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Cloud-based platform for intelligent healthcare monitoring and risk prevention in hazardous manufacturing contexts

Alessandro Simeone[a], Alessandra Caggiano[b,c,]*, Lev Boun[d], Rebecca Grant[e]

[a]Intelligent Manufacturing Key Laboratory of Ministry of Education, Shantou University, 515063 Shantou, Guangdong, China
[b]Department of Industrial Engineering, University of Naples Federico II, Piazzale Tecchio 80, 80125, Naples, Italy
[c]Fraunhofer Joint Laboratory of Excellence on Advanced Production Technology (Fh-J_LEAPT UniNaples), Naples, Italy
[d]Dynamic Computer Systems, PoB 1341, 30300, Atlit, Israel
[e]Wolfson School of Mechanical, Electrical and Manufacturing Engineering, Loughborough University, Loughborough, LE11 3TU, UK

* Corresponding author. Tel.: +390817682371; fax: +390817682362. *E-mail address:* alessandra.caggiano@unina.it

Abstract

This paper presents an intelligent cloud-based platform for workers healthcare monitoring and risk prevention in potentially hazardous manufacturing contexts. The platform is structured according to sequential modules dedicated to data acquisition, processing and decision-making support. Several sensors and data sources, including smart wearables, machine tool embedded sensors and environmental sensors, are employed for data collection, comprising information on offline clinical background, operational and environmental data. The cloud data processing module is responsible for extracting relevant features from the acquired data in order to feed a machine learning-based decision-making support system. The latter provides a classification of workers' health status so that a prompt intervention can be performed in particularly challenging scenarios.

Keywords: Industry 4.0; cloud manufacturing; sustainable manufacturing; smart wearables; hazardous manufacturing context

1. Introduction

The fourth industrial revolution combines the physical, digital, and biological spaces and it is changing the healthcare related contexts [1, 2]. In line with 'Industrie 4.0', operator 4.0 requires careful understanding and consideration to ensure productivity is met in modern manufacturing paradigms [3].

Smart personal technology systems are able to provide a wide range of important information, possibly in real-time, enabling for the recognition of critical parameters and prevent human risks as well as supporting crucial decisions in unplanned or critical scenarios. It is important to ensure that biometric monitoring can be utilized in real-time to identify when health hazards will occur and can be avoided. This enables to carry out a better-informed monitoring, resulting in more efficient processes and increased sustainability over time, by reducing occupational hazards.

The concept of sustainable manufacturing must include the viability of workers health via elimination of agents hazardous to human health [4, 5]. In this context, Santochi and Failli [6] highlighted process sustainability requirements such as the elimination or reduction of waste, chemical or physical agents hazardous to human health and environment since manufacturing is generally based on human work.

Relevant Industry 4.0 Key Enabling Technologies are widely functional to deal with healthcare issues within manufacturing scopes. In this respect, cloud computing is able to provide remote and broad access capabilities to large data [7]. Literature reports a large range of cloud computing approaches for healthcare purposes, analyzing the storage systems, the communication techniques and the technological

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innovations to overcome the gap between centralized data localization and end-user [8].

The growing increase of connected devices, the limitations related to the network bandwidth and the uncertain latency in cloud data transmission call for innovative cloud manufacturing architectures capable of reducing the cloud connectivity issues through new layers like fog computing [9–11]. Fog computing aims at offering data processing and storage capabilities closer to the end devices instead of directly transferring the raw data collected by sensors to the cloud. At the fog layer, small scale cloud functionality is ensured by the so-called fog nodes, i.e. devices with computing, storage, and network connectivity [10, 11]. The objective is to improve efficiency and performance and reduce the amount of data transmitted to the cloud for processing, analysis and storage, hence reducing network traffic and latency [9, 12].

Concerning the hardware and data acquisition devices, Yan et al. carried out a survey on wearable sensor modality centered human activity recognition in health care [13] while [14] provides a comprehensive review of commercial sensors used in wrist-wearable devices and their suitability for intelligent analysis. Islam et al. [15] proposed a sensor-based healthcare system aimed at real-time monitoring of patients' basic health parameters along with their room condition.

The monitoring of environmental conditions within a factory plant has been proposed by [16], using a temperature and humidity monitoring system to investigate the manufacturing environment in a tea factory showing the distribution of temperature and humidity in the factory collected by a sensor system. With more specific application to factory worker health, Thomas et al. developed a sensor network [17] endowed with dust sensor, carbon monoxide sensor, oxidizing gas sensor, temperature and humidity sensor and noise level sensor to measure and assess airborne hazards in a manufacturing facility. Hariri et al. [18] analyzed spectroscopy data from welding fumes exposure towards operator to be correlated with the working posture. Choi et al. [19] developed a prototype for combined monitoring services of air-quality and healthcare integrated into a steering wheel cover to provide real-time measurement of three environmental sensor signals and two healthcare physiological signals with the results displayed on a smartphone.

The use of accelerometers is explored in [20], which reports a detailed analysis of wearable technologies adoption in occupational risk prevention focusing on the data measurement precision and uncertainty issues. With special focus on physical activity monitoring, specifically healthcare oriented behavior monitoring within a building, Magistro et al. [21] developed and implemented an innovative algorithm combining proximity sensors with Bluetooth beacons placed in fixed locations within a multilevel, mixed-use building along with 4 receiver-mode wearable sensors.

Within the scope of remote health monitoring, Vitabile et al. [22] reviewed data collection and fusion methods, with special regard to data ownership and privacy issues along with a number of models and technologies for medical (big) data processing and analysis. Big data are further discussed by Thuemmler et al. [23] in terms of virtually delivering healthcare outside hospitals being tailored to individuals rather than being designed on statistical indicators.

Machine learning is another attractive technology for applications in (healthcare) operations management due to its ability in building reliable models from a large number of weak predictors, and its ability to identify key factors in complex feature sets [24] In this scope, applications range from disease Prediction over Big Data within Healthcare Communities [25] to unsupervised characterization for estimating duration of each repetitive assembly operation process [26].

It is acknowledged that one of the major challenges concerning the application of internet and cloud-based technologies for healthcare as well as industrial monitoring is represented by data security. The reason has to be found in the weak links used to connect the things to the Internet, leading to security issues in various levels of the Internet of Things (IoT). In this respect, Neerugatti et al. [27] analyzed various security issues and novel security architecture for the IoT-enabled personalized healthcare systems.

1.1. Research and industrial practice gap

A literature and industrial practice review highlighted an interesting gap in knowledge around how modern manufacturing tools can be integrated with factories and manufacturing staff, especially in terms of systematic approach, data processing algorithms and decision-making. A gap is present for operator monitoring, in line with the new Operator 4.0 typology [3], as automation is becoming more commonly used to replace manual processing. However, the operator is still required to complete inherent tasks in this new age of cyber-physical systems. From this new typology, the concept of a 'Healthy Operator' requires exploration within hazardous work environment, through the use of wearable trackers for real-time monitoring, as well as an 'Analytical Operator' using big data interaction to monitor safety and predict risks [28]. Integration of IoT and biometric sensors have shown to monitor health information as part of a healthcare case study, which can apply to health in manufacturing environments [28], as well as integration of information for ongoing care [29]. While contributions regarding the development of sensor systems and IoT underline a wide availability of commercially available solutions, an attracting research direction arises from the lack of a systematic approach for the development of an integrated system to be employed within the manufacturing environment. Moreover, the limited contributions available in the literature in terms of decision-making support systems push towards the development of an intelligent system.

The research work presented in this paper aims at filling the mentioned gap by proposing an integrated and intelligent cloud-based architecture for healthcare monitoring and risk prevention in hazardous manufacturing contexts encompassing the latest sensors, internet-based and cloud/fog computing technologies together with machine learning. The proposed cloud-based architecture combines the advantages of local decentralized data acquisition at the factory level, fog-level data pre-processing based on fog nodes close to the end devices and remote intelligent decision-making at the cloud level. This is aimed at enabling a better and automated use of data, finalized at classifying the health state and predict imminent risk. This allows a prompt action in conjunction with factory medical staff.

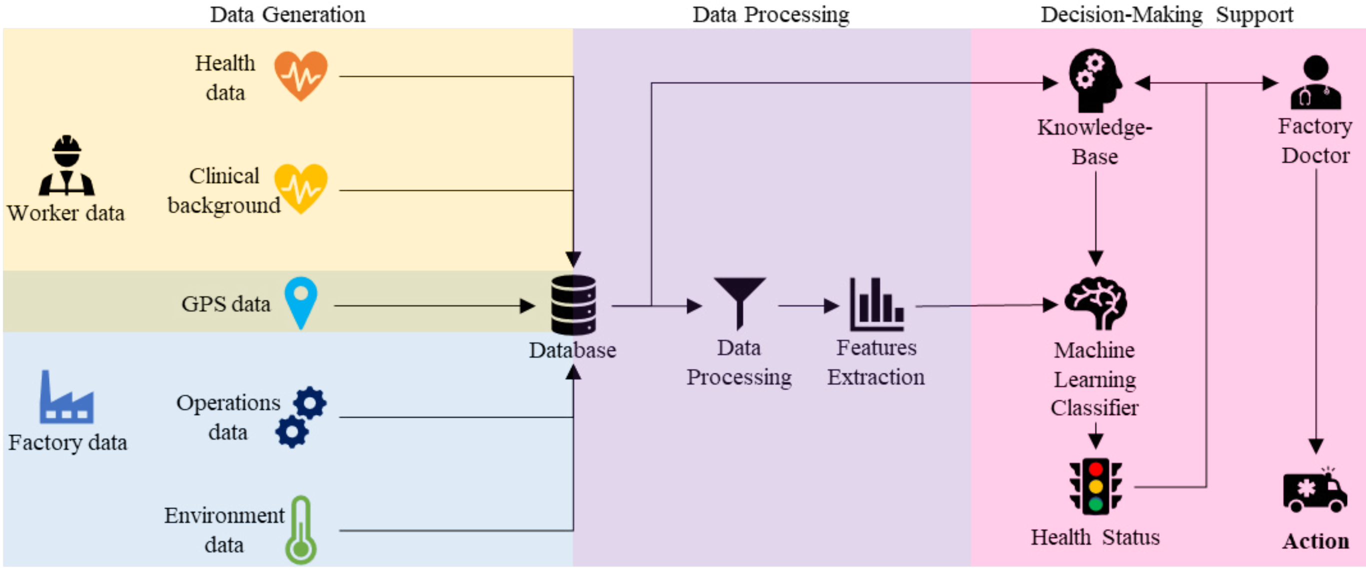

Fig. 1. Cloud-based platform flow-chart

2. Cloud-based framework

The cloud-based platform conceptualized in this paper is structured according to the scheme reported in Fig. 1.

The platform is composed of three main modules, namely Data Generation, Data Processing and Decision-Making Support modules.

Acquisition and storage of sensor data from various sources such as worker's health and position within the factory facilities, along with environmental data and processes related data are carried out within the first module. Here, data pre-processing is performed to prepare the data for further analysis. The output results in a structured and homogeneous dataset.

Subsequently, data are sent to the processing module with the aim of extracting useful information. The output of this step is a set of statistical indicators and features which will be inputted to the decision-making module.

Here, information coming from the processed sensor data and from the clinical background files are matched with the knowledge-based expert system. Such combined information dataset is inputted into a pre-trained machine learning classifier with the aim of estimating the worker health status in terms of risk class to support the medical staff to provide a tailored action based on the worker's specific needs.

The following sections describe the various modules in terms hardware and data requirements, data processing methodologies and information retrieval as well as machine learning approaches for classification tasks.

3. Data Generation Module

3.1. Personal health data acquisition devices

Personal health data generation and acquisition is carried out via wearable devices, such as smart watches, other commercially available devices, customized prototypes to collect a large variety of online relevant data such as: body temperature, blood pressure, heart and breath rates. Personal devices are divided in two main categories, namely pro-active and passive units. Pro-active units collect data continuously during working and potentially detect out of range parameters, enabling visualization and alert functions for the worker The passive units, also known as WOD (wake-up on demand) an energy efficient solution allowing the device to remain idle and triggered only upon specific signal.

Beyond the above-mentioned data, the personal health background has to be available for each worker, including age, gender, weight, previous health problems etc. In this respect, workers could be required to undergo specific check-ups based on the particular activities carried out.

3.2. Environmental data

A set of sensing units has to be installed at factory level to provide information about environmental parameters which are likely to affect the worker's health conditions such as: temperature (heat, cold), humidity, chemical and pollution, biological agents, radiations, noise, dust, vibration, poor ventilation, fire and smoke. In this way it is possible to map critical environmental parameter over space and time.

Monitoring of individuals and their health is not the first objective for some sensors such as air quality sensors, light sensors, smoke detectors, etc. However, the data they collect can, by cross-referencing with data from other sources, contribute to the production of potentially personalized health information, and eventually the generation of alarms [30].

3.3. Manufacturing process data

Beyond personal health and environmental variables, additional information can be provided according to the factory policy in terms of process categorization type. In this respect a job hazard analysis should be preliminary carried out [31] to characterize mechanical hazards (e.g. heavy loads), chemical and radiations hazards etc.

The interaction between man and machine along with the harsh ambient conditions that can sometimes be present, pose particular challenges with respect to health and safety technology in manufacturing industry. Consequently, more and more sensors can be integrated in machine tools and equipment in order to provide relevant data to the users. In this respect, technologies such as RFID, vision sensors, temperature sensors, pressure, force, torque, power, machine status (on/off, idle/processing), limit switches, encoders, etc. can be adopted to collect the required data.

4. Data Processing Module

The high variety of sensors and data acquisition sources yields to a considerable diversity in data types in terms of nature and sampling rate.

High velocity data acquisition from a large number of data sources can create a heavy burden on data transmission infrastructure that can limit transmission bandwidth. Varying latency requirements for different data can create additional challenges. Data compression techniques can alleviate the bandwidth limitation in transmitting manufacturing data, and techniques such as edge/fog computing complement cloud computing in handling data with varying requirements of latency [32].

Moreover, a data homogenization procedure is required to allow for an effective storage and handling.

As the information exchange is produced by a number of sources dislocated in different places across the manufacturing facility, a twofold data storage approach can be adopted:

- Local storage - Smart Chip on device, in which only personal sensors data are stored (short term history) along with the device ID for user visualization purposes.
- Central storage – Cloud Data Center (On-Premise System) endowed with encryption and security certificates, including the device ID, user long term history data, clinical background, factory, operational and environmental data. Moreover, the KB data and the result of the data processing operations are stored on the cloud server.

Given the large amount of data generated and the corresponding diversified nature, a number of data reduction techniques can help to facilitate the data handling for further processing.

In this respect, Principal Components Analysis (PCA) is able to detect correlated variables in a dataset [33, 34], such scenario can occur in correspondence of process conditions and hazard level within a certain spatial unit of the factory. Such analysis could potentially lead to a more effective selection of sensing units.

To uniform the sampling rate, filtering techniques can be adopted such as moving average and resampling.

The data obtained from connected devices have no intrinsic value: the information value depends on both the conditions in which they were obtained as well as the skills and knowledge of the person who qualifies (and potentially filters) and exploits them [30]. For triggering alerts, a decision process based on machine learning is therefore configured.

5. Machine learning-based decision-making support module

The general goal of the proposed framework at the present stage of research can be configured as a classification problem for a qualitative assessment of the worker health status, as illustrated in Fig. 2. The classes correspond to various estimated levels of risk for the worker's health.

The risk class is the output of the pattern occurring between the personal health data, factory data and environment data.

From a computational perspective, input data are made of a data fusion including real-time health data features, GPS data features, operations data indicators and environmental features.

The machine learning classifier is trained offline with ground truth historical data available in the knowledge base, and subsequently retrained and updated with newly generated data from sensors matched and labelled with the medical staff reports. Various technologies can be adopted for this purpose, ranging from the well-established Neural Network (NN), Support Vector Machine, Decision Trees, and Ensemble Learning [35, 36].

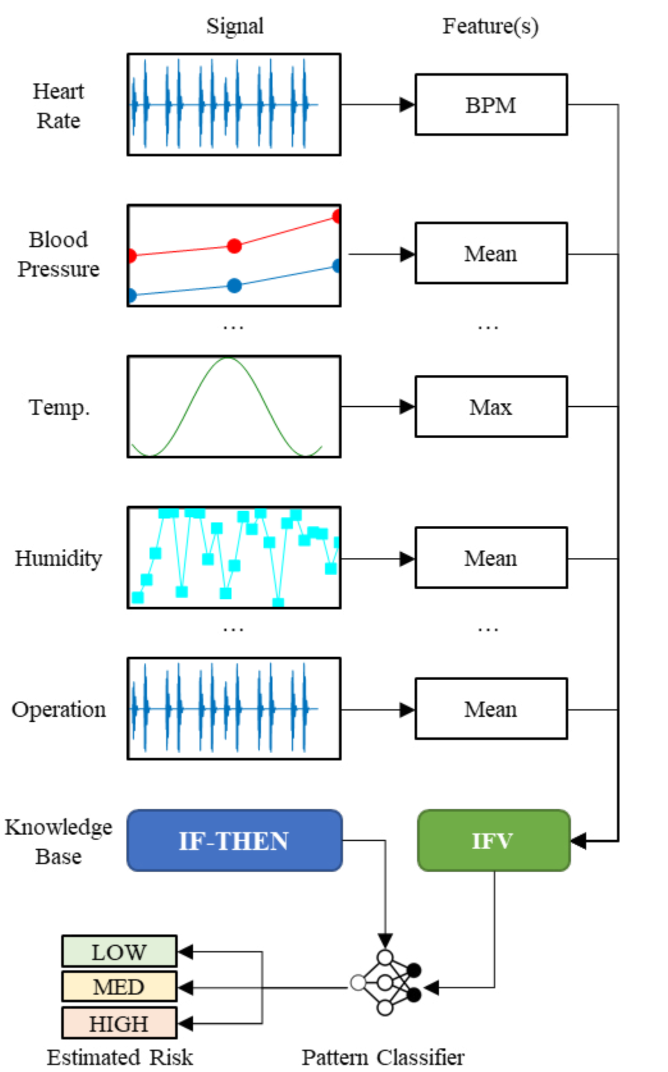

Fig. 2. Example of data flow

The decision-making process can be enhanced and supported by the introduction of expert systems. In this respect, Adaptive Neuro Fuzzy Inference Systems (ANFIS) represent an attractive technology as they combine the ability to learn of the NN with human-like knowledge representation of Fuzzy Logic.

Such hybrid systems have been demonstrated to be successfully implemented for classification purposes [37, 38]. To boost the classification performances when using overlapped data, the Fuzzy paradigm can be effectively coupled with Deep Neural Networks [39].

6. Challenges for industrial implementation

6.1. Data availability challenges

The selection of the hardware should be carefully addressed in terms of ergonomics, size and wearability [40]. The number of devices represents another challenge from economic and hygienic perspective. Data availability should take into account the sampling rate, as every variable can have different significance. This can lead to different choice in the hardware selection. As regards the wearable devices, a network infrastructure should be provided, enabling the data acquisition and exchange via diverse technologies, such as Mobile networking, Bluetooth 3.0, Wi-Fi, wired networking and RF.

To ensure the correct devices-user pairing, authentication procedures are required, possibly carried out via RSA and biometric approaches as illustrated in Fig. 3.

Data storage management process for rapidly growing amounts of data involves performing activities, such as data clustering, replication and indexing, in parallel to optimizing the storage process. Dimensionality reduction operations can be useful to deal with redundant, correlated and dependent data.

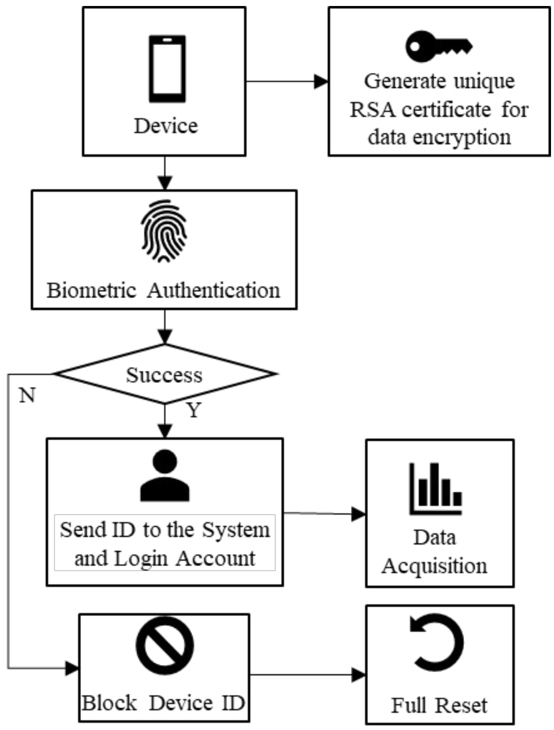

Fig. 3. Authentication process flow-chart

6.2. Knowledge base challenges

Knowledge in this area still needs more measurement and definition to enable solutions to develop. Better measurement and modelling of human operators in harsh or strenuous working environments is needed in order to define needs for operators and to identify appropriate inclusion of automation and machine learning for collaborative work [28].

Automation can be used to replace or support human operation in harsh environments [41], but this needs to be fully validated as there is no 'one-size-fits-all' approach to integration. This can replace hazardous tasks, but automation still needs maintenance and human interaction, so these system elements should always be considered.

The level of complexity also requires consideration, as automation takes over manual tasks, errors that do arise become more challenging for humans to fix, due to potential lack of information or training at line [42]. These are key elements that define why human operator monitoring is needed. Intelligence built in to understand where operators become strained, stressed or potentially endangered identifies where solutions to these problems can be incorporated to improve monitoring and sustain manufacture [43].

6.3. Computational challenges

Data acquisition should be synchronized and triggered to facilitate the handling and processing [44].

Data storage issues, in terms of data memory, should be addressed by considering the needs as technological advances have enabled the measurement of data at higher sampling rates which were not feasible before. The faster availability of a large amount of data has led to questions on how to make effective use of data. Using these data presents challenges that are unique to manufacturing due to the large range of temporal scales over which analysis and decision-making must occur [32].

Classification learner training time can represent a challenge especially when a hybrid system such as ANFIS is used. In this case the number of rules depends on the number of fuzzy sets and membership functions [37], and due to the high number of sensing variables involved the computational complexity can sharply increase. However, the training is carried out offline, and dedicated CPU units can be utilized for this purpose.

Misclassifications, such as false alarms can be minimized by performing periodical re-trainings. In this respect, as new data instances are produced and validated by the medical staff, the knowledge base can be expanded by appending such instances for improving the classification accuracy.

7. Conclusions

This paper proposed a conceptualization for the development and implementation of a cloud-based platform for workers healthcare monitoring in potentially hazardous manufacturing contexts. The key modules have been described in terms of hardware requirements, data flow and algorithms. The critical challenges for the industrial implementation have been analyzed considering data availability, knowledge base construction and computational issues. In this respect, an overview of the suitable data processing and machine learning paradigms as well as the main challenges for industrial implementation was reported.

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References

[1] Jayanthi P, Iyyanki M, Mothkuri A, et al. Fourth Industrial Revolution: An Impact on Health Care Industry. Adv Intell Syst Comput Springer Verlag 2020; 965:58–69.
[2] Byrne G, Dimitrov D, Monostori L, van Houten F, Teti R, Wetrheim R. Biologicalisation: Biological transformation in manufacturing. CIRP J Manuf Sci Technol 2018; 21:1-32.
[3] Romero D, Stahre J, Wuest T, et al. Towards an operator 4.0 typology: A human-centric perspective on the fourth industrial revolution technologies. CIE 2016: 46th International Conferences on Computers and Industrial Engineering 2016[Online] 2016.
[4] Moldavska A, Welo T. The concept of sustainable manufacturing and its definitions: A content-analysis based literature review. J Clean Prod 2017; 166:744–55.
[5] Teti R, D'Addona DM, Segreto T. Microbial-based cutting fl uids as bio-integration manufacturing solution for green and sustainable machining. CIRP J Manuf Sci Technol 2021; 32:16–25.
[6] Santochi M, Failli F. Sustainable work for human centred manufacturing. In: Green Design, Materials and Manufacturing Processes CRC Press 2013; pp. 161–66.
[7] Rajabion L, Shaltooki AA, Taghikhah M, et al. Healthcare big data processing mechanisms: The role of cloud computing. Int J Inf Manage 2019; 49:271–89.
[8] Hu P, Dhelim S, Ning H, et al. Survey on fog computing: architecture, key technologies, applications and open issues. J Netw Comput Appl 2017; 98:27–42.
[9] Atlam H, Walters R, Wills G. Fog Computing and the Internet of Things: A Review. Big Data Cogn Comput 2018; 2(2):10.
[10] Mocanu S, Geampalia G, Chenaru O, et al. Fog-based solution for real-time monitoring and data processing in manufacturing. 2018 22nd Int Conf Syst Theory, Control Comput ICSTCC 2018 - Proc IEEE 2018; 504–09.
[11] Mouradian C, Naboulsi D, Yangui S, et al. A Comprehensive Survey on Fog Computing: State-of-the-Art and Research Challenges. IEEE Commun Surv Tutorials IEEE 2018; 20(1):416–64.
[12] Mishra D, Roy RB, Dutta S, et al. A review on sensor based monitoring and control of friction stir welding process and a roadmap to Industry 4.0. J Manuf Process Elsevier 2018; 36:373–97.
[13] Wang Y, Cang S, Yu H. A survey on wearable sensor modality centred human activity recognition in health care. Expert Syst Appl 2019; 137:167–90.
[14] Kamišalić A, Fister I, Turkanović M, et al. Sensors and functionalities of non-invasive wrist-wearable devices: A review. Sensors 2018; 18(6):1714.
[15] Islam MM, Rahaman A, Islam MR. Development of Smart Healthcare Monitoring System in IoT Environment. SN Comput Sci 2020; 1(3):185.
[16] Uehara Y, Ohtake S. Factory Environment Monitoring: A Japanese Tea Manufacturer’s Case. 2019 IEEE Int Conf Consum Electron ICCE 2019; 1–3.
[17] Thomas GW, Sousan S, Tatum M, et al. Low-cost, distributed environmental monitors for factory worker health. Sensors 2018; 18(5).
[18] Hariri A, Leman AM, Yusof MZM. Experimental Study on Welding Fumes Exposure from Aluminum Metal Inert Gas (MIG) Process . Adv Mater Res 2013; 701:382–86.
[19] Choi S, Kim DJ, Choi YY, et al. A Multisensor Mobile Interface for Industrial Environment and Healthcare Monitoring. IEEE Trans Ind Electron 2017; 64(3):2344–52.
[20] Sigcha L, Pavón I, Arezes P, et al. Occupational risk prevention through smartwatches: Precision and uncertainty effects of the built-in accelerometer. Sensors 2018; 18(11).
[21] Magistro D, Sessa S, Kingsnorth AP, et al. A novel algorithm for determining the contextual characteristics of movement behaviors by combining accelerometer features and wireless beacons: Development and implementation. JMIR mHealth uHealth 2018; 6(4).
[22] Vitabile S, Marks M, Stojanovic D, et al. Medical data processing and analysis for remote health and activities monitoring. In: Lecture Notes in Computer Science 2019; bk. 11400, pp. 186–220.
[23] Thuemmler C, Bai C. Health 4.0: How virtualization and big data are revolutionizing healthcare,. Health 4.0: How Virtualization and Big Data are Revolutionizing Healthcare, 2017 Springer International Publishing: Cham 2017.
[24] Pianykh OS, Guitron S, Parke D, et al. Improving healthcare operations management with machine learning. Nat Mach Intell 2020; 2(5):266–73.
[25] Chen M, Hao Y, Hwang K, et al. Disease Prediction by Machine Learning Over Big Data From Healthcare Communities. IEEE Access 2017; 5:8869–79.

[26] Maekawa T, Nakai D, Ohara K, et al. Toward practical factory activity recognition: Unsupervised understanding of repetitive assembly work in a factory. UbiComp 2016 - Proc 2016 ACM Int Jt Conf Pervasive Ubiquitous Comput 2016; 1088–99.

[27] Neerugatti V, Rama Mohan Reddy A. Secured Architecture for Internet of Things-Enabled Personalized Healthcare Systems. In: SpringerBriefs in Applied Sciences and Technology 2019; pp. 75–80.

[28] Zolotová I, Papcun P, Kajáti E, et al. Smart and cognitive solutions for Operator 4.0: Laboratory H-CPPS case studies. Comput Ind Eng 2020; 139:105471.

[29] Hossain MS, Muhammad G. Cloud-assisted Industrial Internet of Things (IIoT) - Enabled framework for health monitoring. Comput Networks 2016; 101:192–202.

[30] Noury N, Picard R, Billebot MN, et al. Challenges and limitations of data capture versus data entry. In: Connected Healthcare for the Citizen 2018; pp. 85–97.

[31] Tweedy JT. Healthcare hazard control and safety management. Healthcare Hazard Control and Safety Management, Third Edition, CRC Press 2014.

[32] Gao RX, Wang L, Helu M, et al. Big data analytics for smart factories of the future. CIRP Ann - Manuf Technol 2020; 69(2):668–92.

[33] Caggiano A, Angelone R, Napolitano F, Nele L, Teti,ì R. Dimensionality Reduction of Sensorial Features by Principal Component Analysis for ANN Machine Learning in Tool Condition Monitoring of CFRP Drilling. Procedia CIRP 2018; 78:307–12.

[34] Segreto T, Simeone A, Teti R. Chip form classification in carbon steel turning through cutting force measurement and principal component analysis. Procedia CIRP 2012; 2(1):49–54.

[35] Simeone A, Lv D, Liu XY, et al. Collision damage assessment in lithium-ion battery cells via sensor monitoring and ensemble learning. Procedia CIRP 2018; 78:273–78.

[36] Karam S, Centobelli P, D'Addona DM, Teti R Online Prediction of Cutting Tool Life in Turning via Cognitive Decision Making. Procedia CIRP 2016; 41:927–32.

[37] Segreto T, Caggiano A, Teti R. Neuro-fuzzy system implementation in multiple sensor monitoring for Ni-Ti alloy machinability evaluation. Procedia CIRP 2015; 37:193–98.

[38] Teti R, D'Addona DM. Grinding Wheel Management through Neuro-Fuzzy Forecasting of dressing cycle time. CIRP Ann 2003; 52(1):407–10.

[39] Dabare R, Wong KW, Shiratuddin MF, et al. Fuzzy Deep Neural Network for Classification of Overlapped Data. In: Gedeon T, Wong KW, Lee M, Eds. Springer International Publishing: Cham 2019; pp. 633–43.

[40] Mekid S, Schlegel T, Aspragathos N, Teti R. Foresight formulation in innovative production, automation and control systems. Foresight 2008; 9(5):35–47.

[41] Wong C, Yang E, Yan XT, et al. An overview of robotics and autonomous systems for harsh environments. ICAC 2017 - 23rd IEEE Int Conf Autom Comput Addressing Glob Challenges through Autom Comput 2017; 1–6.

[42] Trentesaux D, Millot P. A human-centred design to break the myth of the "magic human" in intelligent manufacturing systems. Stud Comput Intell 2016; 640:103–13.

[43] Schlick J, Ferber S, Hupp J. IoT Applications – Value Creation for Industry. In: Internet of Things: Converging Technologies for Smart Environments and Integrated Ecosystems, River Publisher 2013;

[44] Balsamo V, Caggiano A, Jemielniak K, Kossakowska J., Nejman M., Teti R. Multi Sensor Signal Processing for Catastrophic Tool Failure Detection in Turning. Procedia CIRP 2016; 41:939–44.