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HYBRID MACHINE LEARNING TECHNOLOGIES FOR PREDICTING COMPREHENSIVE ACTIVITIES OF INDUSTRIAL PERSONNEL USING SMARTWATCH DATA

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ABSTRACT

Context. In today’s industrial development, significant attention is paid to systems for recognizing and predicting human activity in real time. Such technologies are key to the transition from the concept of Industry 4.0 to Industry 5.0, as they allow for improved interaction between man and machine, as well as to ensure a higher level of safety, adaptability and efficiency of production processes. These approaches are particularly relevant in the field of internal logistics, where cooperation with autonomous vehicles requires a high level of coordination and adaptability.

Objective. To create a technological solution for the prompt detection and prediction of complex human activity in the internal logistics environment by using sensor data from smart watches. The main goal is to improve cooperation between employees and automated systems, increase occupational safety and efficiency of logistics processes.

Method. A decentralized data collection system using smart watches has been developed. A mobile application in Kotlin was created to capture sensor readings during a series of logistics actions performed by five workers. To process incomplete or distorted data, anomaly detection algorithms were applied, including STD, logarithmic transformation of STD, DBSCAN, and IQR, as well as smoothing methods such as moving average, weighted moving average, exponential smoothing, local regression, and Savitsky-Goley filter. The processed data were used to train models, with the employment of such advanced techniques as transfer learning, continuous wavelet transform, and classifier stacking.

Results. The pre-trained deep model with the DenseNet121 architecture was chosen as the base classifier, which showed an F1-metric of 91.01% in recognizing simple actions. Five neural network architectures (single- and multi-layer) with two data distribution strategies were tested to analyze complex activity. The highest accuracy – F1-metric 87.44% – was demonstrated by the convolutional neural network when using a joint approach to data distribution.

Conclusions. The results of the study indicate the possibility of applying the proposed technology for real-time recognition of complex human activities in intra-logistics systems based on data from smart-watch sensors, which will improve human-machine interaction and increase the efficiency of industrial logistics processes.

KEYWORDS: distributed system, smart watch, industrial personnel, basic classifier, complex activity, classification, prediction.

ABBREVIATIONS

HAR is a human activity recognition;
AGV is an automated guided vehicle;
ML is a machine learning;
FL is a federating learning;
ANN is an artificial neural network;
CWT is a continuous wavelet transform;
TL is a transfer learning;
IQR is an interquartile range;
STD is a standard deviation;
Log-STD is a logarithmic standard deviation;
MA is a moving average;
WMA is a weighted moving average;
ES is an exponential smoothing;
LOWESS is a local regression;
SG is a Savitsky-Goley filter.

NOMENCLATURE

X is a set of raw multivariate signals;
X' is a cleaned time series;
X'' is a smoothed time series;
a_x is a x-axis accelerometer point;
a_y is a y-axis accelerometer point;
a_z is a z-axis accelerometer point;
g_x is a x-axis gyroscope point;
g_y is a y-axis gyroscope point;
g_z is a z-axis gyroscope point;
t is a discrete time dimension;
W is a fixed duration of temporal windows;
Y_b is a set of classes of basic activities;
Y_c is a set of classes of complex activities;
y_b is a basic activity label;

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y_c is a complex activity label;

g_o is an outlier detection function;

g_f is a smoothing filter function;

D_{source} is a pre-processed source dataset;

D_{target} is a labeled target dataset;

N is a number of consecutive windows;

f_b is a basic activity classification function;

f_c is a complex activity classification function;

a is a CWT scaling parameter;

b is a CWT translation parameter;

ψ is a CWT mother wavelet function;

I is a 6-channel CWT representations of sensor signals;

ζ is a model loss function;

F is a target classification function;

F^* is an optimal target classification function;

θ is a set of a model's inner parameters;

S is a higher-level sequence of basic activities.

INTRODUCTION

Human activity recognition (HAR) is a research area that has gained particular importance due to the widespread adoption of wearable technologies. Practical applications of HAR cover a wide range of areas. In healthcare, HAR is used for fall detection and prevention, seizure detection, and physical activity monitoring [1–4]. Security applications include abnormal activity recognition [5]. In sports, HAR is used to evaluate training effectiveness and estimate calorie expenditure [6–8].

In the era of Industry 4.0 and the ongoing transition to Industry 5.0, new fields of HAR applications have emerged, including tasks such as employee well-being assessment and intelligent enterprise management [9–11]. Initially, the main focus of HAR research was on the task of basic activity classification, which has been largely solved. Today, the focus of researchers is on solving more complex tasks, such as recognizing, analyzing, and predicting complex human activities.

In modern manufacturing environments, traditional production line systems, such as conveyor belts or hangers, are increasingly being replaced by automated guided vehicles (AGVs). Unlike traditional systems, AGVs offer greater flexibility and adaptability in dynamic production processes. However, these systems require more complex coordination with human personnel, which makes the integration of advanced human activity recognition, prediction, and analysis systems critically important [12]. These technologies, when integrated into intelligent enterprise management systems, allow for dynamic routing and optimization of AGV planning based on real-time data on personnel activities. Such a combination can significantly improve the efficiency of production lines and internal logistics systems by quickly adapting to changes in the work environment. Therefore, it is relevant to study the application of smart watch-based HAR systems in such contexts, offering a new approach to process optimization in internal logistics systems of Industry 4.0. Solutions based on the proposed approach can be incorporated into the intelligent enterprise management system to improve the efficiency of the production line.

Tasks in the HAR domain can be divided into two categories depending on the characteristics of the activity being studied. The first category includes simple, repetitive actions involving basic human body movements and postures, such as running, sitting, or walking upstairs. These activities can be recognized relatively easily using statistical analysis of signals (so-called shallow features) and basic machine learning (ML) models. The second category includes complex, functional, and contextual activities associated with specific human activities. Examples of this category include working, cooking, playing sports, and driving. These activities are characterized by their complexity, which requires advanced approaches and models for detection, classification, and analysis. In addition, modern applications typically require recognition of these actions in real time, i.e., without the need for manual input of temporal start and end timestamps. While the task of recognizing basic human activities has been largely effectively solved, current research is increasingly focused on developing and improving methodologies for recognizing complex, multi-step activities in real time. The application of the task of recognizing complex human activities extends to areas such as intelligent enterprise management using AGVs in the context of Industry 4.0, healthcare, anomaly detection, and sports analytics.

Existing solutions for monitoring and recognizing industrial personnel actions are typically based on image analysis, the use of portable sensors, or a hybrid of both approaches. Although image analysis-based approaches are widely used, they have several drawbacks, including privacy concerns, the need for full coverage of the production area, and significant financial investment. In addition, such solutions often impose restrictions on personnel movement, requiring their constant presence in the field of view of the cameras. This limitation is particularly problematic in dynamic sectors such as flexible manufacturing and intralogistics, where human personnel often move around vast industrial spaces. Integrating cameras with portable sensors can mitigate some of these problems. However, this approach also has certain disadvantages, including the high cost of the equipment, the need to develop complex sensor data synthesis systems, and the need for large computing resources. On the other hand, solutions based on wearable sensors avoid these problems, as the sensors are placed directly on the worker's body, do not require large area coverage and are relatively cheap. Therefore, this study primarily focuses on developing an approach and solution for classifying and predicting complex personnel activities based on the use of wearable sensors.

The object of study is the process of recognizing complex human activities in real-time within intralogistics systems using autonomous guided vehicles. This process is influenced by many factors, including the qual-

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ity and reliability of sensor data, the presence of noise and missing values, the effectiveness of preprocessing and feature extraction techniques, the choice of machine learning models, and the computational constraints of real-time processing.

The subject of study is the evaluation of methods for recognizing and predicting complex human activities in real-time within dynamic environments, focusing on the integration of signal collection, outlier detection, filtration, continuous wavelet transform and the use ANN with transfer learning (TL).

The purpose of the work is to recognize complex human activities in real-time within intralogistics systems using smartwatch sensor data to enhance human-machine interaction, optimize the coordination of AGVs, improve workplace safety, and increase the overall efficiency of industrial logistics processes.

1 PROBLEM STATEMENT

Let $X = \{X_t\}_{t=1}^{T}$ be a multivariate time series collected from a smartwatch worn by an industrial worker. Each $X_t \in R^6$ consists of six sensor readings: three-axis accelerometer (a_x, a_y, a_z) and three-axis gyroscope (g_x, g_y, g_z). The data is segmented into temporal windows of fixed duration, resulting in windowed sequences (1):

$$X^{(i)} = \{X_t\}_{t=t_0}^{t_0+W-1}, X^{(i)} \in R^{W\times 6}. \quad (1)$$

Each window is associated with a basic activity label $y_b^{(i)} \in Y_b$ (e.g., sit, stand, run). A sequence of N consecutive windows forms a higher-level sequence $S = (X^{(i)}, y_b^{(i)})_{i=1}^{N}$ with a corresponding complex activity label $y_c \in Y_c$ (e.g., “working on a machine”, “performing assembly tasks”). Classification function (2) maps a sequence of N consecutive windows of low-level sensor data to a complex activity label:

$$F : \{X^{(i)}\}_{i=1}^{N} \to y_c. \quad (2)$$

The objective is to find an optimal function (3) given a labeled target dataset $D_{target} = \{S, y_c)\}$, that minimizes a loss function ζ, ensuring the accuracy of predictions, and maximizes the F_1-score, ensuring a balanced trade-off between precision and recall:

$$F^* = \begin{cases} \arg\min\limits_{\theta} \sum\limits_{(S,y_c)\in D_{target}} \zeta(F(S;\theta), y_c); \\ \arg\max\limits_{\theta}(F_1 - score(F(S;\theta), y_c)). \end{cases} \quad (3)$$

The following limitations should be considered during the development of F^*:

1. The collected signals may contain outliers due to sensor noise or incorrect readings. Missing values may arise due to transmission errors or temporary disconnections, requiring robust preprocessing techniques.

2. Only wearable sensor data is used, excluding video-based or multimodal approaches that might provide additional context. This constraint necessitates effective feature extraction and signal representation techniques to compensate for the absence of visual cues.

3. The approach is designed to be compatible with distributed computing and federated learning, ensuring data privacy and security. This requires models that can be trained in a decentralized manner without centralizing raw sensor data.

2 REVIEW OF THE LITERATURE

Methods for recognizing and analyzing basic human activities have been studied in many publications. In [13], the authors used logistic regression, KNN and SVM to analyze the smartphone accelerometer signal to recognize the actions of boarding and disembarking from a bus. The KNN classifier demonstrated high performance, achieving an accuracy of 95.3%. In the study [14], the authors classified accelerometer and gyroscope signals collected from an iPod Touch using C4.5, DT, multilayer perceptron and naive Bayesian classifier, LR, KNN, and meta-algorithms such as boosting and bagging to classify 13 activities. The results show that the KNN classifier is highly effective for HAR tasks based on wearable sensors. For more robust activity classification using shallow features, extreme gradient boosting [15, 16] and ensemble learning [17, 18] have been widely used.

In recent years, deep learning-based approaches have gained considerable popularity in the field of HAR. The authors [19] conducted a comparative analysis of RF, SVM, and Convolutional Neural Network (CNN) algorithms for HAR problems using accelerometer data. The experimental results concluded that deep learning models outperformed traditional classifiers. In another study [20], the authors evaluated the effectiveness of one-dimensional CNN and hybrid models, such as CNN-LSTM and CNN-GRU, for classifying human mobility gestures. The CNN-LSTM architecture demonstrated high performance, achieving accuracies of 99.89%, 97.28%, and 96.78% on the WISDM, PAMAP2, and UCI-HAR datasets, respectively. In [21], the performance of nine popular CNN architectures for HAR problems was compared. The authors also applied methods such as Continuous Wavelet Transform (CWT) and TL to improve performance. The model based on the DenseNet121 architecture with the Morlet 256 CWT configuration was found to be the most effective model for sensor-based HAR.

Despite the large number of available solutions for basic activity recognition, a limited number of works have been published in the field of complex human activity recognition. In [22], the authors proposed the CHARM model, which consists of a two-stage ANN. The first

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stage is an encoder that compresses fixed-size signals into a continuous feature representation. The second stage is designed to classify high-level activities based on the output sequences of the low-level encoder. The model was tested on the Opportunity dataset for the classification of four daily activities, such as morning routine, tea, lunch, and cleaning. The authors compared the proposed model with SVM, RF, and MLP classifiers, as a result of which CHARM outperformed classical algorithms. The advantage of the proposed approach is that it does not require labeling of basic activities. However, because the two-stage ANN is trained using an end-to-end approach, it makes it difficult to integrate distributed computing and use federated learning, which is critical for Industry 4.0 applications.

The authors [23] proposed an adaptive multitask learning approach that consists of two components. The first component provides a feature representation for complex actions and encodes the temporal relationship between the main activities. The output of this component is a set of frequent patterns for the activity. The second component is the a MTL algorithm that captures the relationship between complex actions and selects prominent features. The proposed approach was applied to recognize five ADLs from the Opportunity dataset, demonstrating promising performance. A potential limitation of this approach is its questionable scalability and extensibility, especially when adding new actions or fitting to new data. The authors [24] proposed a method for recognizing human interactions using the analysis of consecutive image frames. The presented model consists of several levels, namely the body part selection level, the pose recognition level, the gesture recognition level, and the interaction level. The model was applied to recognize eight interaction types (approach, retreat, pointing, handshake, hug, hit, kick, and push), achieving an overall accuracy of 91.70%. In [25], the authors developed a framework for detecting composite actions for recognizing complex activities using video data. This approach uses the intrinsic associations between activities and high-level activities to develop a classification network. The proposed approach was tested on the Breakfast Actions dataset, which contains ten complex activities, achieving an accuracy of 80.51%. Although the solutions proposed in the reviewed works achieved promising results, they use a video camera-based approach, which implies certain limitations in applications in Industry 4.0 due to the problems mentioned earlier.

Several publications are devoted to the development of methods and tools for HAR in the context of Industry 4.0. The authors of [26] investigated the performance of various frequency and time domain functions and popular ML algorithms for classifying activities in logistics systems. The SVM, DT, RF and XGBoost algorithms were used to classify inertial measurement device signals from the LARa dataset. The best results were achieved by the XGBoost classifier using time and frequency domain functions with an average accuracy of 78.61%. In [27], an approach for HAR using video from a 360-degree camera is proposed. The authors investigated different ANN models for tracking the direction of movement of people using data collected from the AGVs. Each model was trained using the LboroHAR dataset. The study showed that the Shi-Tomasi angle detection method is the most effective technique for this application. The authors [28, 29] proposed a solution for activity recognition in industrial environments that uses multimodal data from cameras and wearable sensors. The limitations of this solution are the need for the camera to cover the entire production area and the requirement for the worker to remain stationary, which is impractical in a dynamic environment where operators interact with the AGV, move between loading and unloading points, and perform multiple tasks simultaneously. An alternative solution that does not use cameras and does not restrict worker movement is proposed in [30]. This approach uses body capacitance sensors and IMUs with the subsequent use of CNN and LSTM [31] to perform data fusion, which allowed the recognition of 11 actions. The disadvantage of this approach is the need to develop special 10-channel sensors with a total of 20 channels in the system, which requires special equipment capable of operating in specific industrial conditions. In addition, the complexity of such systems increases significantly when collaborative robots that support human work are used in the enterprise, since data from people, AGVs, and CoBots must be combined [32].

CWT offers several advantages over the traditional Fourier transform and the short-time Fourier transform [33]. First, the CWT provides a more accurate representation of the transients and peaks that are characteristic of biomedical signals, such as signals from accelerometers or gyroscopes. Second, this transform handles the non-stationary nature of such signals by representing both temporal and localized spectral information. Hence, the application of the CWT in various studies has led to improved model performance and mitigated overfitting problems [21, 34–38].

In this paper, a solution is proposed that uses smart watches to recognize the actions of industrial personnel. This approach provides a low-cost alternative that avoids the aforementioned limitations, such as the need for complex equipment for signal fusion, the need for full coverage of the production area, or the limitation of personnel mobility. By using a stacking architecture of classifiers, the proposed solution is easily scalable and can be extended to include new actions, facilitating the use of federating learning (FL) and edge computing. The objective is to develop a system and technology for classifying and predicting complex activities of industrial personnel in real time, which requires only a smart watch. This device is widely used in sports, is relatively cheap and is allowed by internal policies of enterprises. The only change from the smart watch is the installation of a program for collecting data from sensors. Depending on the requirements, the data can be processed directly on the device or transmitted to an edge server. Additionally, the stack architecture of the proposed approach supports the implementa-

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tion of distributed computing and FL, ensuring confidentiality and adaptability.

The following goals were outlined:

1. Analyze the current state and challenges of the HAR domain. Consider available solutions for recognizing personnel activities. Highlight the limitations of modern systems and approaches.
2. Develop a system for collecting data from smart watch sensors on the activities of industrial personnel. The developed software solution should allow simultaneous receipt of data from many subjects in real time.
3. Collect a dataset containing smart watch sensor signals from industrial personnel. The dataset should reflect typical personnel activity when performing tasks in the internal logistics systems of enterprises with AGVs.
4. Use methods to detect and eliminate outliers, noise, and partially lost data. Verify the effectiveness of the methods on data collected from industrial personnel's smart watches.
5. Develop a data preprocessing algorithm to isolate outliers and prepare data for training ML models. Develop a strategy for separating the collected data.
6. Develop an artificial neural networks (ANN) architectural framework that will allow classifying and predicting complex activities of industrial personnel in real time. The developed architecture should support distributed computing and FL.
7. Verify the effectiveness of different models and configurations for classifying and predicting complex activities. Apply modern techniques to improve the effectiveness of models, such as TL and CWT.

3 MATERIALS AND METHODS

The proposed methodology is based on the use of advanced signal processing methods and the following usage of classifier stacking with TL to recognize and predict the complex activity label based on sensor signals. Fig. 1 illustrates the general structure of the described methodology.

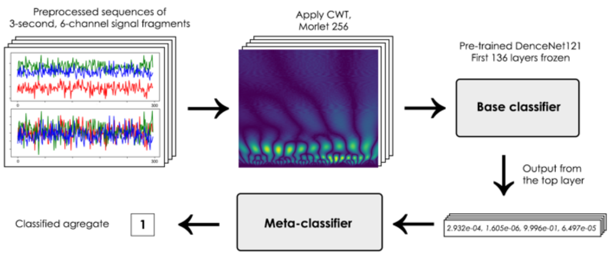

Figure 1 – General structure of the proposed methodology

In the first stage, the dataset undergoes preprocessing, where potential outlier detection and removal interruptions and noise smoothing are taken into account, resulting in continuous, fixed sequences of 6-channel signal fragments that represent the execution of a particular unit. Given raw sensor readings X , an outlier detection function is applied: $X' = g_o(X)$. After that, smoothing filter is used to remove noise: $X'' = g_f(X')$.

In the second stage, CWT is applied to each channel of sensor signals to generate time-frequency representations (4):

$$I^{(i)} = \text{mod}\left(\frac{1}{|a|^{1/2}}\int_0^W X_t^{(i)''} \ \psi\left(\frac{t-b}{a}\right)dt\right). \qquad (4)$$

The output is a 6-channel two-dimensional heat map (scalogram), which allows us to translate the problem of time series classification into an image classification problem. This transition allows us to take advantage of the significant breakthrough in the problem of image classification over the past decade, with many deep and highly efficient models and architectures available. Fig. 2 shows an example of the transformed X-axis signal of an accelerometer using the CWT with the parent Morlet wavelet and scaling parameter values from 0 to 128.

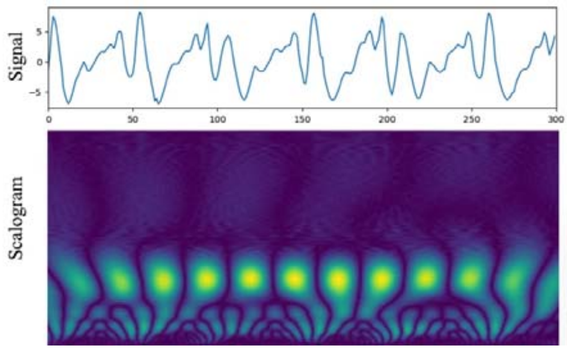

Figure 2 – Accelerometer signal converted using CWT

Third, two classification functions are introduced: (5) for the basic activity recognition using a deep learning classifier maps each window $X^{(i)}$ to a basic activity label:

$$f_b : X^{(i)} \to y_b^{(i)}, \qquad (5)$$

and (6) for the complex activity recognition using a sequence-based model that classifies complex activities based on sequences of basic activity predictions:

$$f_c : (X^{(i)}, y_b^{(i)})_{i=1}^{N} \to y_c. \qquad (6)$$

TL approach is employed to the f_b in order to improve the basic human activities classification accuracy. Pre-processed source dataset $D_{source} = (\{I_s^{(i)}, y_{sb}^{(i)}\})_i^{N_{source}}$ consists of labeled 6-channel time-frequency representations of sensor signals $I_s^{(i)} \in R^{H \times W \times 6}$ via CWT from raw sensor readings, and the corresponding basic activity label $y_{sb}^{(i)} \in Y_{sb}$ from the source dataset. The deep learning classifier f_b is trained

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(7) on this dataset by minimizing the categorical cross-entropy loss function ζ_b:

$$f_b^{pretrained} = \arg\min_{\theta_s} \sum_{(I_s^{(i)}, y_{sb}^{(i)}) \in D_{source}} \zeta_b(f_b(I_s^{(i)};\theta_s), y_{sb}^{(i)}) . \quad (7)$$

TL is performed via fine-tuning. The feature extraction layers of f_b are initialized with pre-trained weights θ_s. The top classification layers are replaced with a new randomly initialized classifier adapted to the target dataset's class distribution. Then, the model (8) is trained on the smartwatch dataset:

$$f_b^* = \arg\min_{\theta} \sum_{(I^{(i)}, y_b^{(i)}) \in D_{target}} \zeta_b(f_b(I^{(i)};\theta_s,\theta), y_b^{(i)}) . \quad (8)$$

This approach allows the model to leverage pre-trained knowledge from a larger dataset while adapting to the specific characteristics of the target domain, improving classification performance on basic activities. After that, labels for all basic activities in the dataset are redefined based on the training from the top-level neurons of the trained base classifier.

In the fourth stage, a metaclassifier (for the complex activity recognition task) is trained (9) on fixed-size sequences of classification results of the base classifier:

$$f_c^* = \arg\min_{\phi} \sum_{(s, y_c) \in D_{target}} \zeta_c(f_c(S;\phi), y_c) . \quad (9)$$

The sequence-based model f_c takes as input the sequence of basic activity predictions $(y_b^{(i)})_{i=1}^{N}$ and classifies the complex activity.

4 EXPERIMENTS

To achieve the goals of this work, a distributed data collection and analysis system was developed. The main components of the system are the Samsung Galaxy Watch 5 smart watch, an application for the WearOS operating system and a cloud server. The application collects data from hardware sensors, provides functionality for controlling the experiment execution process through the user interface and sends data to the cloud. The Kotlin programming language was used as a modern development standard for the WearOS operating system.

The cloud server was developed using the MySQL-Server software solution, which works under the platform-as-a-service (PaaS) model. The cloud solution, in particular the PaaS model, was chosen due to its high scalability and wide data protection capabilities. The system architecture is aimed at the possibility of simultaneously receiving data from different subjects, which increases the efficiency of the research methodology. Fig. 3 illustrates the general structure of the system.

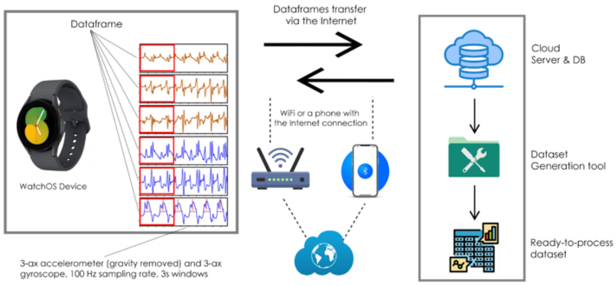

Figure 3 – Structure of the developed data collection system

The application collects data from a three-axis accelerometer and a three-axis gyroscope (six data channels in total) with a sampling rate of 100 Hz. On the smartwatch side, no signal filtering is performed, and gravitational acceleration is excluded from the accelerometer signal. For each channel, a 3-second frames of the signal, along with additional information such as the hand on which the watch is worn, the frames start/stop timestamps, and the data collection subject identifier, is compressed and sent as a data frame.

Data frames containing less than three seconds of signal recording (which can occur during interrupted data collection sessions or loss of connectivity) are not sent to the cloud and are discarded by the application. During the dataset generation phase, data frames with the same start timestamps are combined into a single six-channel signal (data frame group). If one or more channels are lost, incomplete data frame groups are discarded.

The term “aggregate” refers to a sequence of basic activities or actions that are continuously executed in a specific order. Data on aggregates is also collected using the program. It is important to note that since this work focuses on recognizing complex activities in real time, time markers indicating the start and end of a specific instance of aggregate execution are not recorded. Instead, information related to aggregates is obtained during experimental sessions where participants participate in the continuous execution of a specific aggregate. Events related to an aggregate, such as the start and end of data collection sessions, are sent to the cloud as an “aggregate event” data structure.

During the experimental sessions, users entered information about the start and end of the aggregate execution data collection sessions into the application. In case of connection problems, aggregate events are queued and resent when the connection is restored.

In summary, sensor signal data is transmitted as a 3-second data frame for each sensor channel, resulting in a total of six channels. Tags related to basic activities are included as a field in the data frame. Aggregate execution data is collected in the form of aggregate events containing time stamps of the start and end of the aggregate execution data collection sessions.

The implementation program for the smartwatch and the cloud server is presented in Fig. 2. The application is developed for the Samsung Galaxy Watch 5 smartwatch based on the WearOS operating system. The main purpose of the program is to collect sensor data, send it to the

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cloud server, and provide an interface for controlling the data collection process. WearOS was chosen as the operating system due to its robust API and high degree of adaptability for hardware sensor interaction. The Kotlin programming language is used as the current standard for the development of WearOS and AndroidOS. Some of the application user interface screens are shown in Fig. 2, namely: the start/stop sensor data collection screen; the screen for managing data collection sessions and aggregates; the basic activity selection screen; the data collection subject selection screen; the screen displaying sensor information. Examples of some application user interface screens are shown in Fig. 4.

Figure 4 – Examples of application user interface screens

The cloud server solution, implemented in the PaaS model, provides scalability and enhanced security capabilities, and also allows simultaneous data acquisition from different objects, thus ensuring effective data management and significantly increasing the efficiency of the research methodology. The main purpose of the cloud server is to store the collected data and make it available for further processing and analysis. In addition, the MySQL server software was used due to its high performance and scalability characteristics, ensuring optimal data management and integrity during the research process. This choice was due to the easily available cloud solutions compatible with MySQL, as well as a wide range of WearOS libraries and plugins that support it. This makes it a more pragmatic and effective choice for our requirements.

During data collection, the subject manually sent aggregate stop and start events to the program. In case of loss of connection, all events were queued and resent after the connection was established. The structure of the database schema is shown in Fig. 5. The architecture includes two main node tables: "Dataframes" and "AggregateEventLogs". The "Dataframes" table is dedicated to operations on sensor data, storing this information according to the data structure. Meanwhile, the "AggregateEventLogs" table is an integral part of the aggregate-related functionality, recording events. In addition, the "Devices" table is used to manage devices, facilitating the integration of new WatchOS data collection devices into the system. The system also includes other tables that contribute to data normalization and provide system flexibility through periodic cleanups.

During the experiments, data was collected from five industrial personnel involved in the continuous execution of one of two predefined aggregates. Participants were required to use an application on their smartwatch to record the start and end timestamps of each experimental session and each major activity they performed during these sessions.

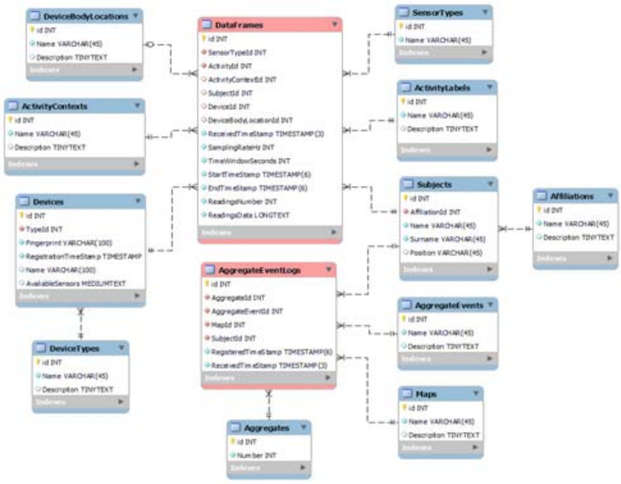

Figure 5 – Structure of the cloud database schema

The topological configuration of each aggregate is depicted in Fig. 6. Both aggregates start from the same starting point. The first unit covers the following sequence of actions: sitting (at point 1), moving from sitting to standing, standing, walking to point 2, performing a 90-degree turn, walking to point 3, standing, moving from standing to sitting, and then sitting. These actions are then performed in reverse order to return to the starting point. The second aggregate consists of the following sequence: sitting (at point 1), moving from sitting to standing, standing, walking to point 2, performing a 180-degree turn in any direction, walking back to point 1, standing, moving from standing to sitting, and then sitting.

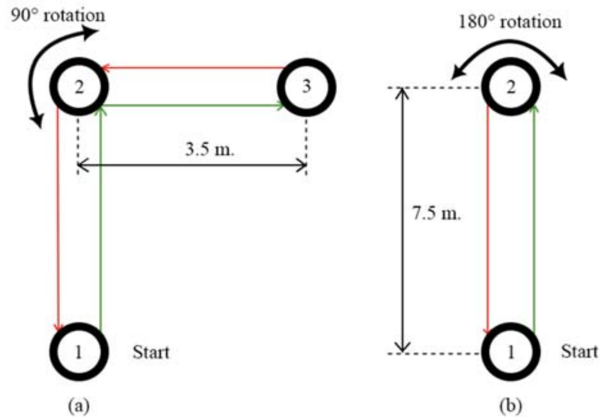

Figure 6 – Topological configuration of the first (a) and second (b) aggregates

All participants wore a smartwatch on either their left or right wrist. During the data collection phase, there were instances where the connection was temporarily interrupted or participants intentionally paused the experiment by pressing the "Stop" button in the app. These incidents will be reviewed and corrected during the pre-processing phase of the dataset to ensure data integrity and continuity.

The dataset collected from this study covers a total of 3.28 hours of six-channel sensor data of a three-axis ac-

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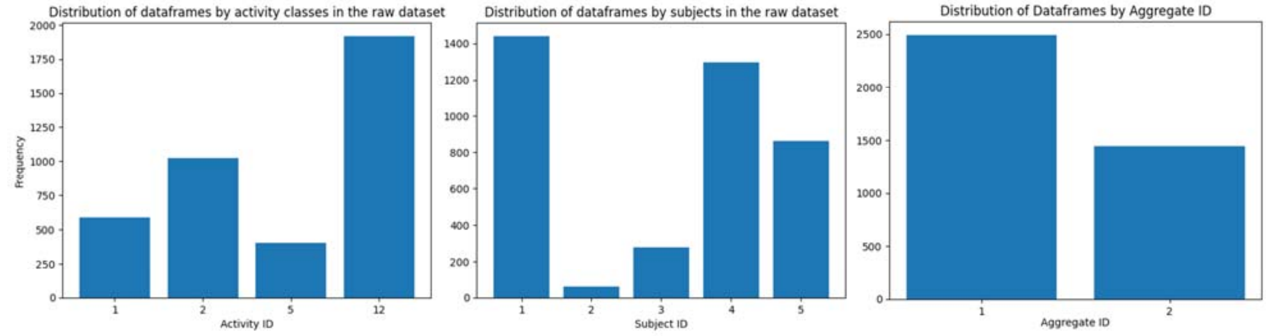
celerometer and gyroscope, accumulated during 18 experimental sessions. During these experiments, subjects continuously performed one of two aggregates and recorded their activities. This dataset contains a unique base activity identifier for each data frame and information about the subject from whom it came, as well as detailed records of the start and end of the experimental sessions.

The distribution of data frames in the collected dataset, classified by activity, personnel identifiers, and associations with aggregates, is depicted in Fig. 7. The activity identifiers are labeled as follows: 1-standing, 2-sitting, 5-transitions between standing and sitting (and vice versa), and 12-walking.



a b c

Figure 7 – data frames distribution by a – basic activities;
b – subjects; c – aggregates

A feature of this dataset is its inherent imbalance, which can be expected given the context of the study. This imbalance is explained by the nature of the studied aggregates, where certain actions (e.g. walking) dominate, which occupies the majority of the dataset.

Outliers in the data affect the accuracy of the collected data of the system in the following ways:

– accelerometer – data loss can lead to errors in the location or speed of the object. Since accelerometers measure changes in speed, the absence of data can negatively affect the accuracy of calculating the trajectory and angle of inclination.

– gyroscope – data loss affects the accuracy of calculating the orientation and angular position of the object. Since gyroscopes measure angular velocity, in the event of data loss, directional errors (gyro bias) can accumulate.

The Kolmogorov-Smirnov statistic indicates a certain deviation from the normal distribution (0.133112). The extremely low p-value (0.0000000347) confirms that the deviation is statistically significant, which means that the data does not follow a normal distribution. Fig. 8 shows a histogram of the distribution of accelerometer values along the x-axis.

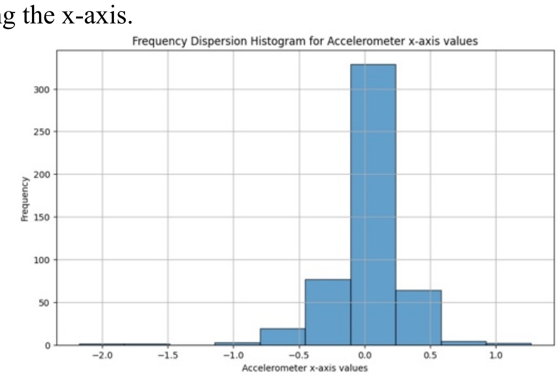


Figure 8 – Histogram of the distribution of accelerometer values along the x-axis

Most of the values are centred around zero, with some deviations in either direction. This indicates that the bulk of the data is concentrated in the central part, but there are some outliers. Figure 9a shows a histogram with outlier thresholds determined using the standard deviation (STD). The red vertical lines show the limits at which values are considered outliers. Most values are within these thresholds, but there are some values that fall outside the limits, indicating the presence of outliers. Figure 9b shows a histogram with outlier thresholds determined using the interquartile range (IQR). The red vertical lines also show the outlier limits. As in the previous case, most values are within these thresholds, but there are some outliers. Figure 9c shows a histogram of log-transformed data with outlier thresholds determined using the STD. It helped reduce the impact of large values, but there are still some outliers.

Figure 10 shows a histogram with outliers determined using the DBSCAN algorithm with parameters eps=0.01, min_samples=10. The percentage of outliers for each method is: STD- 10.80%, IQR- 12.00%, Log-STD- 8.60%, DBSCAN: 26.00%. The STD and IQR methods detect approximately the same number of outliers, indicating their similarity in determining outlier thresholds.

Logarithmic standard deviation (Log-STD) reduces the number of outliers, which can be useful for data with large deviations. The DBSCAN method detects the largest number of outliers, which may indicate its sensitivity to anomalies in the data. Therefore, for further analysis, it is recommended to use a combination of outlier detection methods to obtain more accurate results. In general, logarithmic transformation can be useful for reducing the impact of large values, but it should be noted that it can change the structure of the data. Using DBSCAN can be useful for detecting more anomalies, but caution should be exercised with its sensitivity.

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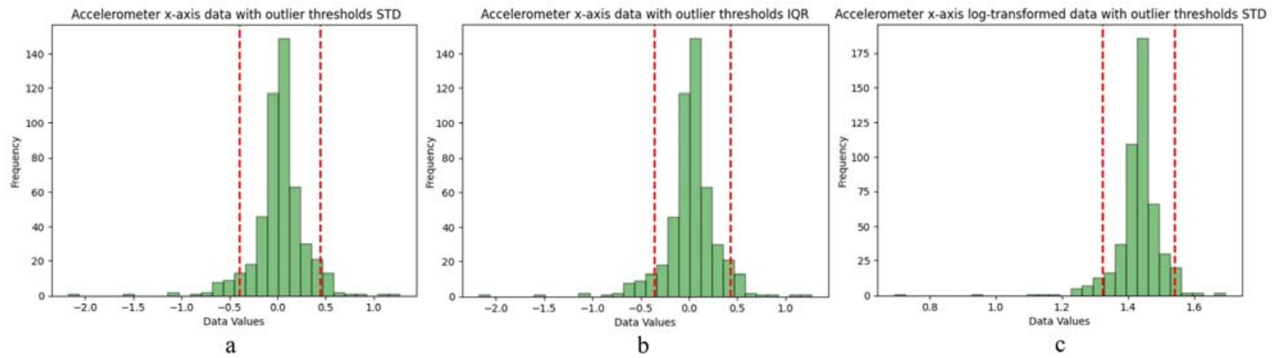

Figure 9 – Histogram with outlier thresholds: a – using standard deviation; b – using interquartile range; c – using log-transformed data with outlier thresholds determined using standard deviation

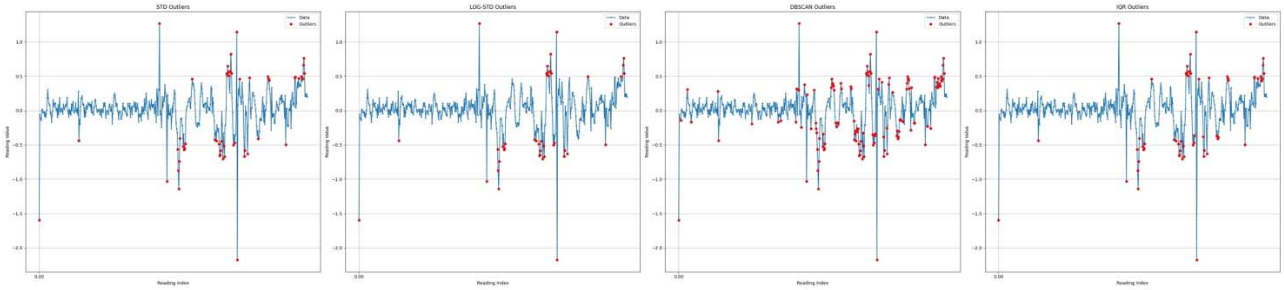

Figure 10 – Outlier detection using STD, Log-STD, DBSCAN, IQR methods

Detected outliers in sensor data in the control system can lead to incorrect analysis of industrial personnel movements, incorrect behaviour of automated devices, or a decrease in the overall efficiency of the production process. Assignment, interpolation, filtering, and smoothing methods are used to minimize the impact of noise on partially lost and distorted data. The filter helps to smooth out noise and eliminate gaps. Smoothing methods are effectively used to restore distorted or partially lost data based on adjacent values. Fig. 11 shows the results of using such filters as moving average, weighted moving average, exponential smoothing, local regression, and the Savitsky-Goley filter.

The results of calculating the deviations of all methods are presented in Table 1. According to the results, it is advisable to smooth the noise by local regression. Since it is used to smooth the data by constructing a local polynomial regression with small intervals between the data. Therefore, it effectively processes nonlinear data by adjusting the degree of the polynomial in each interval, locally adapting it to the shape of the trend in each interval. But this requires a sufficient amount of data in each interval.

In this work, the following parameters of the CWT were chosen: the Morlet mother wavelet, the value of the parameter a from 0 to 256 and the value of the parameter b from 0 to 300. This choice was based on studies [3, 21], where these parameters were determined to be the best for HAR problems based on wearable sensors when used in combination with the DenceNet121 model.

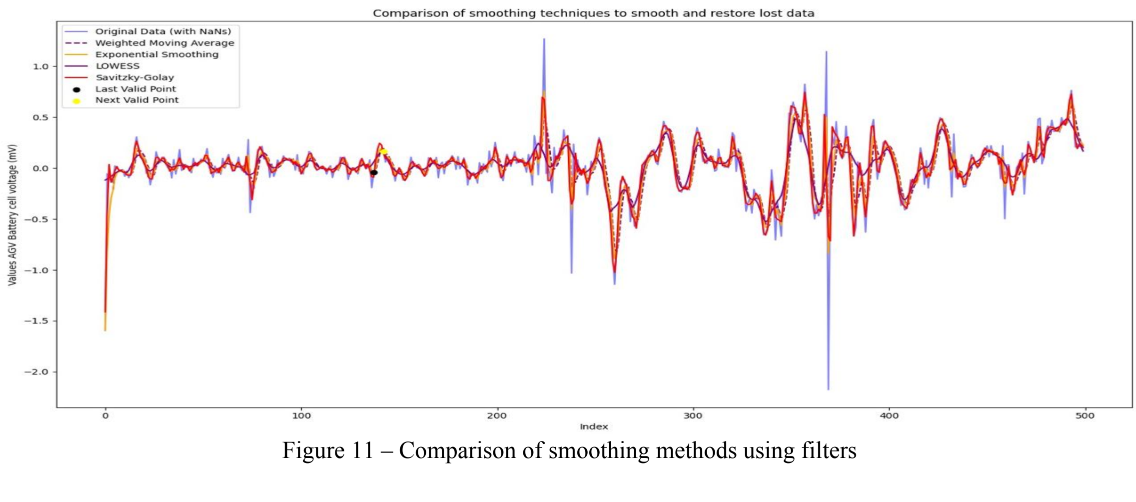

Figure 11 – Comparison of smoothing methods using filters

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Table 1 – Deviations of smoothing filters

Deviation	Orig. Data	MA	WMA	ES	LOWESS	SG
X, axe	0.2824	0.2021	0.2086	0.2291	0.1795	0.2477
Y, axe	0.5635	0.4323	0.4472	0.4618	0.4284	0.5160
Z, axe	1.0584	0.5361	0.5248	1.1328	0.4430	0.9993
X, hyr	0.2244	0.2040	0.2073	0.2074	0.2143	0.2225
Y, hyr	0.1189	0.1076	0.1103	0.1095	0.1130	0.1182
Z, hyr	0.1962	0.1929	0.1934	0.1897	0.1913	0.1964
Dispersion	**Orig. Data**	**MA**	**WMA**	**ES**	**LOWESS**	**SG**
X, axe	0.0798	0.0408	0.0435	0.0525	0.0322	0.0613
Y, axe	0.3175	0.1869	0.2000	0.2133	0.1835	0.2662
Z, axe	1.1203	0.2874	0.2754	1.2832	0.1962	0.9987
X, hyr	0.0504	0.0416	0.0430	0.0430	0.0459	0.0495
Y, hyr	0.0141	0.0116	0.0122	0.0120	0.0128	0.0140
Z, hyr	0.0385	0.0372	0.0374	0.0360	0.0366	0.0386

This study proposes a six-step dataset preprocessing pipeline, shown in Fig. 12. It receives a set of data frames collected during experimental sessions as input, and produces datasets with fixed-size continuous sequences as output. In the first step, data frames recorded outside the experimental sessions are deleted based on their timestamps to eliminate possible outliers. In the second step, gaps in the data frame sequences are identified and highlighted using the time delta criterion. To do this, the timestamp of the end of one data frame is compared with the timestamp of the start of the next frame. If the interval exceeds 500 milliseconds, this indicates a possible pause in the experimental session or a hardware failure. In this case, this marks the end of one continuous sequence and the beginning of a new one. In the third step, the continuous data frame sequences are reduced to a fixed size of 20 frames (equivalent to 60 seconds). This size is chosen based on the fact that the initial activities of both units are the same. Hence, it is expected that a minute will be enough for the subject to perform some basic activities and the metaclassifier and predictor will have enough information to distinguish them. In the fourth stage, 50% overlap between fixed sequences is performed to expand the dataset.

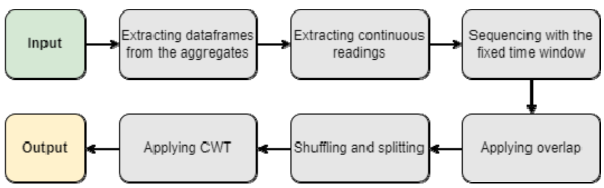

Figure 12 – Dataset preprocessing pipeline

In the fifth stage, shuffling is performed, after which the dataset is divided into subsets for training, testing, and validation. In this study, two strategies are used to divide the dataset, which are illustrated in Fig. 13. In the first partitioning strategy, 40% of the dataset is used to train the base classifier and validate the meta-classifier, the other 40% is used to train the meta-classifier and validate the base classifier, and the last 20% is used for testing. This strategy provides unique data for training the models at each level, which is the "ideal" scenario, but potentially provides insufficient data for training the meta-classifier because it does not use TL. The second strategy allocates 40% to train both classifiers, another 40% to validate the base classifier and further train the meta-classifier, and the remaining 20% for testing. The second strategy provides more data for the meta-classifier, but may result in it not capturing errors from the base classifier on new data. Finally, in the sixth step, the CWT is applied to each of the six channels of the data frames using the Morlet mother wavelet and scaling parameter values from 0 to 256.

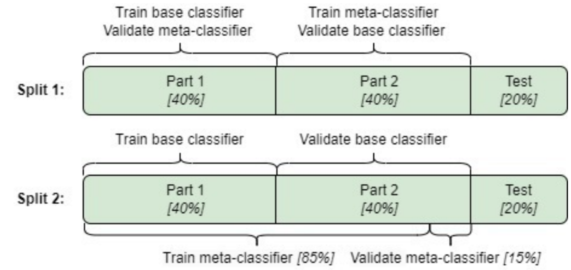

Figure 13 – The dataset partitioning strategies

In this work, the model proposed in [21, 39] was used as the baseline classifier. It is based on the DenseNet121 architecture and is specifically designed for HAR tasks. This model is pre-trained on the KU-HAR dataset [40], and CWT was used to improve performance. The proposed model achieved an F1 score of 97.52% on the KU-HAR dataset, which outperformed state-of-the-art works and demonstrated improved performance on small datasets when using layer freezing.

The original KU-HAR dataset contains 20,750 non-overlapping samples with three-axis accelerometer and three-axis gyroscope signals collected using a smartphone for 18 different activity classes. Fig. 14 illustrates the methodology used to apply knowledge transfer from the KU-HAR dataset to the collected dataset.

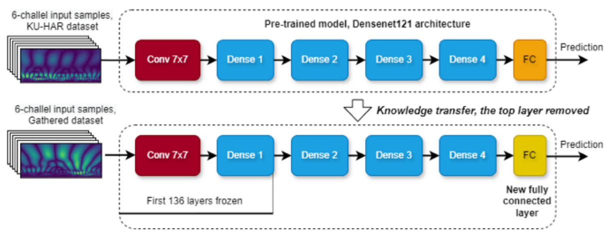

Figure 14 – Knowledge transfer approach used for the base classifier

To fit the DenseNet121 model pre-trained on the KU-HAR dataset, several manipulations are made. First, the top fully connected layer of the pre-trained model is removed and replaced with a new one initialized using the Xavier scheme. The new layer contains four neurons, which corresponds to the number of activity classes in the collected dataset. According to the study [39], freezing the layers of the pre-trained DenseNet121 can improve the performance of the model on small HAR datasets, with the optimal number being 136 layers. Accordingly,

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the same configuration is used in this work. Additionally, appropriate class weights are used when training the base classifier to mitigate the problem of imbalance in the dataset.

The hyperparameters for training the base classifier were chosen experimentally and include the Adam optimizer, 100 training epochs, and a batch size of 32. Callbacks such as “Model checkpoint”, “Early stop”, and “Reduce training intensity at plateau” were used during training. The model was trained 10 times, and the results of the best performing instance are presented in this study.

In this study, LSTM, BiLSTM, GRU, BiGRU, and CNN architectures were used as meta-classifiers. These models were chosen because of their ability to capture temporal dependencies in fixed-size sequential data, which is important in our case. Regarding the CNN-based model, the architecture of the meta-classifier used is illustrated in Fig. 15. The input to the meta-classifier is a matrix (20×4) representing a sequence of 20 classification results from the top-level neurons of the base classifier. The architecture of the meta-classifier based on the CNN includes two convolutional blocks with pooling and batch normalization layers, as well as two fully connected blocks. The Leaky ReLU activation function is used, which prevents the problem of “dying neurons”. Dropout layers were enabled during training to improve generalization.

For the LSTM, BiLSTM, GRU and BiGRU models, experiments were conducted with both single-layer and multi-layer configurations. Each layer consists of 64 neurons, and the models include a fully connected layer with two neurons and a softmax activation function. In multi-layer configurations, two consecutive layers were used, each containing the same number of neurons.

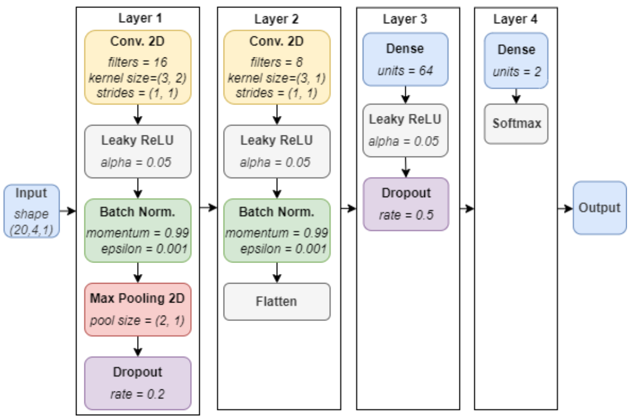

Figure 15 – Architecture of a meta-classifier based on CNN

The hyperparameters used in training the meta-classifiers include a simple gradient descent optimizer, 500 training epochs, and a batch size of 16. As with the base classifier, the same training callbacks were enabled and class weights were set. Each model configuration was trained 100 times, and the results of the best models are reported in this study.

5 RESULTS

Table 2 presents the performance metrics of the base classifier on the test subset [41]. The model generalization result from the base classifier training data is high. Furthermore, the validation accuracy and loss rates show minimal changes with increasing epochs, indicating that the model converges relatively early due to the pre-training. The results demonstrate extremely high accuracy and significant F1 scores. Given that the F1 score metric is insensitive to dataset imbalance, this alignment suggests that the model generalizes well and maintains unbias across activities.

Table 2 – Classification results of the base classifier on a subset of tests

Accuracy	**Precision**	**Recall**	**AUC**	**F1-score**
90.90%	91.33%	90.69%	97.26%	91.01%

After training and evaluating the base classifier, the dataset labels for all samples were updated based on the output from the top fully connected layer neurons of the trained base classifier.

The performance metrics of the metaclassifiers trained using the first dataset partitioning strategy [41] are shown in Table 3. The precision, recall, and F1 scores were calculated using a “weighted” approach. In this method, the metrics are calculated for each class and then the average is weighted by the support (the number of true instances for each class), which is a valid approach in the case of class imbalance. The results show that the CNN-based model showed a rougher performance, achieving an F1 score of 79.07%. Another model with satisfactory accuracy is the single-layer BiLSTM network, which achieved an F1 score of 73.89%. The remaining models showed comparable performance, with F1 scores of approximately 76%. The multilayer BiGRU model was the least efficient with an F1 score of 73.89%.

Table 3 – Classification results of meta-classifiers on the test subset (first partitioning strategy).

Classifier	**Accuracy**	**Precision**	**Recall**	**AUC**	**F1-score**
CNN	79.17%	79.01%	79.17%	84.34%	79.07%
Single-layer LSTM	75.00%	76.11%	75.00%	78.03%	75.32%
Multi-layer LSTM	76.39%	77.15%	76.39%	77.41%	76.63%
Single-layer BiLSTM	77.78%	78.84%	77.78%	79.13%	78.07%
Multi-layer BiLSTM	75.00%	75.49%	75.00%	79.91%	75.19%
Single-layer GRU	76.39%	76.21%	76.39%	84.51%	76.28%
Multi-layer GRU	75.00%	75.00%	75.00%	79.92%	75.00%
Single layer BiGRU	75.00%	74.45%	75,00%	78.13%	74.48%
Multi-layer BiGRU	73.61%	74.42%	73.61%	79.68%	73.89%

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Interestingly, increasing the number of layers in the BiLSTM, GRU, and BiGRU-based architectures did not lead to an increase in performance, but rather to a decrease in it. This may be a case of overfitting with insufficient training data to utilize the additional layers in these architectures. Furthermore, the close correspondence between accuracy and F1 score in all models indicates that the model was not disproportionately affected by the more prevalent class. This was achieved by including class weights during training.

Table 4 presents the classification results of the metaclassifiers for the second partitioning strategy [41]. As can be seen, the CNN-based model also showed good performance, achieving an F1 score of 87.44%. Furthermore, when applying the second partitioning strategy, this model showed higher performance compared to the first. This indicates that the model using the second strategy benefited from the extended knowledge obtained from the shared training data, while effectively using the information from the second subset to mitigate the inaccuracies inherent in the base classifier. Interestingly, applying the second partitioning strategy resulted in a decrease in performance for the other models, indicating their inability to adapt both the extended knowledge and the errors of the base classifier. Among all the models, the single-layer LSTM network showed the lowest performance in terms of precision, granularity, recall, and F1 score. Notably, the inclusion of the second splitting strategy shows that the introduction of multiple levels in the LSTM, BiLSTM, and BiGRU models leads to an overall performance improvement. This suggests that the additional complexity of these models is an advantage when using the second splitting strategy.

Table 4 – Classification results of meta-classifiers on the test subset (second partitioning strategy).

Classifier	Accuracy	Precision	Recall	AUC	F1-score
CNN	87.50%	87.43%	87.50%	92.40%	87.44%
Single-layer LSTM	69.44%	71.42%	69.44%	76.93%	69.96%
Multi-layer LSTM	72.22%	72.75%	72.22%	78.70%	72.43%
Single-layer BiLSTM	72.22%	75.04%	72.22%	78.43%	72.75%
Multi-layer BiLSTM	73.61%	74.42%	73.61%	78.76%	73.89%
Single-layer GRU	72.22%	76.08%	72.22%	79.74%	72.77%
Multi-layer GRU	72.22%	72.22%	72.22%	80.84%	72.22%
Single-layer BiGRU	72.22%	75.04%	72.22%	77.93%	72.75%
Multi-layer BiGRU	73.61%	76.92%	73.61%	80.84%	74.13%

In light of the observed results, we propose a CNN-based metaclassifier with a second partitioning strategy as the optimal configuration among the tested ones. Considering the challenges encountered, including the similarity of the aggregates, different execution speeds, and the possibility of overlap between the main activity labels in the data frames when subjects choose actions during data collection, we evaluate the performance of the metaclassifier as satisfactory. It is important to acknowledge the potential limitations associated with the proposed approach, in particular with regard to the generation of scalograms. The computational intensity of the CWT may make it difficult to directly implement our method on wearable devices such as smartwatches or smartphones. However, this limitation can be mitigated by using edge computing and FLs, which provide decentralized data processing and model training, thereby reducing the computational constraints of individual devices.

6 DISCUSSION

This study proposes a real-time, multi-stage, complex HAR approach that is applicable to, but not limited to, intralogistics systems using AGVs. The proposed approach uses a smartwatch and techniques such as classifier stacking, CWT, and TL. In the context of this study, a distributed data collection system based on a smartwatch was developed. A dataset containing readings from five industrial personnel performing continuous sequences of actions representing typical intralogistics tasks was also collected and published.

A HAR-specific pre-trained DenseNet121 model using CWT was used as the base classifier, achieving an F1 score of 91.01% for the base activity classification. For the multi-stage activity classification task, metaclassifiers based on convolutional neural networks (CNN), long-short-term memory (LSTM), bidirectional LSTM, recurrent gating unit (GRU), and bidirectional GRU were compared. Two strategies for using the dataset were tested to optimize metaclassifier training. The most effective model using CNN and shared training data between classifiers resulted in the metaclassifier obtaining an F1 value of 87.44%. It is important to note that the temporal resolution of the data for the baseline activities is limited by the duration of the data frame, which is 3 seconds. This limitation creates a potential problem, since baseline activities with a duration shorter than this interval (e.g., a subject walk for 1 second) may overlap with the next baseline activity. Similarly, if a data frame contains data for two different baseline activities (e.g., 2 seconds of walking followed by 1 second of standing), the label corresponding to the last activity (standing in this case) will be assigned. This behavior is a potential problem that could affect the performance of classifiers and will be addressed in future research.

We hypothesize that the overall performance of the model can be improved by expanding the dataset, including data from more subjects, and including additional baseline activities such as rotation. Furthermore, the problem of overlapping activities in a time window can be

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addressed by assigning labels based on the majority duration within a particular activity class rather than relying on the last activity. Furthermore, hybrid architectures combining CNNs with LSTMs or GRUs can yield superior results, suggesting promising directions for future research.

With appropriate modifications, the proposed approach can be integrated into an intelligent enterprise management system using CWT, improving the productivity of human-machine interaction and increasing the overall efficiency of the production line.

CONCLUSIONS

The current problem of developing an innovative approach for recognizing complex human actions in real time, focused on internal logistics systems using AGVs, is being solved.

The scientific novelty of the results is the creation of an innovative system for recognizing and predicting complex human activities in industrial intralogistics of enterprises in real time. For this purpose, a data collection system based on a smart watch was developed. This approach combines advanced data preprocessing methods and state-of-the-art machine learning models, including hybrid machine learning technologies based on DenseNet121 and CNN architectures, to achieve high accuracy of classification and prediction of activities.

The practical significance of the study in making industrial environments safer and more efficient by recognizing and predicting worker activities in real time. The system can be integrated into workplaces to streamline processes and support smarter decision-making in fast-paced conditions. By fostering smoother collaboration between humans and machines, it not only enhances productivity but also prioritizes the well-being and comfort of employees, aligning with the principles of Industry 5.0.

Prospects for further research are to focus on expanding the dataset to include more subjects, units, and major activities, and using hybrid models to improve model accuracy. Other promising directions include integrating FL technology and using the proposed architectural framework to predict worker activity.

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ГІБРИДНІ ТЕХНОЛОГІЇ МАШИННОГО НАВЧАННЯ ДЛЯ ПРОГНОЗУВАННЯ КОМПЛЕКСНОЇ ДІЯЛЬНОСТІ ПРОМИСЛОВОГО ПЕРСОНАЛУ ЗА ДАНИМИ СМАРТ-ГОДИННИКІВ

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АНОТАЦІЯ

Актуальність. У сучасному промисловому виробництві значна увага приділяється системам розпізнавання та прогнозування людської активності в реальному часі. Такі технології є ключовими для переходу від Індустрії 4.0 до Індустрії 5.0, оскільки вони забезпечують покращену взаємодію між людиною і машиною, а також вищий рівень безпеки, адаптивності та ефективності виробничих процесів. Ці підходи особливо актуальні в галузі внутрішньої логістики, де співпраця з автоматизованими транспортними засобами вимагає високого рівня координації та гнучкості.

Мета. Створити технологічне рішення для оперативного виявлення та прогнозування складної поведінки людини у системах внутрішньої логістики шляхом використання сенсорних даних зі розумних годинників. Основна ціль – підвищити рівень взаємодії між працівниками та автоматизованими системами, збільшити безпеку праці й ефективність логістичних процесів.

Метод. Розроблено децентралізовану систему збору даних із використанням розумних годинників. У мобільному додатку, написаному мовою Kotlin, фіксувалися показники сенсорів під час виконання серії логістичних активностей п'ятьма працівниками. Для обробки неповних або спотворених даних застосовано алгоритми виявлення аномалій, зокрема STD, логарифмічне перетворення STD, DBSCAN та IQR, а також методи згладжування, такі як ковзне середнє, зважене ковзне середнє, експоненційне згладжування, локальна регресія й фільтр Савіцького-Голея. Оброблені дані використовувалися для навчання моделей із застосуванням таких сучасних підходів, як передавальне навчання, неперервне вейвлет-перетворення та стекінг класифікаторів.

Результати. У ролі базового класифікатора обрано попередньо натреновану глибоку модель з архітектурою DenseNet121, яка показала F1-метрику 91,01 % при розпізнаванні простих дій. Для аналізу складних активностей випробувано п'ять архітектур нейронних мереж (одношарових і багатошарових) з двома стратегіями розподілу даних. Найвищу точність – F1-метрику 87,44 % – продемонструвала згорткова нейронна мережа при використанні об'єднаного підходу до розподілу даних.

Висновки. Результати дослідження свідчать про можливість застосування запропонованої технології розпізнавання складної людської діяльності в режимі реального часу в інтралогістичних системах на основі даних з сенсорів смартгодинника яка покращить взаємодію людини та машини та підвищить ефективність промислових логістичних процесів.

КЛЮЧОВІ СЛОВА: вибірка, фрактальна розмірність, метрика якості, кластер, формування вибірок.

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