards, there is a smaller decay in performance, reaching an average of 43% when  $\max(h) = 25$  cs. As for the performance at the individual level (vertical analysis), the last row of the table presents the overall score per person, when considering the distinct anticipation times. For person A, a perfect risk point detection is obtained

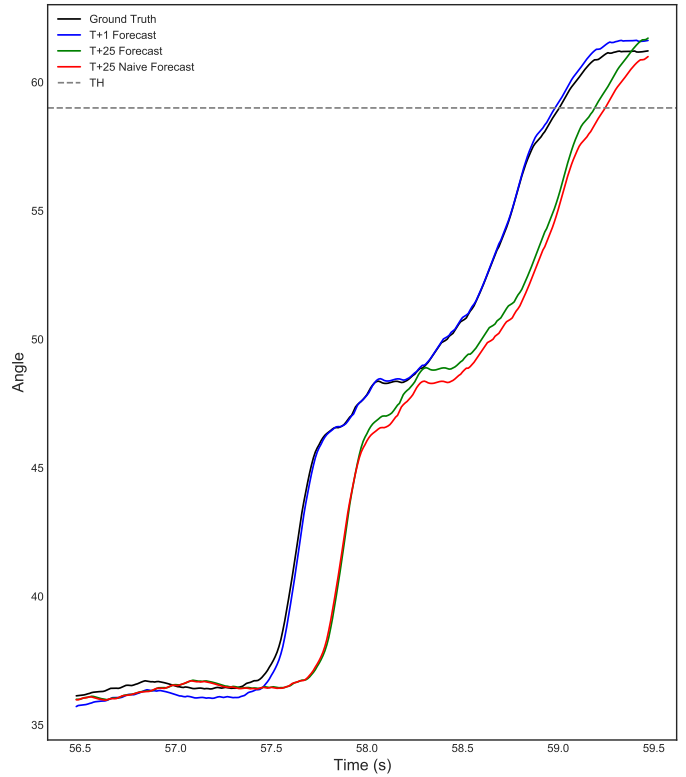


Fig. 4: Example of the Seq2Seq LSTM forecasts for Person A (ground truth - black line;  $T + 1$  ahead forecasts ( $h = 1$ ) - blue line;  $T + 25$  ahead forecasts ( $h = 25$ ) - green line;  $T + 25$  ahead naive forecasts ( $h = 25$ ) - red line Threshold for the risk shoulder angle movement ( $R_u - \tau$ ,  $R_u = 60$ ,  $\tau = 1$ ) - dashed gray line).

for all analyzed anticipation times (100%). Other interesting person results were obtained for series K (76%) and F (71%). However, a small individual performance was obtained for some series, particularly series G. We have further inspected person G results and found that this person produced a more abrupt shoulder movement. For demonstration purposes, we have also tested the performance for person G when increasing the tolerance value to  $\tau = 2$  degrees. As expected, the obtained results (shown in parentheses in the table), have substantially improved (overall score of 57%). We note that there is a trade-off in setting the tolerance value ( $\tau$ ), since a too large value would trigger several false positives. For the sake of consistency with the single person evaluation results, in the remainder experiments shown in this paper, we keep the initial and small  $\tau = 1$  degree value.

The multiple person training and testing evaluation results are presented in Table IV. While assuming the same  $\tau = 1$  that was adopted for the single person evaluation, perfect WMSD results were achieved by the Seq2Seq LSTM forecasts, identifying correctly all risky initial points ( $t_r$ ) and for all analyzed anticipation times ( $\max(h)$ ). These are very interesting results, suggesting that rather than training a distinct ML model for each person, the best strategy to anticipate problematic

TABLE III: Single person risky shoulder anticipation scores ( $\tau = 1$ ).

$\max(h)$	Person											Average Anticipation Score (%)
	A	B	C	D	E	F	G (G $\tau = 2$ )	H	I	J	K	
1	3/3	2/3	1/2	1/1	2/3	2/2	2/3 (3/3)	3/3	2/2	3/3	3/3	86
2	3/3	2/3	1/2	0/1	1/3	2/2	0/3 (3/3)	1/3	1/2	2/3	2/3	54
3	3/3	2/3	1/2	0/1	1/3	2/2	0/3 (2/3)	1/3	0/2	1/3	3/3	50
5	3/3	2/3	1/2	1/1	1/3	1/2	0/3 (1/3)	1/3	0/2	1/3	2/3	46
10	3/3	1/3	1/2	0/1	1/3	1/2	0/3 (1/3)	1/3	1/2	2/3	2/3	46
15	3/3	1/3	1/2	0/1	1/3	1/2	0/3 (1/3)	1/3	1/2	1/3	2/3	43
25	3/3	1/3	1/2	0/1	1/3	1/2	0/3 (1/3)	1/3	1/2	1/3	2/3	43
<b>Overall score per person (%)</b>	100	52	50	29	38	71	10 (57)	43	43	52	76	

TABLE IV: Multiple person risky shoulder anticipation scores ( $\tau = 1$ ).

$\max(h)$	Person				Average Anticipation Score (%)
	C	D	F	I	
1	2/2	1/1	2/2	2/2	100
2	2/2	1/1	2/2	2/2	100
3	2/2	1/1	2/2	2/2	100
5	2/2	1/1	2/2	2/2	100
10	2/2	1/1	2/2	2/2	100
15	2/2	1/1	2/2	2/2	100
25	2/2	1/1	2/2	2/2	100
<b>Overall score per person (%)</b>	100	100	100	100	

movements is to train a single ML model with movements collected from different human subjects.

## V. CONCLUSIONS

Work-related MusculoSkeletal Disorders (WMSDs) are a key issue that affect the health of workers in several industries (e.g., textile, garment, automotive). In this paper, we propose a Machine Learning (ML) pipeline for the automatic prevention of WMSD movements. The pipeline assumes Inertial Measurement Units (IMU) to automate the collection of working movement data. Then, the tri-axis data (acceleration, angular velocity and the magnetic field) is fused into a single angular time series by adopting the Madgwick orientation filter. Next, we perform a pure Time Series Forecasting (TSF) modeling. Finally, the obtained angular forecasts are compared with a risk threshold, allowing to trigger a WMSD alarm in advance. The advantage of using a pure TSF approach is that it is more

flexible, since the same prediction model can be applied to anticipate different angular risk levels.

During the TSF modeling, and using a single time series related with shoulder movements, we compared six different TSF methods: three deep learning architectures, based on the Long Short-Term Memory (LSTM) neural network, and three other ML algorithms (Multiple Linear Regression, Random Forest and Support Vector Machine). Overall, the best TSF results were obtained by a Seq2Seq LSTM model. This method was further evaluated in terms of its capability to anticipate problematic shoulder movements (according to the ISO 11226 norm) by considering two procedures: single person and multiple person training and testing. When executing the single person evaluation, good results were achieved but only for a very small anticipation time (86% for 1 cs). In contrast, high quality results were obtained when training a Seq2Seq LSTM model with movements from 7 persons and then testing it to anticipate problematic shoulder movements from 4 other persons. In effect, the proposed Seq2Seq LSTM model detected perfectly all risky movements for all four human subjects with an interesting anticipation time (one quarter of a second).

The presented research has shown a strong potential of the proposed ML pipeline to trigger WMSD alarms in advance. In future work, we wish to collect data from more human subjects, in order to increase the robustness of the obtained experimental results. Using such extended datasets, we can also further analyze the impact of distinct tolerance values ( $\tau$ ). While only studied for shoulder movements, the proposed methodology could be easily adapted to other body part movements (e.g., leg). Moreover, our research is inserted within a larger R&D project, which aims to adopt exoskeletons to prevent WMSDs. Thus, in the future work, we intend to link the generated WMSD alarms into a real exoskeleton, checking if the current anticipation times are sufficient to trigger a

real-time muscle blocking response that prevents the risky movement.

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