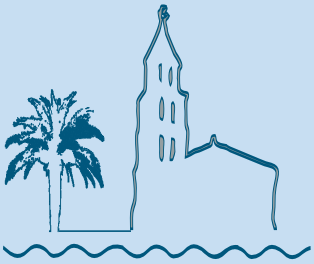
SoftCOM 2022
events

SoftCOM 2022 PhD Forum

Book of Abstracts

Split, Croatia
September 22 - 24, 2022



30th SoftCOM conference

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30th International Conference on Software,
Telecommunications and Computer Networks

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SoftCOM 2022 PhD Forum

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SoftCOM 2022 PhD Forum

Foreword

The PhD Forum hosted by the 30th International Conference on Software, Telecommunications and Computer Networks, SoftCOM 2022, was held in Split, Croatia, on September 23, 2022. An international and IEEE technically-cosponsored conference setting provided the PhD students with the opportunity to present their dissertation topics and work-in-progress to a diverse community of researchers from academia and industry, as well as to network with their peers.

The format of the event was as follows. To be included in the SoftCOM 2022 PhD Forum program, doctoral students were invited to submit a two-page extended abstract for review. The submissions were reviewed by the members of the Program & Organizing Committee and the members of the SoftCOM Technical Program Committee, based on relevance to the conference, innovativeness, and quality of (written) presentation. A total of 9 submissions were accepted and presented in the PhD Forum session at the conference. The final revised versions of the accepted submissions have been included in this booklet.

The PhD Forum session began with a series of fast-paced introductory “pitch talks”, in which each student gave a brief outline of one's doctoral research work in a strictly-timed 2-minute time slot. This part of the program was chaired and moderated by Maja Škiljo (chair) and Petar Krivić as members of the Program & Organizing Committee. After the pitch talks, the students and the audience moved to the poster display area to further discuss individual posters. The photographs at the end of this booklet capture some notable moments from the pitch talks and the poster session.

The winner of the best presentation contest was determined by the audience through a secret ballot. After a tie in the first round of voting, the majority of votes in the second round went to Katarina Mandarić, a PhD student at the University of Zagreb, who was thus declared the winner.

Finally, I would like to thank the General Co-chair of the SoftCOM 2022 conference, Dinko Begušić, and all the members of the Steering and the Program & Organizing Committees, for their help and support. I would also like to extend a well-earned congratulations to Maja Škiljo, the Program & Organizing Committee chair, on a job well done.

Maja Matijašević, University of Zagreb
Steering Committee Chair

A Novel IoT Sensor for Real-Time Crop Monitoring of Chlorophyll Fluorescence

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***Abstract*—The Internet of Things (IoT) offers many data collection use cases that can be used in agriculture for example to increase maize yield. IoT sensors can be used for real-time crop monitoring of chlorophyll fluorescence in order to track crop state and detect early signs of stress caused by varying weather conditions. In this research, we developed an IoT sensor for assessing the physiological state of maize crops based on a non-invasive method that generates data by measuring the spectral response of maize and chlorophyll fluorescence. Collected data will help in the in-time application of agrotechnological measurements and improve yield.**

***Index Terms*—IoT, agriculture, fluorescence chlorophyll, LoRa**

I. Introduction

Internet of Things (IoT) can be applied in agriculture in many ways due to the fact that it collects and processes microclimatic and agronomic data. Collected data helps analyze the impact of drought on crops (special attention is paid to maize) and implement adequate agrotechnical measures. Drought is considered the primary and most common cause of unprofitable crops in Croatia. Thus, monitoring the conditions in the field is necessary to implement appropriate agrotechnological measures.

The concept of precision agriculture was introduced decades ago; however, it was never fully implemented until recent years. The cost of automated systems and limited range of communication are technical constraints of current systems. There are several sensors investigated in the available research that can be used in IoT fluorescence chlorophyll detection systems.

An improved sensor system with multiple ISL29125 sensors and other accompanying sensors was presented in [1]. The system is based on Arduino UNO with a real-time clock and a communication module that utilizes GSM (Global System for Mobile communication). With this system, the authors improved crop chlorophyll levels (CF) estimation. They managed to determine the correct fertilization frequency for different crops. Similar solution is proposed in [2]. The MSP430G2553 microcontroller with infrared excitation light emmiting diodes (LED) lights that shine at 627 nm was used together with the OPT101 monolithic photodiode module to detect ultraviolet (UV) light at 470 nm. A microcontroller uses a filter to activate the diodes accordingly, and a filter blocks light outside the range of 690 to 740 nm. The authors' proposal addresses mesh sensor networks with high data traffic that ensures improved chlorophyll fluorescence detection.

Another sensor network for measuring CF is proposed in [3]. The system is based on UV LEDs, OPT101 sensor, two edge filters, and a launchpad microcontroller MSP430G2553. UV LEDs are used for their energy efficiency and higher excitability to CF. Primary green and red filters are used as edge filters. The proposed solution can be used to differentiate stressed from non-stressed plants in real-time. This approach is cheaper but less accurate.

A novel Chlorophyll Fluorescence Yield (CFY) sensor is proposed in [4]. Although the suggested sensor is less accurate, this inaccuracy is reduced by simultaneous measurements collected from close neighboring sensor nodes of the wireless CFY sensor network.

According to the current state of the art, most proposed devices work offline, where data on chlorophyll fluorescence (CF) is collected locally, and human interaction is required for measurements. Such methodology is a problem considering that the simultaneity of collecting data in multiple locations cannot be achieved. Therefore, a scalable remote sensing solution is needed to speed up the collection of CF data.

The main goal of this research is to deliver newly developed IoT hardware with LoRa communication for the multispectral measurement of chlorophyll fluorescence for maize. Furthermore, the idea was to explore application readiness for the newly developed prototype for remote and non-invasive measuring methods within the IoT framework. The research is focused on investigating the impact of drought on maize growth and yield. Measurements that the sensor node will conduct include determining the physical state of the maize crop by measuring chlorophyll fluorescence and applying appropriate agrotechnical measures. In addition, a real-time chlorophyll fluorescence measurement device shall be deployed in fields near Osijek and connected to a wireless sensor network using the LoRa (”long-range,” physical proprietary radio communication technique) communication protocol for data collection.

The paper is structured as follows. Section II presents the proposed architecture for IoT-based chlorophyll fluorescence

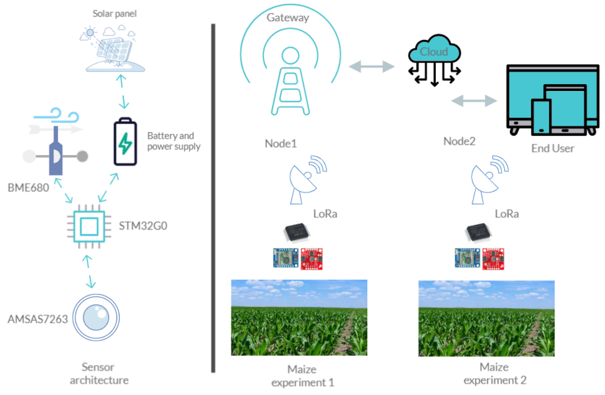

Fig. 1. The proposed architecture of chlorophyll fluorescence sensor (left) and proposed experiment setup (right).

sensors. Section III presents conclusions and plans for future work.

II. Proposed architecture for IoT based chlorophyll fluorescence sensor

This section discusses the implementation of an inexpensive spectral sensor complemented with a long-range LoRa modem, and proposed architecture is shown in Fig 1. The modem is used in an IoT device that monitors the health of a maize crop via the central processor from ST Microelectronics, STM32G030K8T6. Additionally, the proposed sensor node contains a long-range LoRa RFM95W modem with immunity to interference and low power consumption. This component was selected for its ultra-long range and low power consumption capability. The CF sensor uses a built-in Gaussian filter that measures incoming light through six channels in the near-infrared range. These channels measure the light that ranges between approximately 610 and 860 nm with a full-width half maximum of 20 nanometers. The device's optical filter is built into standard CMOS silicon and deposited using nano-optics for filtering light. Additionally, the device measures air pressure, humidity, and temperature with Bosch sensor BME680.

This research aimed to develop a sensor for assessing the physiological state of maize crops based on an IoT framework data generation method. We are measuring chlorophyll fluorescence using a non-invasive method, which significantly improves the number of collected measurements compared to classical (invasive) methods due to the need for artificial lighting, adapting the sample to darkness, and human labor. To meet this challenge, we used NIR (Near Infra Red) spectrometer [5] at the following wavelengths: 610 nm (R), 680 nm (S), 730 nm (T), 760 nm (U), 810 nm (V), 660 nm (W) that detect changes in reflectance (R), transmittance (T) and absorption (A) at multiple wavelengths, which correlates with the photochemical efficiency of photosystem II (PSII) in plants. Fig. 2 shows the spectral response of maize in an experimental field in Osijek near the Osijek Agricultural Institute, the left part of the graph shows a cloudy day when the quality of photosynthesis is reduced due to lack of sunlight, and the right part of the graph shows the spectral response of a corn crop on a sunny day when the quality of photosynthesis is good. The plant shows no signs of stress on a sunny day which we can see on the 860 nm wavelength response (Violet line). As a result of the research, a simple and robust embedded computer system was designed as a sensor for detecting stressful conditions in corn crops.

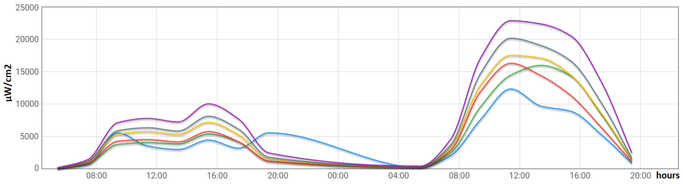

Fig. 2. Spectral response of maize during cloudy (left graph) and sunny day(right graph), wavelengths legend: Blue-610 nm, Green-680 nm, Red- 730 nm, Yellow-760 nm, Dark green-810 nm, Violet-860 nm.

III. Conclusion and future work

In order to reduce the need for human labor and simplify the collection of data on the spectral response of maize to solar-induced fluorescence and calculate the value of chlorophyll fluorescence, a novel sensor for the physiological state of maize is introduced. To meet this challenge, we used a NIR spectrometer, microprocessor, and LoRa modem described in II. The continuation of the research can be set in the direction of monitoring the state of plants in open spaces, but also in the greenhouse, and the development of advanced algorithms supported by machine learning to optimize the production process and maximization of yield. In the future we will compare gathered data with state-of-the-art sensors mentioned in section I.

Acknowledgment

This work is supported by the project ”IoT-field: An Ecosystem of Networked Devices and Services for IoT Solutions Applied in Agriculture” co-financed by the European Union from the European Regional Development Fund within the Operational programme Competitiveness and Cohesion 2014-2020 of the Republic of Croatia.

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Adaptive Data-Driven Edge-to-Cloud Environment

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***Abstract*—The concept of Edge-to-Cloud Continuum (ECC) aims to significantly reduce the overall traffic to the cloud by performing the IoT data processing as close as possible to the data sources, either on near- or far-edge devices. In the highly dynamic ECC environment, where IoT devices and edge nodes are constantly changing state and location, services running on edge nodes have to be scheduled, deployed and managed to ensure high service availability with appropriate Quality of Service (QoS) parameters. However, once the services are deployed in the continuum between IoT devices and the cloud, the question arises how to ensure continuous data delivery from IoT devices to the appropriate services for further processing, either on edge devices or in the cloud. Our goal in this doctoral research is to design and implement an adaptive data-driven ECC environment which combines mechanisms for optimal service placement and enables continuous data delivery from IoT devices to the appropriate services. Finally, we aim to evaluate and verify the solution through a real-world use case to demonstrate that the solution responds efficiently to dynamic changes in the ECC, including node, service, and network failures, while preserving high QoS for IoT devices.**

***Index Terms*—Internet of Things, Edge Computing, Service Orchestration, Data Streaming**

I. Introduction and related work

The majority of Internet of Things (IoT) data traffic is transmitted today over the Internet to cloud servers for processing/storage, causing network congestion and slowing down the overall processing cycle and responsiveness to events detected in local smart environments. The concept of Edge-to-Cloud Continuum (ECC) aims to reverse this trend by enabling the processing of IoT data as close as possible to the data sources, either on near- or far-edge devices, significantly reducing the overall traffic to the cloud.

Devices are organized hierarchically into layers in the ECC, starting with IoT devices, i.e., resource-constrained devices hosting sensors/actuators, at the bottom layer. IoT devices are connected to neighboring gateway nodes and local devices in the far-edge layer. Far-edge nodes are located in close proximity of the IoT devices, either within the same local network or at a distance of one hop, and are also resource-constrained. Near-edge is the following ECC layer consisting of more powerful compute nodes, e.g., a local micro-cloud with a few server racks, followed by the cloud at the top layer with virtually unlimited resources in data centers [1]. The placement of additional compute nodes in the ECC brings the processing and storage capabilities of the cloud closer to the IoT devices. The ECC thus provides the following benefits for IoT solutions [7]: reduced overall Internet traffic, improved responsiveness and shorter processing cycles, enhanced security with privacy control, and lower operational costs.

In a highly dynamic ECC where IoT devices and edge nodes are continuously changing state and possibly also location, service orchestration mechanisms are needed to ensure high service availability with appropriate Quality of Service (QoS) parameters. However, once services are deployed in an ECC, the question arises on how to ensure continuous data delivery from IoT devices to the corresponding services in the ECC, while taking into account the dynamic nature of the ECC. Therefore, within this doctoral research we focus on enabling *adaptive data-driven routing in the ECC* without imposing significant overhead on the resource-constrained IoT devices and services deployed in the ECC.

The problem of service orchestration and placement in ECC is a well-known research topic [5], [9], [10]. However, the problem of continuous and efficient data routing in the ECC, which comes into play once scheduling is performed, is still underexplored. We have identified only the following three papers in this field which are comparable to our solution. The importance of IoT data routing in ECC is highlighted in [4], which proposes a context-aware routing scheme that monitors the behavior of ECC nodes — whether they accept particular data or not — to decide whether to skip certain nodes in the ECC hierarchy and forward the data directly to nodes which typically accept it. Another relevant approach for routing of IoT data is presented in [3]. It uses Semantic Routing Trees (SRT) which allow a node to efficiently determine whether any of the nodes below it in the ECC hierarchy will participate in a given query over an attribute [6]. Pham et al. [8] propose a hierarchical publish/subscribe network for the ECC focused on latency-sensitive IoT applications. Their system delivers IoT data to interested subscribers using topic-based subscriptions that are propagated through publish/subscribe brokers under the coordination of a central system coordinator.

II. Methodology and conceptual approach

Our research is divided into the following stages:

This work has been supported by Croatian Science Foundation under the project IP-2019-04-1986.

A. Analysis of service orchestration algorithms and tools for edge computing environment

Service orchestration is needed to schedule, deploy and manage services in a distributed edge computing environment, so the goal of the first phase is to analyze and evaluate a service scheduling algorithm and to compare appropriate tools for service orchestration at the edge. Therefore, we have proposed a service orchestration architecture at the edge and implemented the architecture using Eclipse ioFog [2] to demonstrate and evaluate the service orchestration strategies in an emulated network [12].

B. Modeling an adaptive data-driven routing architecture for ECC

Once services are deployed in an ECC, the question is how to ensure continuous data delivery from IoT devices to the corresponding services running in the ECC, taking into account the dynamics of the environment. Moreover, data-driven routing between compute nodes at different levels of the continuum hierarchy is required since, on the one hand, the processing output of one node becomes the input of another node, which is typically higher up in the hierarchy. On the other hand, the invocations of actuation functions or device reconfiguration events (e.g., updates of sensing frequency) are sent down in the opposite direction of the hierarchy, and typically require high responsiveness to events. In our last paper [11], we proposed a general architecture for adaptive data-driven routing in the ECC to ensure continuous data delivery to IoT services requiring specific data for further processing, while maintaining high QoS for IoT devices and associated services. The uniqueness of our routing approach is that it limits the number of consumers that can receive the data based on specific QoS parameters such as latency, throughput, or privacy. In addition, we presented an implementation of the proposed architecture which employs the content-based publish/subscribe approach and evaluated the given implementation through a real-world use case using federated learning in an ECC hosting digital twins.

C. Implementation of an adaptive data-driven ECC environment

The goal of the third phase is to design and implement an adaptive data-driven ECC environment in which services are proactively placed on the appropriate edge nodes based on available resources and service invocation frequency in the node's environment, and the data is continuously delivered to the optimal services based on specified QoS parameters. Fig. 1 shows an abstract view of the target ECC environment, where the central component, the orchestrator, is responsible for creating the ECC topology (connecting nodes and devices based on network distance and available resources), and scheduling and deploying services through the selected service orchestration tool. After that, the routing of data between devices and services should be fully autonomous and adaptive based on the measured QoS parameters.

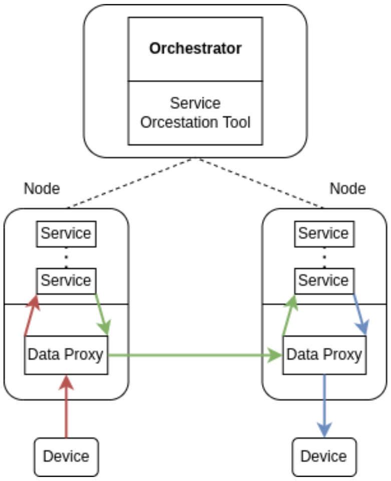

Fig. 1. Adaptive data-driven ECC environment.

D. Verification procedure for the adaptive data-driven routing

The final phase of this doctoral research is to identify and implement a real-world IoT use case which will demonstrate that the solution is stable in a resource-constrained ECC environment. It should efficiently adapt to service failures and reconfigure the ECC with minimal latency and without data loss, while preserving data privacy and security. Moreover, the solution should impose minimal overhead on the employed IoT devices.

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Anomaly Detection in Hybrid SDN Network with Supervised Machine Learning Algorithms

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Abstract — **In anomaly detection, it is important to successfully distinguish normal traffic from abnormal traffic. For this purpose, one could use the existing classification algorithms as a part of the machine learning process. Four classification algorithms were tested on the eight public Intrusion Detection System (IDS) datasets. The impact of two encoding methods, Label (LE) and One-hot (OH) encoding on categorical features as well as different ratios (10% - 90%) of training and test data on classification performance was observed. Due to the unbalanced distribution of normal and abnormal network traffic data, both standard performance scores and additional classification performance scores are used, that better describe the obtained results. Features of dataset were selected in accordance with the structure of the NetFlow data stream. Some features were discarded that had no impact on anomaly detection, such as the IP address or the time of occurrence of the data stream. The best result of 99.98% was achieved by the Random Forest (RF) classifier.**

Keywords — supervised algorithm, machine learning, anomaly detection, NetFlow, software defined network, IDS

I. Introduction

Cybersecurity attacks have increased in frequency and sophistication over the years and nowadays require more advanced and continuous innovation in defense strategy. As computing power increases and both hardware and software costs decrease, machine learning (ML) is considered an alternative method or additional defense mechanism for cybersecurity attacks [1]. The motivation and objective of the research are to correctly and as securely as possible classify network traffic anomalies in the labeled dataset using classification as one of the ML methods and implementation of the hybrid SDN which can additionally improve the proposed Intrusion Detection System (IDS) and Intrusion Prevention System (IPS). Using the Python programming language and scikit-learn platform, which solves the problem of classification through ML, it is possible to test classification algorithms and optimize parameters. The problem of detecting anomalies in network traffic falls under the classification problem, which attempts to predict, correctly mark, and separate normal traffic from anomalies. The literature review highlighted some shortcomings in the research such as testing algorithms on a small number of samples [2] using algorithms without encoding or encoding categorical features in only one way [3], inadequate basic evaluation of algorithm performance on an imbalanced dataset [4] and evaluation of algorithm performance on generated data without comparison with performance on large datasets [5]. Combining classification based on reference or historical datasets with real-time classification of current network traffic, a new model was proposed that introduces an software-defined network (SDN) component into the classic network environment, which is able to react to the occurrence of anomalies with different network settings, all in real time.

II. Methods

The research is divided into several phases (ML classification with reference data and preprocessing, simulation of classification with a real dataset, verification of anomaly detection in hybrid SDN and comparing results with classic security approach).

A. Selection and adjustment of input data

LUFlow2021 dataset of 5.033.685 (70% benign traffic and 30% of anomalies) records with 16 features of dataset were reduced to 8 most relevant. Feature reduction was implemented and confirmed by few feature selection ML methods. The best classification algorithm among four tested (Support Vector Machines, Bernoulli Naive Bayes, K-Nearest Neighbour (KNN) and RF) ML algorithms was RF. They were obtained through a series of data preprocessing processes which consists of:

- deleting irrelevant features in each observed dataset,
- deleting invalid values,
- encoding categorical features,
- separating dataset into train and test portion,
- data scaling,
- selected classifier hyperparameter cross-validation ,
- adjustment of dataset features according to the NetFlow structure

B. Model for network traffic anomaly detection in a hybrid software-defined network

Selecting the RF classifier as the best classifier and its optimal hyperparameters with the reference dataset, it is possible to define a model for anomaly detection which could be used to increase IT system security. The proposed model is based on a traditional network infrastructure that has been upgraded with network devices of an SDN, and thus with the help of ML completes the model in a hybrid SDN. An SDN device is connected within the traditional network and with help of the SDN controller and application programming interface (API) requests can react in real-time on detection of security threats in the form of network traffic anomalies. The anomalies of the reference dataset are added to the collected real NetFlow data from the network devices, and the success of the detection was tested with the selected RF classifier.

C. *Verification procedure of the proposed model in the real environment*

The procedure for verifying the proposed model in a real environment is based on a hybrid SDN environment. Detections of simulated security threats (network anomalies) are compared using parallel detection processes on the SDN device and other IDS systems used in traditional network environments.

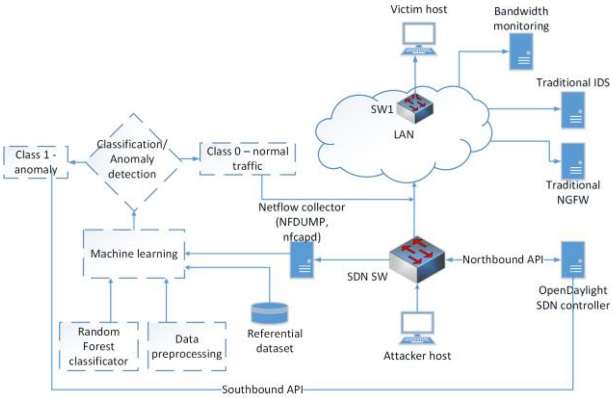

Fig. 1. Real hybrid SDN environment for verification procedure of proposed model

III. Results

During the search of available public datasets for use in the ML model, 8 datasets were found in the last few years: UNSW-NB15, CSE-CIC-IDS2018, LUFlow2021, and their NetFlow versions along with NF-UQ-NIDS. During data preprocessing, irrelevant features such as IP addresses, traffic flow ID and time of flow generation were deleted. The so-called NaN (Not-a-Number) values (0% - 9% of data depending on the observed dataset) were also deleted. In the case of categorical features, an impact study was conducted with the LE and the OH encoding method, where LE proved to be less demanding on preprocesing of input data and computing time and equally successful. When investigating the influence of separation ratios (10/90 - 90/10 in steps of 10) of data on train and test portion, the optimal ratio turned out to be 80/20, taking into account not only Area under the ROC curve (AUC) classification measure but also the time needed for calculations. Improved classification performance was obtained by scaling the data using the MinMax data scaling method with other methods such as Standard and Robust scaler tested. The cross-validation of GridSearchCV determined the optimal hyperparameters for the selected RF classifier, which achieve better AUC results than with the default parameters of the classifier. The best AUC results of 99.98% are achieved by the RF classifier, while KNN also achieves high results (99.97%) on the reference dataset LUFlow2021.

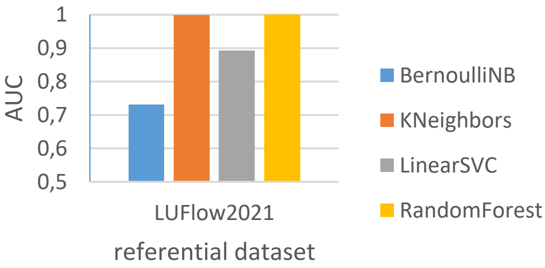

Fig. 2. AUC scores comparison of ML algorithms

The advantage of the RF classifier is that it takes not negligible less time for calculations shown in the logaritmic scale in figure 3.

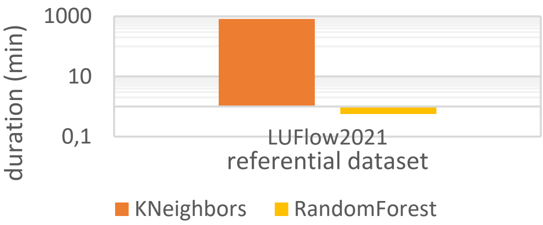

Fig. 3. Duration of calculation between two best ML algorithms

IV. Conclusion

The proposed model for network traffic anomaly detection, with a corresponding set of data and customized selection of features, can be easily applied and adapted to various classification problems. With certain preprocessing of data and adjustment of features, high results of the classification can be achieved, which due to good performance is usable for implementation in real-time environments. Using the advantages of machine learning and SDN capabilities of network devices, adequate activity is possible in preventing security incidents in real-time. The proposed model is equally applicable in SDN and traditional networks, and compared to the traditional approach, it has far more options for reacting to potential security incidents.

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Increasing the Accuracy of Geotagging from Unstructured Text

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***Abstract*—Social networks are an inexhaustible source of data and they are part of most people's daily lives. In times of crises, such as earthquakes, floods, fires and other natural disasters, the activity of users on social networks increases, and this manifests itself in the greater generation of data, such as posts, images, or videos. However, such data, especially textual data, which are unstructured and often written in free form (informal speech), are often inappropriate for use in other crisis management software. Geotagging is a process of adding geographical information to a document. In this research we analyzed the geottaging of social media reports on forest fires and designed a new method for increasing the accuracy of geotagging. The method was evaluated on a dataset of textual media posts from facebook firefighing fun page and results are discussed.**

***Index Terms*—social network, unstructured text, geotagging, natural disasters**.

I. Introduction

Today, social networks are part of our everyday life and when anything happens in our environment the most immediate response are posts on social networks. This also applies in case of natural disasters or any kind of accidents in our environment. Social networks are the simplest way of communicating and transferring information. However, when a natural disaster occurs, the amount of content generated by users is too large to process it manually. The primary goal of most citizen science and crowd-sourcing projects is data collection. In order to use collected data appropriately and successfully one must ensure its quality, usefulness and preservation. In order to utilize the data in crisis management situations, geotagging of data is one of the crucial steps. Geotagging of text is done by geoparsing (extracting the text denoting the location) and associating geographical coordinates to a text.

In paper [1] authors are mentioning multiple knowledge-based algorithms and methods for geoparsing, such as a knowledge based word sense disambiguation method for disambiguation of toponyms. A prototype system called Gipsy (georeferenced information processing system) [2] was developed from that method. Authors proposed an assessment measured based on ranking of closeness relative to the predicted and actual locations of a place name. A research described in [3] describes the process of transforming social media posts into VGI (Volunteered Geographic Information) using geocoding and data mining methods analysing Facebook posts about wildfires in Croatia. Authors used ESRI ArcGIS Pro software and Nominatim for geocoding, where according to their results ESRI outperformed Nominatim in performances for geocoding.

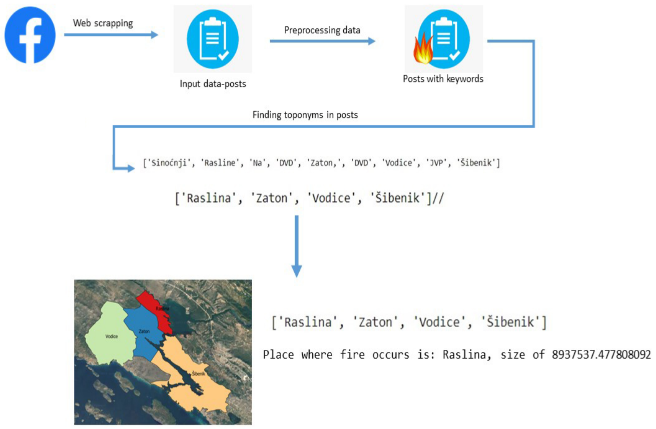
There are many papers about extracting toponyms from other social networks, such as Twitter. One of them is paper [4] where authors proposed a method composed of two levels. First one includes modules for text processing and normalization for feature construction. Second level uses CRF (Conditional Random fields) learner for model learning. First step of analysis is tokenization of input tweets. Step two is morphological analysis applied on the tokens. Tweets are informal text and there can be cases where morphological analysis does not recognize informally written tokens or recognize it wrong. Normalization of data is the next step according to those reasons. Final step is training and testing preprocessed data with the CRF MALLET (Machine Learning for Language Toolkit) engine.

OzCT geotagger module is one of the components of the OzCrisisTracker web application [5]. OzCT geotagger automatically identifies and references geolocations in the tweet contents. Different geographic events can be easily identified which helps with clustering tweets related to the same geographic event. It helps to reduce information overload. In paper [6] authors had focused on extracting and geocoding inferred locations from tweets. Their main goal was to increase the number of georeferenced social media posts for geospatial analysis. For that purpose they used and compared two methods DBpedia Spotlight and spaCy combined with OpenStreetMap Nominatim. SpaCy gave better results on a data set consisting of 50 616, where it identifies more locations than DBpedia Spotlight.

In our research we address the problem of having multiple toponyms geoparsed from the free texts and selecting the appropriate location for geotagging the text.

II. Methodology

In this paper we used posts from the Facebook fan group ”Fire-fighters-They are our heroes” [7] that discuss wildfires in Croatia. The posts contain videos, photos and text, where the only textual part of the post was used in this study. We extracted all posts from 2019 - 2021. The final data set used in analysis contains approximately 1700 textual posts.



```
['Sinoćnji', 'Rasline', 'Na', 'DVD', 'Zaton,', 'DVD', 'Vodice', 'JVP', 'Šibenik']
```

```
['Raslina', 'Zaton', 'Vodice', 'Šibenik']//
```

```
['Raslina', 'Zaton', 'Vodice', 'Šibenik']

Place where fire occurs is: Raslina, size of 8937537.477808092
```

Fig. 1. workflow of extracting toponyms

The whole process of retrieving, extracting and analysing posts contents can be seen in Fig. 1. First step was to preprocess data because the goal was to filter only posts in which wildfire was mentioned. For that purpose a script implemented in Python was used, where the posts were retrieved based on keywords *fire, warning, intervention*. Afterwards, for every post we extracted only those words that have first capital letters, assuming that toponyms were written with first capital letters. The next step was to identify toponyms in posts that were previously filtered. The list of Croatian settlements was used as a list of known toponyms (n=6765) [8].

Since Facebook posts are often written in free form and with use of dialect, we had to apply the stemming procedure for better results. We used the stemmer for Croatian language which is adapted to the Python language. We use it for automatic recognition of words based on root of the similarly word [9]. Thus, we've got a list of one to seven toponyms associated to each post.

For the posts that mention multiple toponyms we applied the following hypothesis: in the text describing the incident, the location is described in more detail by stating the name of a larger nearby settlement and then specifying the location by stating the smaller settlement. Smaller settlement is thus more precise location of the event. For each post, the coordinates of the settelment with the smallest area was selected for geotagging.

III. Results

As a result of applying the methodology to the dataset we obtained posts where toponyms are not mentioned (n=6), posts with one toponym (n=49) and posts with two or more toponyms (n=225). Posts with multiple toponyms in it were taken out and analyzed. For each settlement in the toponym list we calculated the surface area of the settlement. It was assumed that the toponym with the smallest area is the most precise place where the wildfire happened. This assumption was checked manually on dozens of posts. For example [Raslina, Zaton, Vodice, Šibenik]-Raslina is the place with smallest area and it is correct that wildfire was in Raslina. After analysis, we creted a shapefile from the dataset so for each post we can visualize the location of the assigned settlement in some GIS-based tools (e.g. QGIS, ArcGIS, etc.).

IV. Conclusion

Data from social networks can be very useful if they are processed in the right way. When describing an event near settlement that is not famous, usually a bigger place near it is mentioned. The research in this paper utilized this, in order to obtain more precise geotagging. Result of this paper is a geocoded and geotagged dataset that can be used in further work. Additional semantics will be included in future work, to avoid spatial heterogeneity of the data. By reducing data heterogeneity, greater data accuracy could be achieved. This could lead to the first prototype of an application that will be able to predict the location of an incident based on publicly available data and timely notify public services.

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LoRa Overview And Evaluation

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***Abstract*—Technology is improving quickly in the world. There is also a rapid development of network protocols to connect multiple devices in a network where data would be shared within the network or on the Internet. IoT (Internet of things), represents a network containing physical devices that contain hardware, software and other technologies to connect and exchange data with other devices via the Internet. This is how the LoRaWAN specification was created, which has found a variety of applications in the world of IoT. It is characterized by low battery consumption, security, low price, mobility, and connection to devices over a long distance.**

Keywords—LoRa, LoRaWAN, IoT, SNR, RSSI.

I. Introduction

The Internet of Things is a system of connected devices through the Internet, forming a physical network. This implies a network of physical objects that can communicate and transfer data with other systems and devices.. IoT applications require technologies that provide low-cost end devices with low power consumption and the ability to communicate over large distances. In most cases, such devices run on batteries, so it is necessary to devise a consumption system to extend the battery's life. Considering the above characteristics, realization is possible only using low-power broadband network technologies such as LoRaWAN. LoRa is a wireless technology used for communication over long distances and, as such, is one of the most widespread LPWAN (Low Power Wide Area Network) technologies in the world.

II. LoRaWAN Network Architecture

The LoRaWAN network [1] has three main components: network servers, gateways, and end nodes (sensors). End nodes communicate with network servers or data servers through gateways. The communication between the end node and the gateway can be carried out by LoRa or FSK modulation using different data rates and the different number of channels. Communication between gateways and network servers is done using the standard IP protocol, and all data frames sent from the end node must reach the application server through the gateway. LoRaWAN is a physical layer protocol that aims to solve media management problems and network congestion. In a long-haul network, gateways must require the possibility to receive messages from many devices. This large capacity is allocated by applying adaptive data rate and transmission via multi-channel transmitters. Critical factors [2] that affect this ability are the number of simultaneous channels, the data transfer rate, the length of the information, and the frequency transmitted by the end device. The LoRaWAN network is highly scalable. The network can be set up with minimal infrastructure and with the expected capacity, can be expanded by adding new gateways. Also, LoRaWAN works better thanks to a technological compromise, which limits the downlink's capacity or makes the downlink's scope asymmetric to the uplink's bandwidth. In end devices, the downlink delay is an essential factor that decides how much power is consumed. LoRaWAN is an asynchronous protocol based on the ALOHA protocol, which means that the endpoint device can wake up at programmed periods to checkup the downlink and synchronization messages in the synchronization window, thus reducing latency and consumption. Thus, there are different LoRaWAN classes [1] related to the trade-off between downlink delay and battery life. Different classes are used for different needs [3]. A class is the basic, i.e., default, class that must be based on all LoRaWAN end devices. Class A communication starts periodically from the endpoint device and is completely asynchronous. Every uplink transmission could be sent at any time and after that come two short frames, a downlink window, which allows bidirectional communication or network control commands if necessary. The endpoint device can enter a low-power sleep state for considering what is specified by its application; there are no network requirements for the periodical "waking up" from sleep. This makes Class A the lowest power mode while at the same time enabling uplink communication at any time. In addition to received frames initiated by Class A, Class B devices use beacons and downlink ping slots to synchronize with the network at predetermined times. This enables the network to send downlink communications with a deterministic delay, but incurs additional power consumption on the end device. The delay can be programmed up to 128 seconds for different applications, and the additional power consumption is still low enough for battery powered applications. The class C structure further reduces downlink latency by keeping the terminal's receiver open, ie. always free (half duplex) when the device is not transmitting. Based on this, the network server can initiate downlink transmission at any time, provided that the receiver of the terminal device is free, that is, there is no delay. The trade-off is increased consumption, ie. power consumption of the receiver (up to $\approx$ 50 mW), so class C is suitable for constant power situations. Temporary switching between class A and class C can be done on battery powered devices and is useful for intermittent tasks such as firmware over-the-air updates [4]. Different LoRaWAN security design adheres to state-of-the-art principles and uses standard, well-tested algorithms and end-to-end security. The security mechanisms rely on well-tested and standardized AES cryptographic algorithms. These algorithms are well-vetted and analyzed by the cryptographic community, approved by NIST (National Institute for Standards and Technology), and widely accepted as best practices in implementing security. LoRaWAN supports encryption and signing of packets sent over the network. For encryption, symmetric keys known to nodes, network servers, and application servers are used. They are distributed in two different ways, depending on the activation method. Those two activation methods are the OTAA and ABP. Actual applications of LoRa technology are tested and further described in Section III.

III. Measurement Results

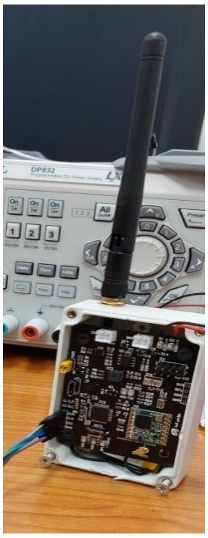

Fig. 1. RFM95 LoRa module

Testing RFM95 LoRa module shown in Figure 1 is performed by sending 5 packets from 5 different urban locations (from close proximity to significant urban distance), measuring SNR, RSSI and paying attention to the number of unsent packets. RSSI is determined by measuring the signal strength at the receiver. The RSSI value is a good indicator of the distance between the transmitter and the receiver because the signal strength decreases proportionally to the distance from the transmitter to the receiver. The measurement results shown in Table 1 confirm that the RSSI decreases with increasing distance so that the RSSI value at the shortest distance (50 m) is the highest (-82.7 dBm) while the RSSI value at the longest distance (5 km) is the lowest (-118.5 dBm) [5]. The signal-to-noise ratio value represents the comparison of signal strength and noise strength. It gives us the signal-to-noise ratio, called S/N or SNR, and is used in decibels (dB). The SNR value can be positive, meaning the signal is stronger than the noise. At negative SNR, the noise is superimposed on the signal. The measurement results in table 1 show that the SNR decreases with increasing distance, that is, the noise power increases with larger distances.

TABLE I.
Measurements

Range (m)	50m	680m	1,3km	2km	5km
Average RSSI (dBm)	-82,7	-108,8	-108,5	-116,5	-118,5
Average SNR (dB)	9,45	3,4	0,45	-8	-8
Failed transsmision	0	0	1	3	3

At locations that are 2 km and 5 km away, the measured SNR has a negative value, which means that the strength of the noise overpowered the signal strength [6].

If an unsuccessful packet transmission occurs, we cannot monitor the parameters, which in our case are RSSI and SNR. Many factors influence the unsuccessful transfer of packages (distance, obstacles, rainfall…). The packets were successfully transmitted at the first two locations with a smaller distance (50 m and 680 m), but as the distance increases (1.3 km, 2 km, 5 km), the packets are lost, and some transmissions fail. In Table 1, the number of lost packages increases proportionally with the distance (3 lost packets at distances of 2 km and 5 km).

IV. Conclusion

The results show that different combinations of parameters may be viable options for different distances and urban or rural areas. At shorter distances, the signal strength is also significantly reduced. RSSI is variable, and at a distance of 5 km, RSSI can be seen to approach -120 dBm, which means that 5 km is the limit of the range in urban and suburban areas. At shorter distances, the SNR is positive, indicating that obstacles are not a problem at shorter distances, and at longer distances in urban areas, the SNR is negative. The results indicate that LoRa is a viable option for a variety of IoT solutions even though there is a significant noise. As a continuation of this work, LoRa technology will be tested in rural areas with significantly larger distances.

Acknowledgment

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Multi-Agent System for Service Provisioning in an Internet of Things Smart Space based on User Preferences

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***Abstract*—Intelligent software agents offer many possibilities in Smart Spaces to enhance the user's comfort in such a way that the ambient conditions do not need to be adjusted manually, but the system does it automatically for the user by monitoring the user's preferences based on the context. In our proposed solution, a Multi-Agent System is implemented to ensure the adaptation of device settings to the user's previously entered or detected preferences. Each user is represented by a separate agent, so that even in the problematic scenario where multiple users with different preferences are in the space, a decision that satisfies all users is made through negotiation between the agents. The preliminary results of the proposed Multi-Agent System under development outperform the results of our previously tested approaches - centralized and semi-decentralized approaches.**

***Index Terms*—Multi-Agent System, Software Agents, Internet of Things, Context-Awareness, User Preferences**

I. Introduction

Every day we are flooded by advertisements for numerous ”smart” home solutions, most of which do not have the cognitive ability to automatically adjust to the user's wants and needs, but instead rely on the user. The user himself must define the settings that suit his preferences, and in fact the user is the brain of these ”smart” solutions for the Internet of Things, which simply connect the devices and provide the user with an application to control them. Connecting devices, which was the original goal of IoT, has been achieved, so research is now focused on realising its full potential, which means integrating cognitive capabilities into IoT solutions.

In order to create such a smart IoT solution that enhances user experience and comfort by reducing the amount of manual input required by the user, we propose a Multi-Agent System where each user is represented by a dedicated software agent that studies his preferences and ensures that device settings are adjusted to the user's preferences based on context. Much research has shown that Multi-Agent Systems are a valuable tool for modeling and simulating complex, dynamic, and especially distributed systems [1]. Software agents given their characteristics: autonomy, learning, and collaboration [2], stand out as a valuable option for improving service provisioning, which has already been demonstrated [3]–[5].

II. Service provisioning based on User preferences

The focus of our proposed solution is on managing device settings in a room (e.g., ambient settings: lighting, heating, cooling, etc.) while taking into account the different preferences of all users present in the room at the same time, based on context. Context awareness is an indispensable part of this system and is not a novelty, as its importance has been widely discussed for years [6] and many definitions of context have been published [7], [8]. The context relevant to this system is divided into two parts - one describing the physical environment (conditions, devices, etc.) and the other describing the user (preferences, flexibility factor, etc.).

The proposed user-centric, context-aware Multi-Agent System for service provisioning based on user preferences features two types of software agents to ensure the seamless adaptation of ambient conditions to user preferences: the Smart Space agent *s_agent* and the user agent *u_agent*. There is only one Smart Space agent per Smart Space (room, office, etc.), while the number of user agents corresponds to the number of users present, with each user *i* having its own user agent u_agent_i, as shown in Figure 1.

The Smart Space agent has the following tasks: monitoring the number of user agents present in the space, monitoring sensor values and actuator settings that affect the context, and in certain scenarios, managing the negotiation and/or decision-making process to save time. The last task will be discussed in more detail later.

A user agent is responsible only for its own user. The user agent uses an Artificial Neural Network to study its user's preferences with respect to the context in order to predict the user's preferences for the unseen context. This must be done continuously, as the user's preferences may change over time. The inputs and outputs of ANN are defined in regard to the user preference, i.e., the relevant conditions in the space that directly affect the preference choice, this depends on the study case and the application of the system. The ANN is trained on previously detected or defined preferences. In addition, the user agent must be able to negotiate settings with other user agents, with each user agent advocating for its own user. An important part of the negotiation process is the flexibility factor, which is set individually by each user. This allows users to express their willingness to give up their own preferences because they are open to other settings, not just their preferred settings. The user's preferences and flexibility are described by a Gaussian function. The device options (e.g., light intensity) are expressed on the x-axis, and the Gaussian function is centered on the user's preferred value. The flexibility factor is the standard deviation of the Gaussian function, and the smaller it is, the narrower the function is. This indicates the inflexibility of the user, as his utility function decreases with distance from the initial preference. In most cases, the flexibility factor significantly reduces the negotiation time. It becomes problematic when there are two or more users with different preferences and low flexibility factors. Therefore, the number of negotiation rounds is limited depending on the number of users present and the complexity of the negotiation problem. If no agreement is reached in the maximum number of negotiation rounds, the Smart Space agent determines the settings based on all user preferences using the multiple user calculation model described in our previous work [9].

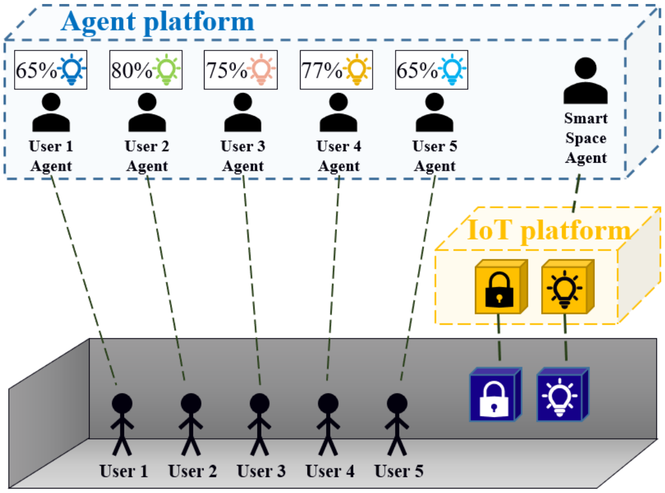

Fig. 1. System overview

III. Study Case

The proposed system is explained in more detail using the Smart Lighting study case. For this study case, the relevant conditions based on which the user defines his preferences are outside luminosity level and the time of day. The user specifies his preferred lighting intensity and color. The user's presence is detected via a smart lock that allows him to enter the Smart Space. This could also be done via an indoor location service to further enhance user comfort. The inputs of the ANN used by each user agent are the outside luminosity sensor reading and the time of day, and the outputs are the user's preferred settings of light intensity and color.

The study case is explained using the scenario in which the luminosity sensor reading changes, i.e., the context that influences user preferences. When the sensor data changes, the Smart Space agent informs the user agents about the change and asks them if they still agree with the current device settings even though the context has changed. If a user agent believes that it can maximize its utility function according to its new preference, the negotiation process starts again. It is important to note that the relevant sensor data does not affect preferences if it is changed by only one unit of measurement (minute for time or lux for luminosity). Sensor readings are grouped together, so only a change in the data that changes the group is considered a trigger. The same applies to a change in the time of day, with the time of day divided into seven groups.

IV. Conclusion

The system under development represents an advance in providing intelligent services to users by eliminating the need for manual intervention by the user. The preliminary results of the proposed solution surpass the results of our two previously studied solutions - fully centralized and partially decentralized. In a fully centralized solution, an Artificial Neural Network has to learn the preferences of all users, which is not optimal, and in a partially decentralized solution, for each user there is an agent with a ANN, but they do not negotiate, instead the preferences are computed using a centralized mechanism, the multiple user calculation model, based on the preferences of all users present.

The proposed system can be used in many different use cases - for example, the users do not necessarily have to be humans. It is possible to adapt the system for plants in a greenhouse or animals in a zoo as users. For these study cases, the knowledge of domain experts is required.

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Overview and Comparison of Different Techniques for Reducing the Amount of Data Transferred in IoT

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***Abstract*—Due to the progress and development of new technologies, most of the devices used today are connected to the Internet. As a result, a huge amount of data is generated and transmitted over the network. Generally, the mentioned devices have certain resource constraints such as memory, processing power and battery life. Reducing the amount of data reduces the power required to process this data, minimizes data storage, and reduces the transmission load. The need to apply data reduction techniques to devices is becoming increasingly apparent. This paper provides an overview of the most commonly used data reduction techniques in IoT. It describes the different types of data reduction, their limitations and application areas.**

***Index Terms*—Data reduction, Internet of Things, Data compression, Data prediction, In-network processing**

I. Introduction

The idea of mass networking presents many challenges and obstacles, such as scalability, heterogeneity, security issues, energy requirements, etc. Finding the best solutions to the mentioned issues presents the motivation for scientists to conduct research in this area [1].

IoT sensors can have high sampling rates, which can lead to faster device power consumption and limited memory. It has been shown that up to 80% of the total energy consumption in IoT sensor networks is due to wireless data transmission [2]. Of course, it should be emphasized that bandwidth, the aforementioned energy consumption, data storage and processing are in themselves very burdensome. One way to solve the described problem is to reduce the data before it is sent over the network. Most of the currently available solutions focus on data reduction at only one layer of the IoT architecture or simply perform post-transmission manipulation of the data after the data transmission has already taken place, i.e., in the cloud. However, due to the above issues, reducing the amount of data before the actual transmission becomes a pivotal issue. Reducing data at or near the source not only saves energy. Rather, transmitting compressed and/or filtered data also diminish network bandwidth, making more efficient use of available resources. Additionally, edge computing (EC) has paved the way for alternative ways of analyzing and processing IoT data compared to the centralized cloud computing approach. [3].

The focus of this research is to answer the following question: *”How can the amount of data in IoT environments that needs to be transmitted over the network be reduced?”* with emphasis on reduction techniques that can be applied near the source of the generated data. This paper provides an overview of existing methods and techniques. In the following sections, each method is briefly described, followed by available solutions. Finally, conclusions and future steps for research are explained.

II. Data reduction techniques and proposed solutions

All data reduction techniques aim to reduce the amount of data delivered to the destination node. However, the principles on which they are based are quite different. In general, the techniques can be divided into three main categories: Data compression, Data prediction and In-network processing. The characteristics of each approach are presented in Table 1. Based on background research, several studies have been conducted to address this issue. The following provides a brief review of the specifics of each approach.

A. In-network processing

Network processing consists of aggregating and filtering data in intermediate nodes between the data source and the destination, reducing the amount of data in the network. Sensors can filter data and transmit only relevant data while ignoring the rest, saving transmission costs. Complex filtering algorithms require computing power and more memory, which is why they are usually performed by gateways. In data aggregation, the data is presented in summary form. The sensor device can aggregate the data at a predefined interval and send only the aggregated values. It can also compare the collected value with the aggregated value and send both values if they differ significantly. Ismael et al. [4] propose a solution that combines filtering and data fusion within the network. In the filtering layer, redundancy detection is based solely on the deviation of the data values. The second layer is based on a MSE criterion and fuses the data of the same time domain for specific sensors deployed in a given area. Although the proposed approach has shown good performance and efficiency in filtering and fusing the linear IoT data, handling non-linear data could still be a challenge for the proposed method.

TABLE I
CHARACTERISTICS OF DIFFERENT APPROACHES

Approach	Characteristics
In-network processing	eliminating redundant samples, application-specific
Data prediction	reducing communication load, application-specific, high computational costs
Interpolation compression methods	lower computational complexity, simple configuration process, suitable for real-time compressions
AI compressioon methods	computational complexity, require pre-training, suited for approaches with many inputs
Transformation methods	require data vectors as inputs, need a larger number of measurements to achieve satisfactory compression result
Hybrid compression methods	computational complexity, good data reduction results

B. Data compression

In data compression (DC), information is encoded on the nodes that generate the data and decoded on the destination node. There are several methods of data compression, which are divided into two major subgroups: lossy and lossless compression. The authors in [5] compared several lossy compression techniques with a focus on applying the algorithms in IoT environments. It was concluded that best approach depends on the specific application. The compression algorithms used for evaluation in [6] paper were chosen for their compression performance when the probability distribution of the values is not known in advance. Both static and adaptive coding methods were evaluated and results show that adaptive algorithms have better compression, while static algorithms are more robust in the presence of unreliable communication channels. Al-Qurabat et al. [7] propose a two-tier data reduction (TTDR) method. At the node level, a delta coding followed by run length coding (RLE) is used. In the second phase, all data is sent to the aggregator. When the aggregator receives the data, it finds the data redundancy and compresses the data size.

C. Data prediction

Data prediction consists of creating an abstraction of the sensory phenomenon, i.e., a model that describes the data. The model can predict the values sensed by the sensor nodes within a certain margin of error and is stored on the sensors themselves, but also on other nodes in the network. If the required accuracy is met, individual queries can be evaluated against the model without having to send measurement data from the sensor. On the other hand, explicit communication between the sensor and other nodes is required if the model is not accurate enough. Consequently, data prediction reduces the need for communication between nodes, thus saving the energy and network load required for communication. In the recent research study, the authors in [8] proposed a two-phase data reduction method. The data reduction phase (DRP) is mainly used to reduce the number of transmissions while detecting erroneous data. The discarded erroneous data at the sensor nodes are replaced with estimated values (based on the Kalman filter). The obtained results show the data transmission reduction by up to 75.75%.

III. CONCLUSION AND FUTURE WORK

The research consists of several phases. Initially, to get into this field of research, an analysis of the solutions already proposed was made. All potential problems and challenges associated with the research area had to be identified. As our research focusses on IoT environments, only such studies have been considered. It was found that finding an optimal balance between data reduction and energy consumption while maintaining data reliability and accuracy is a major challenge. Some of the main issues and questions raised relate to the limited capabilities of current sensor devices, the impact of data reduction techniques on data reliability/accuracy, security issues, etc. It appears that a hybrid algorithm combining various techniques is required in order to achieve the best result. In addition, the search for the best approach depends heavily on the usage scenario, so finding an appropriate dataset is one of the challenges.

Based on the analysis, improvements of existing and newly developed methods suitable for sensor systems will be proposed and a conceptual model will be created. It is planned to focus specifically on compression algorithms and AI methods. In the third phase of this research, an algorithm will be developed based on the previously created model. To calculate the most efficient algorithm, we will examine the following factors: available computation resources, processing time, resource consumption, reduced data accuracy and reliability and transmission protocols. The final phase will focus on testing the developed algorithm in the IoT environment.

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Supervisory Control and Data Acquisition (SCADA) Systems in Continuous Manufacturing Process Control

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***Abstract*—This work provides a holistic approach to Supervisory control and data acquisition (SCADA) systems implemented in continuous flow production control emphasizing the steel industry production environment. We outline the aspects of interoperability and interconnection within the Industry 4.0 (I4.0) architecture reference models, together with the research challenges and opportunities of the future trends with key aspects of the Industry 5.0 (I5.0) paradigm. Furthermore, we explore the challenges in SCADA systems transition from standard automation pyramid structure to service-oriented architecture, heterogeneous networks and digital twins (DT). In that respect Our research contribution is focused on improved data availability near data sources in real time, data-centric approach to DT and improved operational visibility.**

I. Introduction

In terms of Industry 4.0 (I4.0)[1] reference architectures and approach to design and development of supervisory control and data acquisition SCADA systems, it is not realistic to expect that a one-size-fits-all approach can produce satisfactory results across industries. In this regard, our research rests on a comprehensive understanding of SCADA systems in continuous manufacturing process control with a focus on the steel industry domain and in the following aspects (1) Continuous flow production process and steel plant environment conditions related requirements for SCADA systems in terms of architecture, integration, computational demands, accessibility, Industrial Internet of Things (IIoT), communication protocols and operators assistance. (2) Impact of the I4.0 on SCADA architecture, network topology, communication protocols and standard automation pyramid i.e. ISA-95 (ISO 62264) model of functional hierarchies. (3) Concept of the 4th generation SCADA systems in terms of the ISA-95 model transformation, integration of IIoT, cyber-physical systems (CPS), cloud, services, and convergence of information technology (IT) and operation technology (OT) into heterogeneous networks. (4) The concept behind various reference architectures and mapping a standard SCADA system into reference architecture model for Industry 4.0 (RAMI4.0) [2] (5) SCADA-related concerns in manufacturing plant industrial control system (ICS) development life cycle. (6) Conceptual understanding of I5.0 and the impact of human-centric approach to next-generation SCADA systems.

II. SCADA in heterogeneous IIoT network

As a consequence of IIoT implementation in the manufacturing industry, i.e. the steel plant production floor, SCADA systems have become part of a highly integrated and interconnected flattened Service-oriented architecture (SoA) with no boundaries between field, process and SCADA networks. Such an architecture additionally relies on cloud solutions and services that expose ICS to the internet.

From the practical point of view, considering the operative lifetime of equipment in steel plants that easily extends over twenty years, although this may not be the case for IT hardware, a common practice for replacing or upgrading IT hardware is to gradually migrate the existing SCADA software to the new one. This practice has a number of drawbacks, but it reduces the downtime required for commissioning of the new SCADA system, which could otherwise take weeks and greatly impact the production plan. For the same reason, a major revamping or replacement of the entire SCADA system is not considered unless there is an obvious and significant improvement in question.

As a consequence, in a real-life scenario, the concept of a 3rd generation SCADA systems integrates the targeted solutions and enabling technologies of a 4th generation SCADA systems, potentially resulting in several independent systems. An unambiguous data structure, unified namespace and a centralized repository as prerequisites for achieving the level of integration necessary for I4.0 concept do not imply in such a structure.

III. beyond I4.0

In line with the aforementioned SCADA transition and the six key aspects of research, fig. 1 depicts components in focus related to I4.0 SCADA system, technologies and fields of innovations the research is relying on, and finally, targeted contributions within I5.0 SCADA system, i.e. components that benefits from improved real-time data availability, and data-centric approach

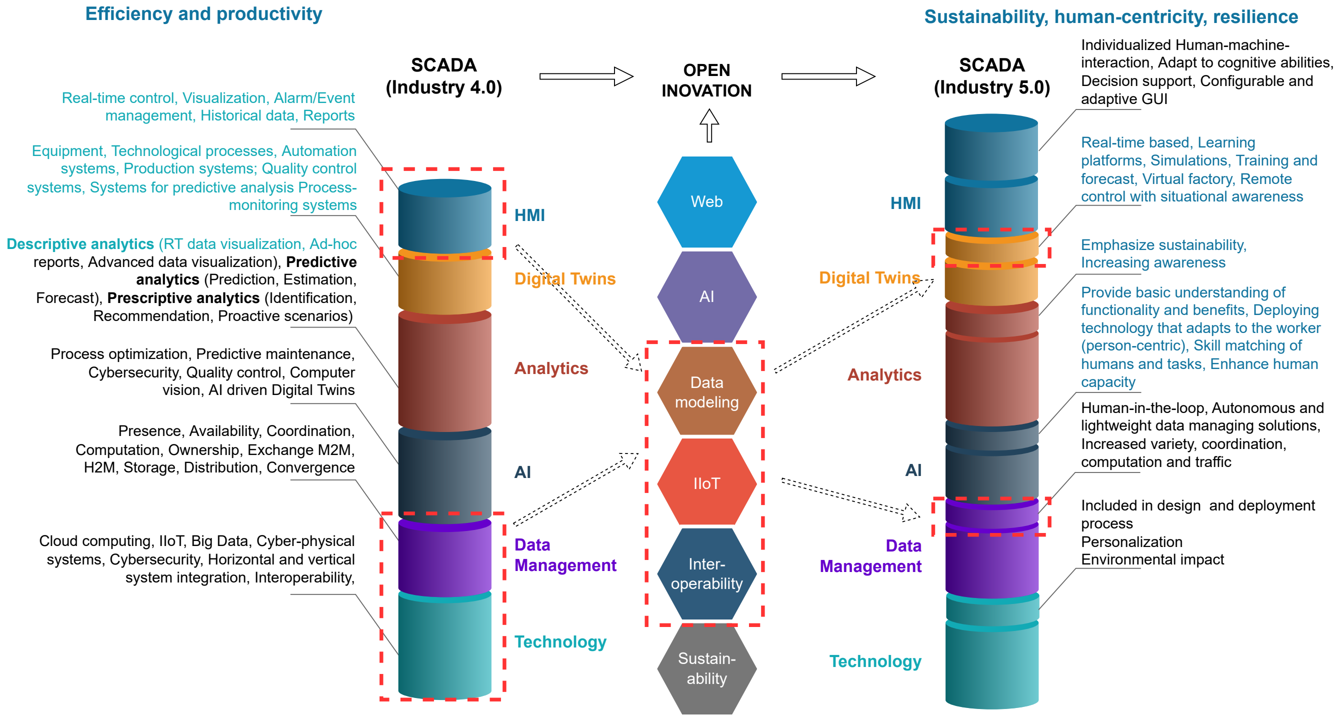
Efficiency and productivity
Sustainability, human-centricity, resilience
SCADA (Industry 4.0)
OPEN INOVATION
SCADA (Industry 5.0)
Real-time control, Visualization, Alarm/Event management, Historical data, Reports
Equipment, Technological processes, Automation systems, Production systems; Quality control systems, Systems for predictive analysis Process-monitoring systems
Descriptive analytics (RT data visualization, Ad-hoc reports, Advanced data visualization), Predictive analytics (Prediction, Estimation, Forecast), Prescriptive analytics (Identification, Recommendation, Proactive scenarios)
Process optimization, Predictive maintenance, Cybersecurity, Quality control, Computer vision, AI driven Digital Twins
Presence, Availability, Coordination, Computation, Ownership, Exchange M2M, H2M, Storage, Distribution, Convergence
Cloud computing, IIoT, Big Data, Cyber-physical systems, Cybersecurity, Horizontal and vertical system integration, Interoperability,
HMI
Digital Twins
Analytics
AI
Data Management
Technology
Web
AI
Data modeling
IIoT
Inter-operability
Sustain-ability
HMI
Digital Twins
Analytics
AI
Data Management
Technology
Individualized Human-machine-interaction, Adapt to cognitive abilities, Decision support, Configurable and adaptive GUI
Real-time based, Learning platforms, Simulations, Training and forecast, Virtual factory, Remote control with situational awareness
Emphasize sustainability, Increasing awareness
Provide basic understanding of functionality and benefits, Deploying technology that adapts to the worker (person-centric), Skill matching of humans and tasks, Enhance human capacity
Human-in-the-loop, Autonomous and lightweight data managing solutions, Increased variety, coordination, computation and traffic
Included in design and deployment process
Personalization
Environmental impact

Fig. 1. SCADA transition toward Industry 5.0 supported by open innovation

IV. Issues and Challenges

In addressing the aforementioned six aspects of comprehensive approach to SCADA systems, as well as technological frameworks towards a sustainable and resilient industry[3], following issues and challenges related to SCADA systems stand out:

- Divergence of reference architectures and architectural standardization.
- Development and transition of SCADA systems toward I4.0
- Redefinition of the SCADA system role and functionality within Industry 5.0 paradigm[4].
- Legacy systems drawbacks.
- DT as real-time based learning and simulation platforms (virtual factory).
- Data modeling and lightweight data management solution.

Considering the above challenges and research goals with targeted domain of implementation within heterogeneous networks of IIoT and I4.0 SCADA systems for given process-specific requirements, the most obvious advantage of the IIoT wireless network is real-time data collection directly at the physical level leveraging open IIoT protocols[5], data preprocessing at the edge level, and therefore achieving improved data flow, reconfigurability and subsequent reduction of plant downtime. In addition, given the principle idea of the IIoT infrastructure to provide access to all data and information when and where it is needed[6], centralized access to data, i.e. a unified namespace implies. All of the above, interconnected with the existing ICS, provides an enhanced data framework capable of supporting advanced process monitoring and optimization. In addition, it provides the real-time data stream necessary for DT[7] implemented in a production floor assisting field-level maintenance operations and field equipment performance simulation in what-if scenarios.

Acknowledgment

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Use of Supervised Machine Learning Techniques to Counter the Coronavirus Advancement

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***Abstract*—The coronavirus pandemic has had a major impact on the lives of all people on the planet. Its progress has been slowed down both using vaccines and appropriate distancing techniques, some also implemented through machine learning systems. To train such systems, it is often necessary to use appropriately labeled image databases. Hence, this paper contains details about the creation and implementation of two different databases for mask detection. They focus both on how masks or respirators are worn and on determining their typology. A brief analysis of the aforementioned problems and the results obtained so far will therefore be briefly discussed in this paper.**

***Index Terms*—Artificial intelligence, Computer vision, Image databases, Machine learning, Neural networks**

I. Introduction

Since 2019, the coronavirus pandemic has been plaguing our world. The lives of all the people on the planet have been subject to radical changes. An example of this are lockdowns, which are still performed locally in China and other parts of the world. Vaccines have always been seen as the first weapon against the virus, but adequate distancing techniques have proved indispensable, especially in the first year of the pandemic. Some of them use machine learning systems, which for their training often require appropriately labeled image databases. This paper will then discuss the creation and implementation of two different masks and respirators databases that address two slightly different problems, concerning both the identification of the type of mask or respirator and the way in which they are commonly worn.

II. Detection of the Type of Mask or Respirator Worn

Masks and respirators do not offer the same degree of protection. Depending on their type, they can protect variably the wearer from droplets, gases, dust, and more. They can also be reusable, can have a valve for easier breathing, and so on. For this reason, their detection could be useful to implement automatic control systems to allow entry into high-security areas only those wearing one with a high level of protection.

To allow the creation of such a system, we created the *Facial Masks and Respirators Database* (*FMR-DB*) [1] [2]. It is made up of 2565 images taken from the Internet and depicting people wearing or not wearing masks or respirators. Images containing people wearing one have the following classification: *Surgical Masks*, *Non-Medical Masks*, *Half-Face Respirators*, *Full-Face Respirators*, *Disposable Respirators Without Valve*, and *Disposable Respirators With Valve*. Those showing people wearing *Disposable Respirators With* and *Without Valve* have an additional classification relating to their degree of protection, which can be one of the following: *FFP1*, *FFP2 – N95 – KN95*, *FFP3* and *Other – Unknown*. Moreover, images portraying people wearing *Surgical Masks*, *Half-Face* and *Full-Face Respirators* have an additional classification for the presence or absence of *eye* or *head protection*. Regarding people who do not wear any mask or respirator, there is an additional classification for the presence or absence of *occlusions*. It can contribute to increasing the robustness of the automatic classification systems trained through the database itself, which can thus deduce that any occlusions of the face can be caused not only by the presence of a mask or a respirator but also by a scarf, a hand, or other. The entire dataset was then used to create a mask detection system via a transfer learning of the EfficientNet-B0 [3] neural network, previously trained with the ImageNet database [4]. For the

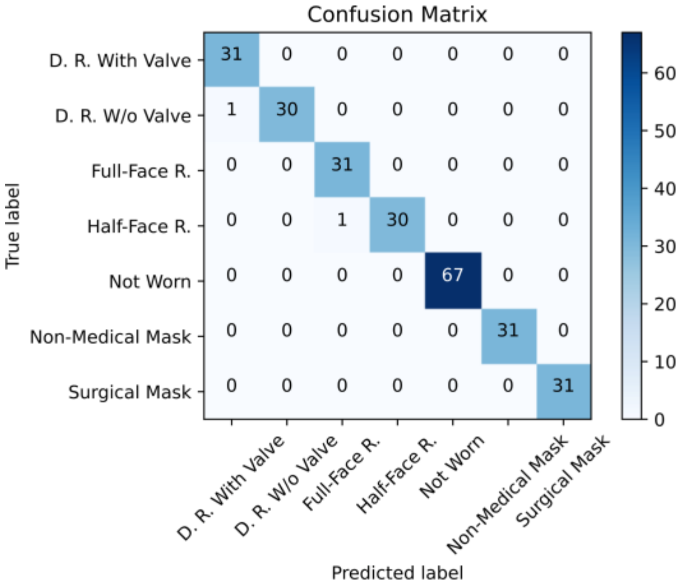

Fig. 1. Confusion matrix of the best neural network obtained [1].

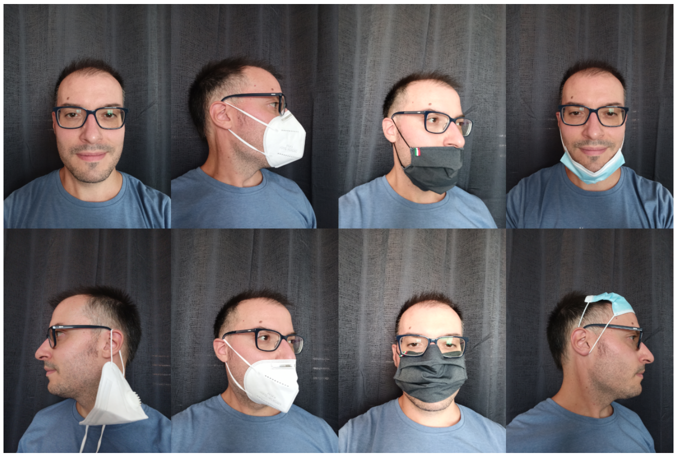

Fig. 2. An example of the classes contained in the WWMR-DB [5].

full list of settings and hyperparameters used, please refer to [1]. The best neural network obtained through a 9-fold cross-validation obtained an accuracy of 99.209%. The respective confusion matrix is visible in Fig. 1.

III. Detection of How the Mask or Respirator is Worn

The mere verification of the presence and type of mask or respirator on the face is not sufficient for rigorous control of the entrances in safety. This is because they are often worn in ways that differ from the correct one. Therefore, if the problem is to be considered in its entirety, methodologies are needed to verify the way in which masks and respirators are worn. Starting from this reasoning, it is possible to deduce that a complete masks and respirators detection system should at least be able to classify between these three main classes: the *Not Worn* case, containing only images of people who are not wearing masks or respirators, the *Correctly Worn* case, containing images of people wearing masks or respirators, and the *Incorrectly Worn* case, containing images of people wearing masks or respirators incorrectly. Some machine learning systems and databases created for their implementation have the limit of discretizing only between the *Not Worn* and the *Correctly Worn* case. This denotes a flaw in the analysis of the problem, as they do not model it completely.

For this reason, we worked on the *Ways to Wear a Mask or a Respirator Database* (*WWMR-DB*) [5] [6]. It is made up of 1222 images depicting 42 people wearing masks and respirators in 8 different ways, which we considered as the most used after careful research on the subject. They are the following: *Not Worn*, *Correctly Worn*, *Under the Nose*, *Under the Chin*, *Hanging From an Ear*, *On the Tip of the Nose*, *Folded Above the Chin*, and *On the Forehead*. An example of them is shown in Fig. 2. As far as we know, this dataset currently has the broadest classification regarding how a mask or respirator can be worn. It was used to test two different ResNet-152 [7] neural networks: the first was provided alongside the Face-Mask Label Dataset (FMLD) [8] paper, while the other was trained by the authors of this paper with the same hyperparameters as above but using the MaskedFace-Net dataset [9]. The tests were conducted in a *Rigorous* and a *Non-Rigorous* configuration, which also considers the *Under the Nose*, *Folded Above the Chin*, and *On the Tip of the Nose* positions as correct. In the *Rigorous* configuration the aforementioned networks achieved an accuracy of 75.2% and 18.33% respectively, while in the *Non-Rigorous* configuration it increased to 94.19% and 24.71%. Tests with the *FMLD* fared much better than those with *MaskedFace-Net*, but they are not excellent and indicate the need for databases with a finer granularity than those currently available. In this regard, the WWMR-DB can be an example of how to fill these gaps.

IV. Conclusions

This paper discusses coronavirus countermeasures through supervised machine learning techniques. We have worked on two slightly different projects, dealing with both identifying the type of mask or respirator a person wears and how they wear it. For this purpose, we have created two different databases, called FMR-DB and WWMR-DB. The former was successfully used to train neural networks for mask detection, while the latter was used to test the response of two neural networks trained with different databases, revealing a shortage in the analysis of the problem itself. We are currently working on increasing the size of both datasets to raise the accuracy obtainable from neural networks or other systems that can be trained through them.

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Author index

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Welcome and openning address

30th International Conference on Software, Telecommunications and Computer Networks – SoftCOM 2022 PhD Forum
FER
Faculty of Electrical Engineering and Computing
Adaptive Data-Driven Edge-to-Cloud Environment
Student: Ivan Čilić
University of Zagreb
Faculty of Electrical Engineering and Computing
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Advisor: Prof. Ivana Podnar Žarko, PhD
September 23, 2022
Split, Croatia

Pitch talk presentations

How Masks or Respirators are Worn
The Ways to Wear a Mask or a Respirator Database (WWMR-DB) is composed of 1222 images
It depicts 42 people wearing masks and respirators in 8 different ways
It was used to test two mask detection systems based on FMLD and MaskedFace-Net datasets, revealing lacks in the problem representation
available in IEEEDataPort
SPLIT, CROATIA
Radisson Blu Resort
September 22 - 24, 2022
SoftCOM 2022
30th International Conference on Software Telecommunications & Computer Networks
Patrons
The City of Split
ERICSSON
KRON
www.fesb.hr/SoftCOM
30th SoftCOM conference

Pitch talk presentations

IoT in Agriculture

- The research aims to develop a sensor for assessing the physiological state of maize crops based on chlorophyll fluorescence spectral response.
- Internet of Things (IoT) can be applied in agriculture in many ways due to the fact that it collects and processes microclimatic and agronomic data.
- Drought is considered the primary and most common cause of unprofitable crops in Croatia.
- Monitoring the conditions in the field is necessary to implement appropriate agrotechnological measures.

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Overview and Comparison of Different Techniques for Reducing the Amount of Data Transferred in IoT

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September 23, 2022

Split, Croatia

Pitch talk presentations

SCADA Systems in Continuous Manufacturing
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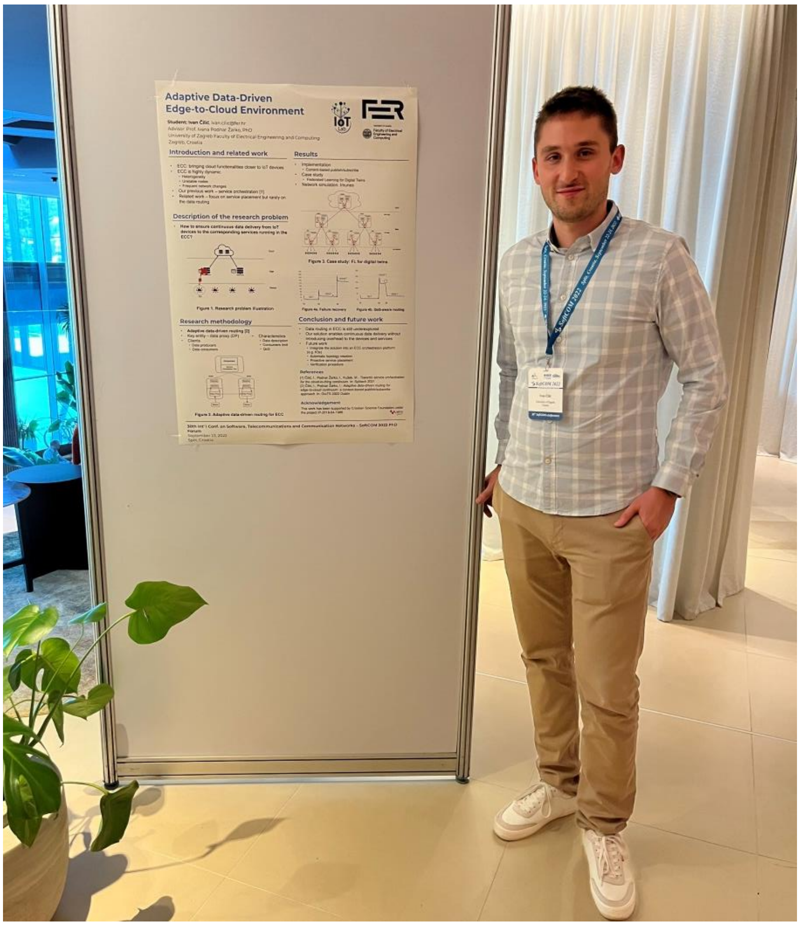
Pitch talk presentations

Poster session



Overview and Comparison of Different Techniques for Reducing the Amount of Data Transferred in IoT

Poster session

Multi-Agent System for Service Provisioning in an Internet of Things Smart Space based on User Preferences
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A Novel IoT Sensor for Real-Time Crop Monitoring of Chlorophyll Fluorescence

Poster session

Detection in Hybrid SDN Network with
Supervised Machine Learning Algorithms

Poster session

Increasing the accuracy of geotagging from unstructured text

Multi-Agent System for Service Provisioning in an Internet of Things Smart Space based on User Preferences
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Poster session

Poster session

Awards ceremony

Awards ceremony