The 7th International Symposium on Emerging Information, Communication and Networks (EICN 2020)
November 2-5, 2020, Madeira, Portugal

Edge Computing and Artificial Intelligence for Landslides Monitoring

Meryem Elmoulat[a,c,*], Olivier Debauche[b,c], Saïd Mahmoudi[b], Sidi Ahmed Mahmoudi[b], Pierre Manneback[b], Frédéric Lebeau[d]

[a]University Mohammed V, Research Unit GeoRisk: Geological Risks, Battouta Avenue, Rabat 10140, Morocco
[b]University of Mons, Faculty of Engineering - ILIA / Infortech, Place du Parc 20, Mons 7000, Belgium
[c]University of Liège - GxABT, TERRA, Passage des déportés 2, Gembloux 5030, Belgium
[d]University of Liège - GxABT, BioDynE, Passage des déportés 2, Gembloux 5030, Belgium

Abstract

Landslides are phenomena widely present around the world and responsible each year of numerous life loss and extensive property damage. Researchers have developed various methodologies to identify area of high susceptibility of landslides. However, these methodologies cannot predict 'when' landslides are going to take place. Indeed, Wireless Sensors Network (WSN), Internet of Things (IoT) and Artificial Intelligence (AI) offer the possibility to monitor in real-time parameters causing the triggering factors of rapid landslides. In this paper, we suggest a real-time monitoring of landslides in order to precociously alert population in dangerous situation by means of a warning system. The novelty of this paper is the coupling of wireless sensors network and a multi-agent system deployed on an edge AI-IoT architecture by means of Kubernetes and Docker.

Keywords: Landslides susceptibility; Internet of Things; Artificial Intelligence; early warning system; landslides monitoring

1. Introduction

Landslides are phenomena widely occurred around the world causing numerous deaths and extensive property damages every year. Landslides are movements by the gravity of soil, rock, or both slopes down, which can be caused by the combination of multiple factors. This latter can be climate characteristics, geology structure and/or topography of certain areas predisposed to a greater risk of landslides. To these factors are added the anthropic footprints linked,

* Corresponding author. Tel.: +212-657-296-490 ; fax: +32-71-140-095.
  E-mail address: m.elmoulat@gmail.com

in particular, to deforestation, the over-exploitation of land that highlights the risk of land movement. In addition, the modification of the water regime related to climate change in certain parts of the world has further accentuated these phenomena. Moreover, many human lives and properties have been destroyed by these natural phenomena each year that have led researchers to develop methods to map the susceptibility of areas where landslides could occur. The variety of landslides, their kinematics, and their triggering factors pushed us to the development of several methods. The performance of these techniques is directly impacted by the quality of available data which itself influenced by the robustness of our results.

In this paper, we propose a real-time monitoring of landslides in order to precociously alert population in case of danger. In the subsequent paragraphs our paper will be organized as follow: Section 2 describe our background in terms of Internet of Things (IoT) and Artificial Intelligence (AI) at edge level of the network. Then, we list the main susceptibility and monitoring methods. Afterwards, we aims to develop more specifically ANN works achieved to monitor landslides. In section 3, we describe our contribution based on WSN, IoT, and AI at Edge Level in collaboration with the cloud. In section 4, we experiment our proposition, and then we discuss our findings. Finally, we conclude in section 5 and we give an overview about our future works.

2. Literature review

This section is structured in two parts. The first part summarizes our past developments and contributions in term of Edge IoT and AI Architecture, Cloud Architecture that are validated on various use cases. The second part gives an overview about WSN applied to landslides field.

2.1. Background

In our previous works, we have progressively developed our proposition of Edge Internet of Things and Artificial Intelligence Architecture[23] through diverse use cases: patients and elderly monitoring[24], smart poultry real-time monitoring[19], cattle behavior[20], smart irrigation[13][17], and urban agriculture[2][21]. We have also proposed a system of landslide monitoring using LoRaWan and a Wireless Sensors Network (WSN) to monitor soils parameters causing ground movements[41] that we aim to improve in this paper. Additionally, we have also developed a HPC cloud architecture [29] and a Lambda cloud architecture on various use cases: bee health[30], elderly and patient monitoring[24], smart campus[12], smart home[16], smart city[18], smart building[27], cattle behavior[15][26][14][20], phenotyping[25][28], urban gardening[2], climatic enclosure[22], and smart bird[1].

2.2. Related Works

Plethora of study are dedicated to the evaluation of landslide susceptibility area by diverse methods such as Support Vector Machine (SVM), Particle Swarm Optimization (PSO), Logistic Regression (LR), Frequency Ratio (FR), Analytical Hierarchy Process (AHP), Bivariate Statistics (BS), Kernel Logistic Regression (KLR), Multi Criteria Decision Making (MCDM), Logistic Model Tree (LMT), Frequency Ratio (FR), Decision Tree (DT), Weights of Evidence (WoE), Random Forest (RF), Classification and Regression Tree (CRT), Boosted Regression Tree (BRT), and Artificial Neural Networks (ANN)[47][8][48][36][49][34][40]. Many of these techniques are also combined to develop more complex approaches.

These methods allows us to produce maps indicating areas with their susceptibility of landslides; in other terms their level of risk to have a major mass movement. Behavior of mass movements are determined based upon their type and triggering factors. In fact, areas with an important level of susceptibility must be followed, however, the parameters to monitor are controlled by the type of landslides. When human lives and/or economic issues are threatened, early warning systems are used to alert people as soon as possible and recommend their evacuation.

The Table 1 shows a synthesis of traditional approaches of monitoring used for each kind landslide. The analysis of this table shows that parameters that are classically triggered landslides are seismicity, rainfall, lithology, geotechnical characteristics, and ground water level.

Table 1. Comparison of monitoring approaches - Synthesis of Literature review

Technique	Triggering	Parameters	Type	Characteristics	Location	Authors
Geocube	Rain Slope Hydrology	Micro-seismicity Seismic Waves	Landslide	0.005 to 0.03 m.day^{-1} 100m to 1 or 2km	Southern French Alps	Benoit et al., 2015[6]
WSN	Sedimentary deposit Slope	Vibrations	Landslide	Undefined	Nusa Tenggara Timur	Kotta et al., 2011 [37]
EWS	Geologica Formation	Rainfall	Rockslide	182,000 m^3	Torgiovannetto, Italy	Intrieri et al., 2012 [35]
GB-InSAR	Limestone formation Slope	Rock wall	Rockfall	0.30 m^3	San Leo Rock Cliff, Italy	Casagli et al., 2018[10]
SAR[1]	Rainfall	Undefined	Translation Landslide	a 100m high, 90m wide	Santa Trada Landslide, Italy	Casagli et al., 2018[11]
GB-InSAR	Topographic, Geologic formation	Rainfall	Rockslide	30Mm^3	Valfurva, Italy	Casagli et al., 2018[9]
TIAMS	Environment and severe conditions	Undefined	Landslide	Undefined	Coastal Slope of the River Yenissei	Ginzburg et al., 2018[32]
UAE	Undefined	Meteorological Conditions	Landslide	Undefined	Russia–Turkey Gas Pipeline	Ginzburg et al 2018[33]
SANF	Rainfall Slope movements Precipitation	Rainfall	Landslide	Undefined	Italy	Rossi et al., 2018[44]
KLO	groundwater changes Earthquakes	Geodetic, Hydrological and geotechnical charachteristics	Landslide	32Mm^3	Zagreb, Croatia	Arbanas et al., 2018[3]
Remote Sensing Photogrammetry GPS	Topography Geologic Formation	Geodical and geotechnical characteristics	Landslide	3Mm^3	Grohovo,Croatia	Arbanas et al., 2018[4]
EWS	Rainfall	Rainfall	Debris Flow	10 Mm³	Mt. Merapi volcano Indonesia	Fathani et al., 2018[31]
CLLS	Earthquakes Anthropogenic Activities Naturals ones	Groundwater levels in boreholes, angles of slope, and litho-dynamics	Landslide	1500, 500, 700m^3	Tsar's Palace and Livadia Palace, Ukraine	Trofymchuk et al., 2018[45]
LEWIS	Rainfall	Hydrological and Geotechnical Characteristics	Landslide Debris Flow	Undefined	Southern Italy	Versace et al., 2018[46]
TLS	Sliding rotational	Rainfall, Groundwater level	Landslide	Undefined	Pisciotta, Italy	Barbarella et al., 2012[5]
UAV	Topographic	3D dense point cloud	Landslide	Undefined	Hollin Hill, UK	Peppa et al., 2016[43]
D-InSAR	Topographic	Topographic	Landslide	Undefined	Three Gorges region, China	Liao et al., 2012[38]
VSN	Slope	Vibration	Landslide	Undefined	Uttaradit province, Thailand	Biansoongnern et al, 2016[7]

Legend: CLLS = Central Livadia Landslide System; D-InSAR = Differential interferometric Synthetic Aperture Radar; EWS = Early Warning System; GB-InSAR = Ground-Based Interferometric Synthetic Aperture Radar; KLO = Kostanjek Landslide Observatory; LEWIS = Landslides Early Warning Integrated System; SANF = National Early Warning System for rainfall-induced landslides; TIAMS = Topsides Induced Acceleration Monitoring System; TLS = Terrestrial Laser Scanner; UAE = Unified Automatic Equipment; VSN = Vibration Sensor Network; WSN = Wireless Sensor Network

More recently, new approaches have been tested to improve the capabilities to detect landslides at earlier stage. Among these approaches we can mention the following major contributions such as: Luo et al. have tested tree expressions of programming and artificial bee colony [39]. In addition, artificial intelligence has been used to produce more accurate susceptibility map. Among majors contributions, we can cite Nguyen et al. who have developed a new hybrid approach using multiboost based naïve bayes trees tested on 248 landslides and fifty parameters [42].

3. Our contribution

In this paper, we propose an adaptable and distributed landslides monitoring system able to monitor several kinds of landslide based on Multi Agent System (MAS) deployed on an Edge heterogeneous cluster composed of Odroid N2 and Nvidia Jetson Nano previously described in [23]. In order to limit the use of the cloud for training artificial intelligence models, we have added an NVIDIA Xavier to perform training locally at the edge.
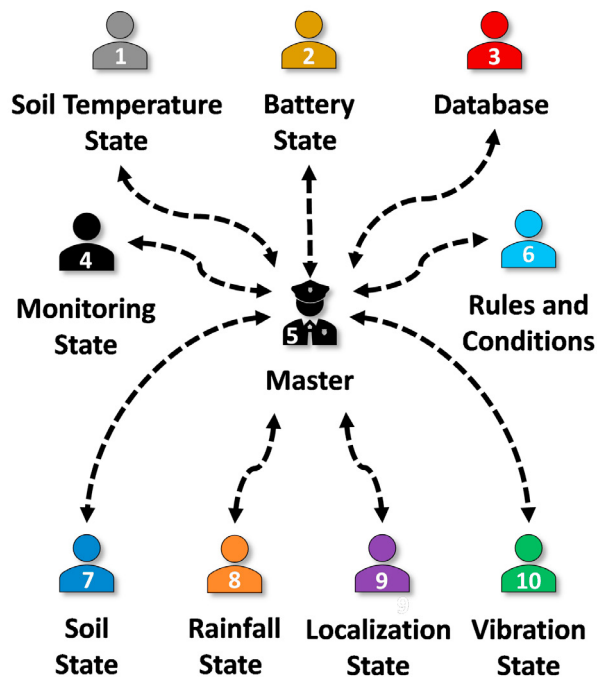

Fig. 1. Detailed View on Multi Agents System (MAS)

The Figure 1 shows the different agents composing the MAS playing following roles:

(1) The **Soil Temperature State** agent assesses the state of drought, normal functioning or freezing of the soil. Indeed, it implies a runoff of all precipitation; however, a desiccated soil accentuates the vertical infiltration of water in depth.

(2) The **Battery State** agent follows the level of battery of each sensor.

(3) The **Database** agent stores states of soil and air temperature, soil moisture, rainfall, localization, and vibration states. This data is useful for Rules and Conditions (4) to detect anomalies and launch an early warning alert.

(4) The **Monitoring State** agent detects failed sensors.

(5) The **Master** agent plays a role of coordination between all independent agents composing the system.

(6) The **Rules and Conditions** agent makes decision on base of the state of following parameters: soil, rainfall, localization, vibration, and soil temperature.

(7) The **Soil State** agent identify the soil moisture state, which means the available amount of water contained in a terminated volume of soil.

(8) The **Rainfall State** agent evaluates the maximum intensity of the rain and the volume of precipitation. This is a major landslide settlement.

(9) The **Localization State** agent measure the displacement on specific points of the landslide susceptibility area. Low displacement or deformations may occur.

(10) The **Vibration State** agent analyses earthquake signal to detect pattern announcing event likely to trigger landslides.

Our system, allows to monitor wide panel of different type of landslides without questioning the monitoring system operation mode. In addition, it is scalable to monitor numerous landslides at once and can easily accept new monitored parameters to address specific situations and use case.

4. Experimentation and Discussion

The Figure 2 gives an overview about the different implemented components of the system. To experiment our architecture, we have used a weather node and several ground nodes implemented at chosen point of the landslides. These nodes have been completely described in our previous paper [41]. All these nodes use LoRa RF protocol to transmit data to a LoRa gateway connected with our Edge AI-IoT Cluster [23] which is linked to a cloud computing infrastructure and an alert system. The database is store on the master node which is equipped of SSD.
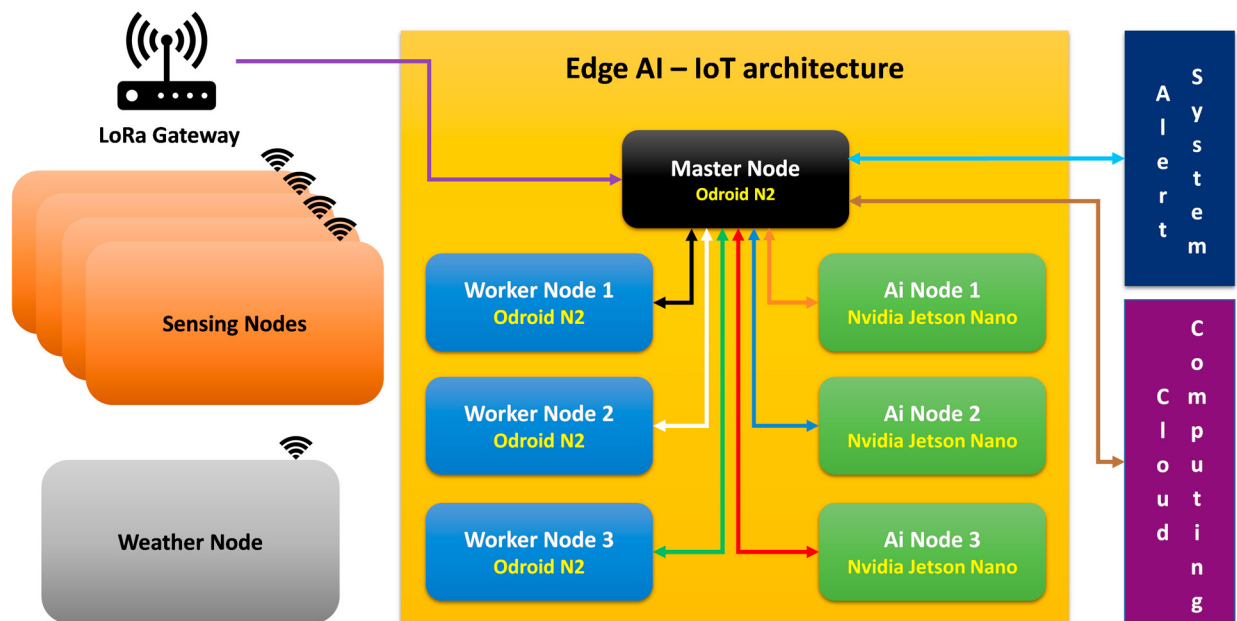

Fig. 2. Overall scheme of the experiment achieved

The Edge AI-IoT architecture uses Kubernetes and Docker to deploy multi-agent system on the heterogeneous cluster composed of an association of Odroid N2 and Jetson Nano that provides its computing power and AI capabilities. The cloud computing punctually assists the edge architecture by providing it with additional computing

power when necessary. All data are also archived on the cloud in order to reevaluate regularly rules and conditions of landslides detection.

The Table 2 presents mean results obtains by comparison with our previous paper [41].

Table 2. Performance comparison between cloud and edge approaches.

Metric	Cloud centric approach [41]	Edge centric approach (this paper)
Network latency	208ms	53ms
Processing time	2.06s	12s
Mean bandwidth	2.63Mbits	249.5Kbits
Data transferred to the cloud	1180.06 Mb	112 Mb

5. Conclusion and Future Work

In this paper, we have adapted our previous work [41] to implement Artificial Intelligence algorithms and better detect patterns of landslides on basis of measures achieved by means of connected things. Most of the treatment has been displaced from cloud to the edge to limit the bandwidth, improve the latency, and obtained a reduced time of reaction. The data processing a the edge of the network hardened the system against network outage. Our in-situ experimentation has shown a reducing of the latency from 208 ms in the previous configuration to 53 ms with the edge architecture. While mean bandwidth has been reduced from 2.63 Mbits to 249.5 Kbits and the amount transfer to the cloud has decreased from 1180.06 MB per hour to 112 MB per hour. The processing time at edge level has increased; because, computing power of our edge AI-IoT architecture is more than the cloud. At this stage, the whole of our proposed architecture has not been tested yet; because, there are no landslides' occurrence until the present moment.

As a perspective, we would like to monitor, mainly, active landslides whose nature and kinematics are based on diverse triggering factors in order to completely validate our proposal, and collect numerous data to be able to train our artificial intelligence models.

Acknowledgments

References

[1] Ait abdelouahid, R., Debauche, O., Mahmoudi, S., Abdelaziz, M., Manneback, P., Lebeau, F., 2020. Smart nest box: IoT based nest monitoring in artificial cavities, in: 2020 3rd International Conference on Advanced Communication Technologies and Networking (CommNet) (CommNet'20), Marrakech, Morocco. pp. 1–7.

[2] Ait Abdelouhahid, R., Debauche, O., Mahmoudi, S., Marzak, A., Manneback, P., Lebeau, F., 2020. Open phytotron: A new iot device for home gardening, in: 2020 5th International Conference on Cloud Computing Technologies and Applications (Cloudtech), pp. 1–7.

[3] Arbanas, S.M., Krkač, M., Gazibara, S.B., Komac, M., Sečanj, M., Arbanas, Ž., 2018a. Txt-tool 2.385-1.1 a comprehensive landslide monitoring system: The kostanjek landslide, croatia, in: Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer, pp. 449–464.

[4] Arbanas, Ž., Arbanas, S.M., Prodan, M.V., Peranić, J., Jovančević, S.D., Jagodnik, V., 2018b. Txt-tool 2.385-1.2: Landslide comprehensive monitoring system: The grohovo landslide case study, croatia, in: Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer, pp. 465–478.

[5] Barbarella, M., Fiani, M., 2012. Landslide monitoring using terrestrial laser scanner: georeferencing and canopy filtering issues in a case study. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences 39, B5.

[6] Benoit, L., Briole, P., Martin, O., Thom, C., Malet, J.P., Ulrich, P., 2015. Monitoring landslide displacements with the geocube wireless network of low-cost gps. Engineering Geology 195, 111 – 121. URL: http://www.sciencedirect.com/science/article/pii/S001379521500174X, doi:https://doi.org/10.1016/j.enggeo.2015.05.020.

[7] Biansoongnern, S., Plungkang, B., Susuk, S., 2016. Development of low cost vibration sensor network for early warning system of landslides. Energy Procedia 89, 417–420.

[8] Bui, D.T., Tuan, T.A., Klempe, H., Pradhan, B., Revhaug, I., 2016. Spatial prediction models for shallow landslide hazards: a comparative assessment of the efficacy of support vector machines, artificial neural networks, kernel logistic regression, and logistic model tree. Landslides 13, 361–378.

[9] Casagli, N., Catani, F., Del Ventisette, C., Luzi, G., 2018a. Txt-tool 2.039-3.3: Ground-based radar interferometry for landslide monitoring, in: Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer, pp. 287–295.

[10] Casagli, N., Morelli, S., Frodella, W., Intrieri, E., Tofani, V., 2018b. Txt-tool 2.039-3.2 ground-based remote sensing techniques for landslides mapping, monitoring and early warning, in: Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer, pp. 255–274.

[11] Casagli, N., Morelli, S., Frodella, W., Intrieri, E., Tofani, V., 2018c. Txt-tool 2.039-3.2 ground-based remote sensing techniques for landslides mapping, monitoring and early warning, in: Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer, pp. 255–274.

[12] Debauche, O., Ait abdelouahid, R., Mahmoudi, S., Moussaoui, Y., Abdelaziz, M., Manneback, P., 2020a. Revo campus: a distributed open source and low-cost smart campus, in: 2020 3rd International Conference on Advanced Communication Technologies and Networking (Comm-Net) (CommNet'20), Marrakech, Morocco. pp. 1–9.

[13] Debauche, O., El Moulat, M., Mahmoudi, S., Manneback, P., Lebeau, F., 2018. Irrigation pivot-center connected at low cost for the reduction of crop water requirements, in: 2018 International Conference on Advanced Communication Technologies and Networking (CommNet), pp. 1–9. doi:10.1109/COMMNET.2018.8360259.

[14] Debauche, O., Mahmoudi, S., Andriamandroso, A., Manneback, P., Bindelle, J., Lebeau, F., 2018. Cloud services integration for farm animals' behavior studies based on smartphones as activity sensors. Journal of Ambient Intelligence and Humanized Computing URL: https://doi.org/10.1007/s12652-018-0845-9, doi:10.1007/s12652-018-0845-9.

[15] Debauche, O., Mahmoudi, S., Andriamandroso, A., P., M., J., B., Lebeau, F., 2017. Web-based cattle behavior service for researchers based on the smartphone inertial central. Procedia Computer Science 110, 110 – 116. URL: http://www.sciencedirect.com/science/article/pii/S1877050917313066, doi:https://doi.org/10.1016/j.procs.2017.06.127. 14th International Conference on Mobile Systems and Pervasive Computing (MobiSPC 2017) / 12th International Conference on Future Networks and Communications (FNC 2017) / Affiliated Workshops.

[16] Debauche, O., Mahmoudi, S., Belarbi, M.A., El Adoui, M., Mahmoudi, S.A., 2018a. Internet of things: Learning and practices. application to smart home, in: 2018 International Conference on Advanced Communication Technologies and Networking (CommNet), pp. 1–6. doi:10.1109/COMMNET.2018.8360247.

[17] Debauche, O., Mahmoudi, S., Elmoulat, M., Mahmoudi, S.A., Manneback, P., Lebeau, F., 2020b. Edge ai-iot pivot irrigation, plant diseases and pests identification. Procedia Computer Science The 11th International Conference on Emerging Ubiquitous Systems and Pervasive Networks (EUSPN 2020) / The 10th International Conference on Current and Future Trends of Information and Communication Technologies in Healthcare (ICTH 2020) / Affiliated Workshops.

[18] Debauche, O., Mahmoudi, S., Mahmoudi, S.A., 2018b. Internet of things: learning and practices. application to smart city, in: 2018 4th International Conference on Cloud Computing Technologies and Applications (Cloudtech), pp. 1–7. doi:10.1109/CloudTech.2018.8713337.

[19] Debauche, O., Mahmoudi, S., Mahmoudi, S.A., Manneback, P., Bindelle, J., Lebeau, F., 2020c. Edge computing and artificial intelligence for real-time poultry monitoring. Procedia Computer Science 175, 534 – 541. URL: http://www.sciencedirect.com/science/article/pii/S1877050920317762, doi:https://doi.org/10.1016/j.procs.2020.07.076. the 17th International Conference on Mobile Systems and Pervasive Computing (MobiSPC),The 15th International Conference on Future Networks and Communications (FNC),The 10th International Conference on Sustainable Energy Information Technology.

[20] Debauche, O., Mahmoudi, S., Mahmoudi, S.A., Manneback, P., Bindelle, J., Lebeau, F., 2020d. Edge computing for cattle behavior analysis, in: 2020 Second international conference on Embedded Distributed Systems (EDiS), pp. 1–5.

[21] Debauche, O., Mahmoudi, S., Mahmoudi, S.A., Manneback, P., Lebeau, F., 2020e. Edge computing and artificial intelligence semantically driven. application to a climatic enclosure. Procedia Computer Science 175, 542 – 547. URL: http://www.sciencedirect.com/science/article/pii/S1877050920317774, doi:https://doi.org/10.1016/j.procs.2020.07.077. the 17th International Conference on Mobile Systems and Pervasive Computing (MobiSPC),The 15th International Conference on Future Networks and Communications (FNC),The 10th International Conference on Sustainable Energy Information Technology.

[22] Debauche, O., Mahmoudi, S., Mahmoudi, S.A., Manneback, P., Lebeau, F., 2020f. Edge computing and artificial intelligence semantically driven. application to a climatic enclosure. Procedia Computer Science The 17th International Conference on Mobile Systems and Pervasive Computing (MobiSPC) / The 15th International Conference on Future Networks and Communications (FNC 2020) / Affiliated Workshops.

[23] Debauche, O., Mahmoudi, S., Mahmoudi, S.A., Manneback, P., Lebeau, F., 2020g. A new edge architecture for ai-iot services deployment. Procedia Computer Science 175, 10 – 19. URL: http://www.sciencedirect.com/science/article/pii/S1877050920316859, doi:https://doi.org/10.1016/j.procs.2020.07.006. the 17th International Conference on Mobile Systems and Pervasive Computing (MobiSPC),The 15th International Conference on Future Networks and Communications (FNC),The 10th International Conference on Sustainable Energy Information Technology.

[24] Debauche, O., Mahmoudi, S., Manneback, P., Assila, A., 2019. Fog iot for health: A new architecture for patients and elderly monitoring. Procedia Computer Science 160, 289 – 297. URL: http://www.sciencedirect.com/science/article/pii/S1877050919317880, doi:https://doi.org/10.1016/j.procs.2019.11.087. the 10th International Conference on Emerging Ubiquitous Systems and Pervasive Networks (EUSPN-2019) / The 9th International Conference on Current and Future Trends of Information and Communication Technologies in Healthcare (ICTH-2019) / Affiliated Workshops.

[25] Debauche, O., Mahmoudi, S., Manneback, P., Massinon, M., Tadrist, N., Lebeau, F., Mahmoudi, S.A., 2017. Cloud architecture for digital phenotyping and automation, in: 2017 3rd International Conference of Cloud Computing Technologies and Applications (CloudTech), pp. 1–9. doi:10.1109/CloudTech.2017.8284718.

[26] Debauche, O., Mahmoudi, S., Manneback, P., Tadrist, N., Bindelle, J., Lebeau, F., 2017. Improvement of battery life of iphones inertial measurement unit by using edge computing application to cattle behavior, in: 2017 Symposium International sur les Sciences Informatiques et

Applications (ISCSA2017), pp. 1–4.

[27] Debauche, O., Mahmoudi, S., Moussaoui, Y., 2020. Internet of things learning: a practical case for smart building automation, in: 2020 5th International Conference on Cloud Computing Technologies and Applications (Cloudtech), pp. 1–7.

[28] Debauche, O., Mahmoudi, S.A., De Cock, N., Mahmoudi, S., Manneback, P., Lebeau, F., 2020. Cloud architecture for plant phenotyping research. Concurrency and Computation: Practice and Experience n/a, e5661. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/cpe.5661, doi:10.1002/cpe.5661, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/cpe.5661. e5661 cpe.5661.

[29] Debauche, O., Mahmoudi, S.A., Mahmoudi, S., Manneback, P., 2018a. Cloud platform using big data and hpc technologies for distributed and parallels treatments. Procedia Computer Science 141, 112–118.

[30] Debauche, O., Moulat, M.E., Mahmoudi, S., Boukraa, S., Manneback, P., Lebeau, F., 2018b. Web monitoring of bee health for researchers and beekeepers based on the internet of things. Procedia Computer Science 130, 991 – 998. URL: http://www.sciencedirect.com/science/article/pii/S1877050918304654, doi:https://doi.org/10.1016/j.procs.2018.04.103. the 9th International Conference on Ambient Systems, Networks and Technologies (ANT 2018) / The 8th International Conference on Sustainable Energy Information Technology (SEIT-2018) / Affiliated Workshops.

[31] Fathani, T.F., Legono, D., 2018. Txt-tool 2.062-1.2 a monitoring and early warning system for debris flows in rivers on volcanoes, in: Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer, pp. 479–490.

[32] Ginzburg, A., Nikolaev, A., Svalova, V., Manukin, A., Savosin, V., 2018a. Txt-tool 2.007-1.1: Monitoring alarm system of landslide and seismic safety for potentially hazardous objects, in: Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer, pp. 309–325.

[33] Ginzburg, A., Nikolaev, A., Svalova, V., Postoev, G., Kazeev, A., 2018b. Txt-tool 2.007-1.2 landslide and seismic monitoring system on the base of unified automatic equipment, in: Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer, pp. 327–340.

[34] Huang, Y., Zhao, L., 2018. Review on landslide susceptibility mapping using support vector machines. CATENA 165, 520 – 529. URL: http://www.sciencedirect.com/science/article/pii/S0341816218300791, doi:https://doi.org/10.1016/j.catena.2018.03.003.

[35] Intrieri, E., Gigli, G., Mugnai, F., Fanti, R., Casagli, N., 2012. Design and implementation of a landslide early warning system. Engineering Geology 147, 124–136.

[36] Kalantar, B., Pradhan, B., Naghibi, S.A., Motevalli, A., Mansor, S., 2018. Assessment of the effects of training data selection on the landslide susceptibility mapping: a comparison between support vector machine (svm), logistic regression (lr) and artificial neural networks (ann). Geomatics, Natural Hazards and Risk 9, 49–69.

[37] Kotta, H.Z., Rantelobo, K., Tena, S., Klau, G., 2011. Wireless sensor network for landslide monitoring in nusa tenggara timur. TELKOMNIKA Indonesian Journal of Electrical Engineering 9, 9–18.

[38] Liao, M., Tang, J., Wang, T., Balz, T., Zhang, L., 2012. Landslide monitoring with high-resolution sar data in the three gorges region. Science china earth sciences 55, 590–601.

[39] Luo, Z., Luo, Z., Qin, Y., Wen, L., Ma, S., Dai, Z., 2019. Developing new tree expression programing and artificial bee colony technique for prediction and optimization of landslide movement. Engineering with Computers , 1–18.

[40] Moayedi, H., Mehrabi, M., Mosallanezhad, M., Rashid, A.S.A., Pradhan, B., 2019. Modification of landslide susceptibility mapping using optimized pso-ann technique. Engineering with Computers 35, 967–984.

[41] Moulat, M.E., Debauche, O., Mahmoudi, S., Brahim, L.A., Manneback, P., Lebeau, F., 2018. Monitoring system using internet of things for potential landslides. Procedia Computer Science 134, 26 – 34. URL: http://www.sciencedirect.com/science/article/pii/S1877050918311037, doi:https://doi.org/10.1016/j.procs.2018.07.140. the 15th International Conference on Mobile Systems and Pervasive Computing (MobiSPC 2018) / The 13th International Conference on Future Networks and Communications (FNC-2018) / Affiliated Workshops.

[42] Nguyen, P.T., Tuyen, T.T., Shirzadi, A., Pham, B.T., Shahabi, H., Omidvar, E., Amini, A., Entezami, H., Prakash, I., Phong, T.V., et al., 2019. Development of a novel hybrid intelligence approach for landslide spatial prediction. Applied Sciences 9, 2824.

[43] Peppa, M., Mills, J., Moore, P., Miller, P., Chambers, J., 2016. Accuracy assessment of a uav-based landslide monitoring system. ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences 41, 895–902.

[44] Rossi, M., Marchesini, I., Tonelli, G., Peruccacci, S., Brunetti, M.T., Luciani, S., Ardizzone, F., Balducci, V., Bianchi, C., Cardinali, M., et al., 2018. Txt-tool 2.039-1.1 italian national early warning system, in: Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer, pp. 341–349.

[45] Trofymchuk, O., Kaliukh, I., Klymenkov, O., 2018. Txt-tool 2.380-1.1: monitoring and early warning system of the building constructions of the livadia palace, ukraine, in: Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer, pp. 491–508.

[46] Versace, P., Capparelli, G., De Luca, D.L., 2018. Txt-tool 2.039-4.2 lewis project: an integrated system for landslides early warning, in: Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools. Springer, pp. 509–535.

[47] Wang, L.J., Guo, M., Sawada, K., Lin, J., Zhang, J., 2016. A comparative study of landslide susceptibility maps using logistic regression, frequency ratio, decision tree, weights of evidence and artificial neural network. Geosciences Journal 20, 117–136.

[48] Yalcin, A., Reis, S., Aydinoglu, A., Yomralioglu, T., 2011. A gis-based comparative study of frequency ratio, analytical hierarchy process, bivariate statistics and logistics regression methods for landslide susceptibility mapping in trabzon, ne turkey. CATENA 85, 274 – 287. URL: http://www.sciencedirect.com/science/article/pii/S0341816211000233, doi:https://doi.org/10.1016/j.catena.2011.01.014.

[49] Youssef, A.M., Pourghasemi, H.R., Pourtaghi, Z.S., Al-Katheeri, M.M., 2016. Landslide susceptibility mapping using random forest, boosted regression tree, classification and regression tree, and general linear models and comparison of their performance at wadi tayyah basin, asir region, saudi arabia. Landslides 13, 839–856.