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AnoML-IoT: An End to End Re-configurable Multi-protocol Anomaly Detection Pipeline for Internet of Things

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Abstract

The rapid development in ubiquitous computing has enabled the use of microcontrollers as edge devices. These devices are used to develop truly distributed IoT-based mechanisms where machine learning (ML) models are utilized. However, integrating ML models to edge devices requires an understanding of various software tools such as programming languages and domain-specific knowledge. Anomaly detection is one of the domains where a high level of expertise is required to achieve promising results. In this work, we present AnoML which is an end-to-end data science pipeline that allows the integration of multiple wireless communication protocols, anomaly detection algorithms, deployment to the edge, fog, and cloud platforms with minimal user interaction. We facilitate the development of IoT anomaly detection mechanisms by reducing the barriers that are formed due to the heterogeneity of an IoT environment. The proposed pipeline supports four main phases: (i) data ingestion, (ii) model training, (iii) model deployment, (iv) inference and maintaining. We evaluate the pipeline with two anomaly detection datasets while comparing the efficiency of several machine learning algorithms within different nodes. We also provide the source code of the developed tools which are the main components of the pipeline.

Keywords: Internet of Things, Data Science, Pipeline, Data Analytics, Multi-Protocol

1 1. Introduction

Edge AI which is critical for resource-constrained environments that operates in the Internet 2 of Things (IoT) domain where intelligent tasks are performed has started to become a hot topic 3 with the arrival of Industry 4.0 [1]. It manages the interaction with the physical world that 4 is provided by sensors and actuators. Management of such an environment requires series of 5 tasks (e.g., data collection, anomaly detection) that are operated by microcontrollers running 6 ML models. Data-related professions (e.g., data scientists, ML engineers) define rules/ranges and search for the best practices to increase the operability of edge mechanisms in their relevant 8 scientific disciplines. Finding hidden information from big data can enhance the quality of living 9 but it is not a straightforward task [2]. 10

While for data scientists, being an expert in edge-related infrastructures (e.g., programming
 languages, microcontrollers, sensors) is not expected, they should be able to utilize data science
 pipelines which are executable workflows of data-related tasks that automate the desired process.
 Thus, we developed a reconfigurable data science pipeline based on an IoT sensing infrastructure
 that utilizes open-source software to facilitate developing an interconnected anomaly detection
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system that runs on edge, fog, and cloud platforms. We define the edge as the platform where the 16 first interaction between the cyber and physical world happens. Hence, microcontrollers (e.g., 17 Raspberry Pi Pico) that gather physical data are edge devices. We define fog as the platform 18 where several edge devices can be supervised. Hence, single-board computers (e.g., Raspberry 19 Pi 4B) are fog devices that might act as edge devices as well. Cloud is the platform where real-20 world data gathered by the edge and fog devices are progressed. We implemented our system 21 based on an example use case scenario to describe how to proposed system works while providing 22 some results. 23

²⁴ The contributions of this paper are as follows:

We provide reconfigurable IoT sensing infrastructure that consists of two main opensource components: (i) The Edge to Cloud Code Generator (EECG) that generates readyto-deploy codes to enable data circulation from edge to fog. (ii) The Node-RED package is hosted on Node-RED servers that enables accessing and processing to the edge data from anywhere that has access to Node-RED servers while offering visualization via the graphical user interface (GUI). We also provide one Python library and executable shell script that facilitate data training and inference phases.

We propose a data science pipeline that interconnects edge, fog and cloud devices/services to provide end-to-end anomaly detection system development. The pipeline contains four main stages: (i) the data collection which is provided by the components mentioned at the first contribution point, (ii) the anomaly detection model training, (iii) model deployment to the edge, fog, and cloud, (iv) inference, and maintaining the model based on the new data. We demonstrate how the proposed tools are utilized during these stages.

We provide a dataset that is generated via the utilization of proposed tool. We analyze the performance of Convolutional Neural Network (CNN) [3], Recurrent Neural Network (RNN) [4], Isolation Forest [5] and One-class Support Vector Machines (OC-SVM) [6] on the proposed dataset [7] and the WADI dataset [8]. We also evaluate them according to the platform (edge, for or cloud) where the anomaly detection model is deployed via the utilization of proposed pipeline. In the edge, we only evaluated CNN due to lack of application programming interface (API).

45 Structure of the Paper: This section provides a high-level understanding of what we pro-46 posed. We outlined the previous commercial and academic works in section 2. Section 3 contains 47 the architecture of an IoT anomaly detection pipeline infrastructure. Section 4 presents details 48 about how the data circulated and progressed within the AnoML-IoT pipeline. We demonstrate 49 our evaluations and results in section 5. Then, we discuss about the results in the section 6 and 40 finally provide our conclusions in section 7.

51 2. Related Work

In this section, we introduce the data science pipelines that are offered either by academia or commercial entities, and anomaly detection techniques in time-series sensor data. We also analyze the capabilities of open-source platforms that facilitates data circulation.



Figure 1: Illustrates the utilized algorithms. TensorFlow also has an API [27] for decision trees, but due to having better documentation we prefer using scikit-learn for implementing Isolation Forest.

55 2.1. Unsupervised Anomaly Detection in Time Series Sensor Data

Anomaly detection is one of the fundamental fields that utilize the machine learning (ML) 56 57 model as the main component. There is extensive research being done in this field [9, 10, 11]. There are three types of anomalies: (i) point anomalies, (ii) contextual anomalies, (iii) collective 58 anomalies. If the anomalies are contextual where the context is time, the time series anomaly 59 detection models are applied. For example, in an environment where the weather temperature 60 decreases at night if the temperature value generated by the sensor acts otherwise, there is a con-61 textual anomaly. While point anomalies are easier to detect, contextual and collective anomaly 62 detection requires additional tasks to identify the normal behavior of the system. 63

The nature of the input data is the core element that determines the efficiency of the ML model. The features of the data may depend on several complementary terms such as labels, context, and domain. For example, if the input data do not contain any labels that define normality, unsupervised algorithms [12] are applied, if the data is related to a certain context, context-aware [13] methods are selected, if the environment is industrial, because of the importance of detection time, faster models with reduced complexity [14] are preferred.

In an interconnected domain such as IoT, cyber-physical systems [15] are utilized to supervise 70 the environment. These systems observe the behavioral changes (e.g., change in the temperature 71 or movement) in surroundings through modules that manage sensors [16]. They can also act as 72 controllers if they contain actuators. In such environments, the anomaly might occur either by 73 independent or dependent events. If the events are independent, univariate analysis [17] is ap-74 plied. For example, the behavioral changes in temperature, loudness, light density, and humidity 75 can be detected via the related data only, hence require univariate analysis. However, changes in 76 the angular momentum or acceleration are measured by sensors (e.g., accelerometer, gyroscope) 77 that generate data per dimension. Hence, the relation between the data points should also be 78 analyzed to detect anomalies. Then, the multivariate analysis [18] is applied. 79

While academia keeps offering new anomaly detection algorithms [19, 20], most of the time these are based on the fundamental ones [21]. Hence, for this work, we selected the following algorithms as they are the most common ones that are utilized for the unsupervised anomaly detection in time series data and accessible via common ML programming libraries/frameworks (e.g., scikit-learn [22], TensorFlow [23]) : (i) convolutional neural networks (CNN) [24, 25], (ii) recurrent neural networks (RNN) [26], (iii) isolation forest (IF) [5], and (iv) one-class support vector machines (OC-SVM) [6]. Figure 1 demonstrates the used algorithms in this study.

⁸⁷ 2.2. Machine Learning Platforms and Data Science Pipelines

Machine learning platforms. After showing promising results in a variety of tasks includ-88 ing speech recognition, image processing, anomaly detection, and medical diagnosis, ML has 89 taken an interest in both academic and commercial entities, hence resulting in the creation of 90 many open-source and proprietary ML platforms and pipelines. ML models can be generated via 91 hand-coding, code generators, or interpreters. Hand coding. There are many machine learning 92 libraries available [22, 23, 28] that allows user to create ML models or to deploy and evaluate ML 93 algorithms. A person with the profession might prefer hand-coding as it offers high customiza-94 95 tion, allows the development and employment of novel algorithms, and is easy to maintain. However, hand-coding might be very resource-consuming, thus most of the time it is done by a 96 group of programmers. Code generators. ML consists of many steps (e.g., data acquisition, data 97 pre-processing, and fitting). Rather than hand-coding all these steps, code generators [29, 30] 98 might be utilized to facilitate the process. Due to the variety of complicated tasks, most code 99 generators provide a specific code for a specific task. Interpreters. One of the main challenges 100 of ML is the portability of the generated model. Interpreters provide portability by generating a 101 model file that can be run on other platforms with minimal coding. TensorFlow [23] is the most 102 common one that offers model generation for resource-constrained platforms. 103

Data science pipelines. Raw data are needed to be interpreted to be utilized within data 104 science-related tasks. If the data science pipeline contains all the steps that are required to in-105 terpret the data from data gathering to deployment of a machine learning model, it is called 106 end-to-end. These end-to-end pipelines can be either manual where the user provides many in-107 puts and sets parameters each time before a new model is generated or automated where little to 108 no input is taken. Due to a variety of data types, automated pipelines put a certain set of rules 109 (e.g., time format) for their system to accept the input data [31]. These pipelines can also be 110 named according to the performed tasks (e.g., anomaly detection pipeline). Now we introduce 111 pipelines that are presented by either industry or academia. 112

Azure Machine Learning Pipeline [32]. Microsoft provides an ML pipeline based on run-113 ning Python scripts on the cloud while automatically handling resource usage. Each step of the 114 pipeline can be independently customized hence offering scalability to the end-user. One of the 115 practical features that Azure Machine Learning Pipeline offers is the automated dependency han-116 dling that allows the usage of a variety of hardware and software environments. Microsoft also 117 provides Azure Cognitive Services [33] where you can utilize their ML pipeline and Anomaly 118 Detector [34] service. They apply Graph Attention Network (GAN) [35] for multivariate analy-119 sis, apply SR-CNN [31] for the univariate analysis. 120

Amazon Web Services (AWS) Machine Learning Pipeline [36]. Amazon provides an endto-end ML pipeline as a service for detecting anomalies in real-time. Inside the pipeline, there are many different services (e.g., database, data formatting) that can be utilized for pipeline tasks. Amazon SageMaker [37] is the main service that provides anomaly detection for both univariate and multivariate data. It allows users to either use a built-in unsupervised anomaly detection algorithm based on Random Cut Forest (RCF) [38] or use a custom algorithm that can be deployed via a Docker image. Now we introduce the pipelines proposed by the academia.

Prado et al. [39] propose an end-to-end modular AI pipeline that allows users with less expertise to implement their AI applications such as keyword spotting, image classification, and object detection to systems that contain embedded devices. Their framework relies on Low Power Deep Neural Network (LPDNN) that contains an Inference Engine (LNE) that is compatible with Caffe [40]. LNE is a code generator that facilitates the deployment to the embedded devices. The authors use FIWARE [41] for IoT hub integration and Kurento Media server [42]
 for media streaming which are required to run live inference. The authors define Raspberry Pi
 devices as edge and evaluate the efficiency of LPDNN compared TF Lite [43] on these devices
 by running benchmarks that are included in the TF Lite repository.

¹³⁷Drori et al. [44] propose an automatic ML (AutoML) system that optimizes the ML pipeline ¹³⁸according to the given dataset. Their pipeline utilizes LSTM-RNN as a base ML algorithm. ¹³⁹Monte Carlo Tree Search (MCTS) [45] is applied to the predictions generated by the LSTM-RNN ¹⁴⁰to evaluate the performance of the pipeline and decide on the better pipeline. They evaluate the ¹⁴¹proposed pipeline compared to baseline stochastic gradient descent (SGD) [46] estimators from ¹⁴²scikit-learn [22]. They claim their pipeline provides faster run time according to its peers.

Sutton et al. [47] propose an open-source ML pipeline that receives physiological data that
is used to identify anomalous behaviors as an input in real-time. The authors try to detect Paroxysmal atrial fibrillation (PAF) by applying Probabilistic Symbolic Pattern Recognition (PSPR)
to the Electrocardiogram (ECG) signals. PSPR is used for online feature extraction while they
apply random forest (RF) to classify ECG data. The proposed pipeline is based on Spark's ML
library (MLlib) [48], hence allows other anomaly detection techniques included within MLlib.

Nitsche and Halbritter [49] propose a data science pipeline that is optimized for text classi fication. The authors benchmark different GPUs to evaluate the performance of their hardware
 setup which consists of 10 NVIDIA Quadro P6000 and the effect of the number of GPUs on the
 image processing time. They apply the Naive Bayes classifier that is included in scikit-learn API
 and achieve above 90% accuracy on Deutsche Presse-Agentur (dpa) dataset.

Shaikh et al. [50] focus the challenges of ensuring policy fairness within end-to-end ML pipelines. They claim the ML-based tasks are done by engineers that have a variety of professions including data creators and future engineers. Hence, each step of the ML pipeline might be subjected to a policy violation. The authors provide an end-to-end ML pipeline that is based on log management to prevent these violations as manually ensuring policy fairness is highly resource-consuming.

Boovaraghavan et al. [51] propose an adaptive end-to-end ML system for IoT applications. 160 Their pipeline is optimized for activity recognition-based tasks including object recognition. Au-161 thors claim that the main challenge regarding end-to-end pipeline is due to the heterogeneity of 162 IoT applications. Authors evaluate their pipeline with various hardware platforms and datasets 163 while comparing prediction time and accuracy per each machine learning technique they applied. 164 Molinara et al. [52] propose an end-to-end ML-based indoor air monitoring system for con-165 taminant classification. Authors compare the performances of Multi Layer Perceptron (MLP) to 166 CNN and LSTM based deep learning techniques while testing the performance of MLP and CNN 167 on ESP32 MCU. They investigate the power consumption of the MCU regarding the utilized ML 168

technique. They claim the proposed system is only lacked to classify alcohol and acetone due to their chemical similarities.

Vinzamuri et al. [53] propose an end-to-end context-aware anomaly detection system that
 requires time-series data. The proposed system utilizes a semi-supervised algorithm with Sparse
 Gaussian Graphical Models. They benchmark the pipeline on several public datasets. The au thors claim semantics can improve the Gaussian Graphical Models further beyond other anomaly
 detection techniques. Their ML comparison is based on F-Score as the authors mention that the
 proposed pipeline is promising for industrial IoT environments.

Li et al. [54] develop an end-to-end automated anomaly detection system. They utilize Apache Spark backend server to run the query-based operations. After the user provides a dataset, the proposed system automatically selects the most appropriate algorithm then applies

Related Work	Topic	Environment	Commercial	Open-source	End-to-End	Time-series Data	Adaptability
Azure Machine Learning Pipeline [32]	General	General	1		1	1	
AWS Machine Learning Pipeline [36]	General	General	1		✓	✓	1
Prado et al. [39]	Classification	IoT	1		✓	✓	
Sutton et al. [47]	Anomaly Detection	Medical		1		✓	
Nitsche and Halbritter [49]	Classification	Linguistics					
Shaikh et al. [50]	Policy	General			1	✓	
Boovaraghavan et al. [51]	Classification	IoT			1	✓	
Molinara et al. [52]	Classification	IoT			1		
Vinzamuri et al. [53]	Anomaly Detection	IoT			1	√	
Li et al. [54]	Anomaly Detection	General			✓	√	1
AnoML-IoT	Anomaly Detection	IoT		✓	✓	✓	1

Table 1: Comparison of AnoML-IoT with the Previous Works

anomaly detection. Finally, the results are shown in figures within the pipeline. They benchmark
 the proposed system based on several datasets while applying quantification analysis.

Our pipeline utilizes scikit-learn and TensorFlow for the anomaly detection while relying on TensorFlow Lite for the deployment on the fog, TensorFlow Lite Micro for the deployment on the edge devices. Hence, it allows the lightweight implementation of anomaly detection techniques while offering a variety of communication protocols (e.g., Bluetooth low energy (BLE)) and sensor types for the inference. The Table 1 compares our pipeline with the previous works based on significant features that determine the efficiency of the pipeline.

3. The Architecture of the AnoML-IoT Pipeline

In this part, we present the overall architecture of our pipeline by defining main components,
 describing the workflows that differ according to application scenario, and explaining how to
 automate these workflows to maintain the pipeline.

192 3.1. AnoML-IoT Layers and Application Scenarios

IoT infrastructures should provide semantic data exchange to be considered as completely 193 ubiquitous. Current technologies that are utilized in IoT architectures are rapidly evolving to 194 achieve semantic interoperability, hence causing the debate of what kind of infrastructure is 195 needed for a certain task. Due to each technology has a variety of pros and cons per IoT en-196 vironment, extensive testing is required to decide on IoT elements (e.g., wireless technologies, 197 198 edge/fog node types, sensors, and actuators). Building an IoT application from scratch to perform these tests requires intensive labor. Thus, reconfigurable IoT sensing architecture that allows the 199 implementation of various ML-based application scenarios including anomaly detection with 200 minimum user (e.g., data scientist) interaction is required. AnoML-IoT allows the implemen-201 tation of a variety of application scenarios where the scenarios are evolved around the platform 202 that the anomaly detection is implemented. In this context, AnoML-IoT consists of three layers: 203

- *Edge Layer*: The edge layer contains edge nodes that consist of microcontrollers, sensors, and actuators. These nodes are physically observing the IoT environment by gathering data via sensors while conducting physical operations via actuators (e.g., the fan stops working when a certain degree is reached).
- *Fog Layer*: The fog layer contains fog nodes that get the data from edge nodes and process it according to the end user's preferences. Usually, fog nodes offer more computing power



Figure 2: Overview of the data circulation and the pipeline application scenarios based on the location of anomaly detection: (i) If the anomaly detection is done on the cloud, the edge and fog devices only forward data, (ii) if the anomaly detection is done on the fog, the edge sends raw data to fog, then the fog might send processed data to the cloud, (iii) if the anomaly detection is done on the edge, the processed data might be sent to fog and then to cloud. Each scenario has its pros and cons that we introduce in section 5. Here processed data contains information to be used to decide if the data is anomalous or not. Thus, it might be either binary (e.g., 0 for normal data, 1 for anomalous data) or a decimal(float) as an anomaly score that varies in the range of -1 to 1. The model in the cloud will be updated with the new normal data according to the predetermined intervals.

than edge nodes while allowing flexible deployment options. Even though fog computing
may be considered as an alternative to cloud computing, fog nodes can also act as an IoT
gateway between the edge nodes and the cloud. In this work, we utilize Raspberry Pi 4 as
a fog device and present our results. We believe, similar Linux-based devices can be used
as fog devices instead of the Raspberry Pi for the proposed pipeline.

Cloud Layer: The cloud layer provides services ranging from data management, storing, applying anomaly detection to developing multi-purpose frameworks. Even though, cloud computing offers many benefits (e.g., automatic service integration, and high accessibil ity), edge/fog computing is preferred where time-critical or confidential applications (e.g., industrial) are present to reduce reliance on cloud services. While the edge and fog layer might contain standalone nodes, the cloud layer requires interaction with other layers.

Figure 2 summarizes the working principle of the machine learning pipeline. The anomaly 221 detection can be done within the pipeline on edge, fog, or cloud. The edge and fog devices also 222 can be utilized just to forward raw data to the platform at one upper level. The initial training 223 requires prior data. Hence, if there is no dataset to be used for initial training, the edge and fog 224 will send only raw data until the cloud can generate an efficient ML model. Then the model will 225 be deployed to edge, fog, or cloud. According to the given intervals, the new model will replace 226 the old model to keep the system up-to-date. Having an up-to-date ML model is significant to 227 prevent a decrease in efficiency that depends on the dynamic context. 228

229 3.2. The AnoML-IoT Open-Source Tools

AnoML-IoT consists of three main tools: (i) Edge to Cloud Code Generator (ECCG), (ii) Node-RED package, (iii) python library. Now we introduce what these tools provide, what are their functionalities, use cases, and roles within the AnoML-IoT pipeline. The source code of the tools is published in GitLab¹.

234 3.2.1. The Edge to Cloud Code Generator

The ECCG is a web-based code generator that generates edge code to be either used for inference or to transmit data to the fog node. Currently, it is only compatible with Arduino IDE [55]. It has a user-friendly interface, where even the data scientist with minimal IoT knowledge can design a basic IoT application that contains several sensors where the sensor data can be transferred between layers. The characteristics of ECCG including the justification for design choices are given below:

Currently, five sensor types are available: *temperature*, *humidity*, *air quality*, *light*, *loudness*. The end-user can simultaneously select all sensors. Selected sensor data will be included within the pipeline. *Justification*. These five sensor types are among the most common sensors that are utilized in IoT applications. The generated code clearly describes how the sensor data is received, and processed, thus allowing the easy adaptation of the code for a similar type of sensor.

- Four communication protocols are available: *Wi-Fi* [56], *Bluetooth Classic* [57], *BLE* [58], 247 and Zigbee [59]. The end-user can only select one. The application also includes additional 248 settings regarding communication protocols for advanced users. Justification. The selected 249 four communication protocols occupy the vast majority of the IoT market and offer a 250 variety of topologies (e.g., mesh, star, tree). Understanding the basics of how to establish 251 these wireless technologies enables the implementation of high-range IoT applications. 252 The generated code by ECCG defines how to handle the required network elements (e.g., 253 MAC address, personal area network (PAN) ID). An advanced user may conveniently adapt the generated code to be used with other IoT communication protocols that are out-255 of-scope of this project such as WirelessHART [60]. 256
- The data transfer rate determines the time between two data blocks. It is in milliseconds that ranges from 30000 to 300000. After copying to code the user can set the data transfer rate as desired. However, we do not recommend setting it below 30 seconds as it is the time that is required for the module to initialize. *Justification*. Data generating time differs per sensor module. Controlling the data transfer rate is necessary to ensure the integrity of transmitted data.
- The sensor locations are determined by the end-user. Identification (ID) number starting 263 from 00 is given per location. The application supports up to 99 locations. Justification. 264 Data scientists work with comma-separated value (CSV) files, to handle the further pro-265 gressing of the data. The data in CSV files mostly in pairs as *text-value* where *text* is the 266 identifier, and *value* is digital presentation of a physical quantity. To generate such files, 267 data is transmitted in data-serialization formats (e.g., JavaScript Object Notation (JSON), 268 Extensible Markup Language (XML)) supported by IoT application standards. Thus, the 269 ECCG allows an end-user to define location. Then, it generates a unique location ID num-270 ber to be used in data transmission. 271

¹https://gitlab.com/IOTGarage/anoml-iot-analytics

The Edge to Cloud Code Generator



Figure 3: Illustrates the main input section of the ECCG. Each input is strictly controlled for the following reasons: (i) to prevent cross-site scripting attacks, (ii) to prevent bugs that may occur in the code due to mistyping. Each text input has a tooltip that clarifies what kind of information should be given. In addition, placeholders demonstrate an example input.

• Three microcontroller types are available: Arduino Nano 33 BLE Sense, Arduino Nano 272 RP2040 Connect, and Raspberry Pi Pico. The end-user can select one of the microcon-273 trollers to obtain the edge node ID number to be used to identify the microcontroller types 274 when needed. Justification. The ECCG supports the top three microcontrollers that are 275 officially supported by TensorFlow Lite for Microcontrollers (TFLM) [61]. Supporting a 276 variety of microcontrollers allows users to design a heterogeneous IoT application, where 277 the environment benefits from different features of these devices (e.g., RAM, flash mem-278 ory). 279

The ECCG allows sending lowest, mean, or highest sensor data which are generated during the time interval determined by the user. *Justification*. In some cases, the normal range might just be determined by lower or upper limits. Hence, we allow the user to decide on the data to be sent. If the user selects mean, the mean of the number of data points generated by the sensor during the predetermined time interval will be sent.

The user interface of the ECCG facilitates usability by navigating users via input controls. Figure 3 demonstrates the main input section of the code generator while the example inputs are given. Minimalist design is preferred to assist a data scientist with no prior IoT knowledge. Thus inputs are controlled, tooltips are included, and example inputs are given as placeholders.

After the inputs are given, the final step is clicking on the "Generate Code" button. The 289 ECCG will output the followings: (i) the edge code that is ready to be deployed to the micro-290 controller via Arduino IDE, (ii) the Python3 script that should be run on the fog device, (iii) the 291 Linux commands to be run via terminal, (iv) example Node-RED setup. The outputs differ ac-292 cording to the given inputs. For example, the Linux commands are only required if the Bluetooth 293 Classic will be used within the pipeline. The Figure 4 illustrates how the generated code blocks 294 are presented. Two main buttons are included for each code block: the first button generates the 295 code shown in the pre-scrollable division to let a data scientist examine the codes before further 296 progression, the second button copies the code without breaking the format to prevent possible 297 errors. The user manually uploads the code into the microcontroller. 298

We assume the following scenario: the edge node (micro-controller) gathers physically observed data via sensors and sends it to a fog node(a single-board computer (SBC)) where the data is either processed or forwarded to the cloud via Node-RED. Thus, the ECCG consists of three main sections: (i) the input field where the end-user determines the basic characteristics of the desired IoT application, (ii) the transmitter field where the edge node code is generated for a microcontroller, and (iii) the receiver field where the fog node code is generated for a single-board

Generate Code	
Transmitter Co	de
	/*Please replace with your own correct variables if you see "!R" near the given variable.* #include "DHT.h" #include "Air_Quality_Sensor.h"
	<pre>#define DHTPIN 4 //!R #define DHTTYPE DHT11 //!R DHT dht(DHTPIN, DHTTYPE); AirQualitySensor sensor(A2); //!R //send data per interval seconds(end user decides) unsigned long interval =30000L; unsigned long pass_time = millis(); int exit_while = 0;</pre>
	<pre>void setup() {</pre>
Copy Transmitte Receiver Node-RED	r Code Code Example Setup
Example Des	ign
0 connections	msg payload
TCP Input No	ode Settings
⊙ Туре	Listen on v port 4448
6 Output	stream of v String v payload(s)
	delimited by In
📰 Торіс	Торіс
Name Name	Name

Figure 4: Illustrates the generated code block and the example Node-RED setup. In the example scenario, Raspberry Pi Pico is selected as an edge node/transmitter. The generated transmitter code is written in C++ and should be deployed via Arduino IDE. The Raspberry Pi 4B is acting as a fog node/receiver.

³⁰⁵ computer. Table 2 illustrates the specifications of the ECCG in detail.

306 3.2.2. The Node-RED Package

Node-RED [62] is an open-source browser-based workflow development tool that runs on 307 Node.js [63] based runtime. We can develop workflows via utilizing drag-and-drop nodes on 308 resource-constraint environments such as Raspberry Pi thanks to the non-blocking nature of 309 Node.js. Hence, we use Node-RED on the fog device to develop and control the workflows 310 within the AnoML-IoT pipeline. Even though Node-RED contains many open-source packages 311 developed for the IoT networks, we could not find any up-to-date package that provides the devel-312 opment of Bluetooth Low Energy (BLE) modules while offering customization choices. Hence, 313 we developed and published our package under the name of "node-red-contrib-IoT-procotols". 314 The package contains the following nodes: 315

BLE Scanner. BLE devices can operate in four different roles: broadcaster, observer, central, and peripheral. The task of the BLE Scanner node is to scan for the advertising BLE peripherals. It can specifically search for a local name and output one of the followings: whole peripheral as an object, MAC address, and advertisement data. So, the user can use

		Temperature					
		Humidity					
	Sensor Types	Loudness					
		Light					
		Air Quality					
Main Inputs		Wi-Fi					
	Communication Protocols	Bluetooth Classic					
		BLE					
		Zigbee					
		Arduino Nano 33 BLE Sense					
	Edge Node Types	Arduino Nano RP2040 Connect					
		Raspberry Pi Pico					
	Edaa Nada Idantifana	Edge Node Location					
	Edge Node Identifiers	Edge Node ID Number					
		Service Set Identifier (SSID)					
	W7 F	Password					
	WI-FI	Host IP Address					
		Host Port					
Advanced Inputs		*MAC Address					
Auvanced inputs	Bluetooth & BLE	Module Name					
		Module PIN					
		PAN ID					
	Zigbee	Destination Address High					
		Destination Address Low					
		Node Settings					
	Node-RED Example Setup	Workspace Design					
		Example Functions					
Generated Outputs	Tronomittan Cada	Arduino Scripts					
	Transmuter Code	Python Scripts					
	Baasiwar Coda	JavaScript Function Nodes					
	Receiver Code	Python Scripts					

Table 2: The Specifications of The Edge to Cloud Code Generator

* Among advanced inputs, only the MAC address is obligatory. The default options that are included in the code are explained via comments in detail.

this node either to discover the MAC address of the target BLE peripheral or to get the advertisement data.

BLE Connect. This node establishes a BLE connection with the target peripheral device.
 While one peripheral device can only be connected to one central, central devices can manage multiple peripherals. Hence, our pipeline allows the deployment of multiple edge devices via BLE while the maximum number of peripherals that can be connected depends on the system-on-a-chip (SoC) of the microcontroller. For example, the Arduino Nano 33 BLE Sense [64] SoC nRF52840 [65] supports up to 20 parallel connections.

Figure 5 introduces nodes that offer the establishment of multiple network communication protocols in the Node-RED environment within the AnoML-IoT pipeline. Each communication protocol might have different pros and cons according to the application domain. Hence, it is important to offer multiple options to the end-user. We consider providing more choices in the future.

333 3.2.3. The AnoML.py and SetupAnoML.sh

AnoML.py. Library of functions in python which can support most of the tasks in developing
 ML models with various types of normalization and data points. Generating different models for



Figure 5: Illustrates the developed nodes to be used within to Node-RED environment hosted by the fog device.

the cloud, fog and edge platforms using various normalization methods and data points is a labor-336 intensive task. Evaluating different models for unsupervised ML when there is a small amount 337 of anomalous data is also another challenge. Our Python library supports data preprocessing to 338 generating ready to deploy ML models for the cloud, fog, and edge for unsupervised ML. It also 339 provides performance visualization for each data point while including normalization techniques 340 which helps to select the most efficient model. The proposed library provides data cleaning, 341 normalization, reduction, scaler, and visualization functions before feeding into machine learning 342 models. The library also provides various functions that allow training and testing. The inference 343 part of the library provides functions to evaluate different machine learning models generated 344 using our library at both fog and cloud platforms so the performance of the platforms can be 345 compared. 346

SetupAnoML.sh. It acts as an installer to prepare both fog and cloud platforms for action. 347 It installs correct versions of necessary packages and libraries required to run inference. Once 348 the prerequisites are handled, it can then download, install and configure packages such as Node-349 RED and TensorFlow runtime. Also, it sets our custom-developed services to listen on web ports 350 to order to allow microcontrollers to interact with fog devices and fog devices to interact with 351 the cloud platform. The script can be configured to download files and configurations either 352 from Google Drive or a local/remote FTP Server. Users also can manually download, install and 353 configure all prerequisite requirements and model files if it is desired. 354

355 4. The Data Circulation

The nature of the input data shapes the characteristics of the data science pipeline. Hence, 356 gathering raw data is the first step in this kind of pipeline. In the IoT environment, the sensors 357 generate a variety of data in various formats. While most of the temperature sensors generate data 358 in floating-point numbers (floats) to provide more accuracy, the light sensors that measure light 359 density usually provide data in integer. This is significant for two main reasons: (i) each data type 360 occupies memory in different sizes, (ii) there might be different regulations [66, 67] according 361 to the application domain for certain data types such as floats. Hence, the memory usage should 362 be optimized for microcontrollers that have very limited memory. The memory usage might also 363 differ according to the microcontroller architecture. For instance, while Arduino Uno [68] stores 364 int values in two bytes, Arduino Due [69] stores int values in four bytes. The data circulation 365 within the AnoML-IoT pipeline consist of four main steps: (i) data ingestion, (ii) data training, 366 (iii) model deployment, (iv) inference and maintaining. 367

368 4.1. Data Ingestion

Data ingestion is the first step of all kinds of data science pipelines unless the user already has a ready-to-deploy ML model. In our pipeline, the ECCG is the main tool that utilizes the data ingestion process. Figure 3 illustrates the choices offered by the ECCG. The user can se lect among the offered choices to obtain a generated code. The generated code can be copied
 without disrupting the format. Multiple communication protocols and Node-RED example that
 demonstrates how to receive data via fog device are also provided.

What the ECCG generates is an example edge code. Besides, in our setup, we use Grove 375 sensors and shields [70] while utilizing Raspberry Pi 4B as a fog device. The IoT environment is 376 very heterogeneous hence, the user might have or want to use different sensors, microcontrollers, 377 or fog devices. The generated code by the ECCG should require minimal editing even when this 378 is the case as we also provide instructions via comments for the exact lines within the code that 379 might require editing due to individual preferences. If needed, the user can edit the generated 380 code after copying it from the ECCG to Arduino IDE. Then, the code can be uploaded to a 381 microcontroller. To complete these tasks the user needs a computer that can access the internet 382 and run Arduino IDE. So, the tasks of copying the code and uploading it to a microcontroller are 383 handled manually. Figure 6 demonstrates the data ingestion process. 384

385 4.2. Model Training

Model training can be done before ingestion if the user already has a training dataset. Oth-386 erwise, the user should follow the steps mentioned in the data ingestion phase. The AnoML.py 387 library contains all the required functions that are needed to generate a ML model. Uploading 388 the dataset to a cloud platform is handled manually. After uploading the dataset, the user should 389 preprocess the data to convert to an appropriate format for the ML algorithms. Then, the ML 390 models are generated based on the user preferences. User can generate multiple ML models at 391 the same time. Here, we facilitate the model training by providing user a python library that is 392 capable of preprocessing the time series data and generating multiple ML models based on given 393 parameters with only a few line of codes. The required time depends on the capabilities of a 394 cloud platform that is used during the training. The user should decide on the followings: (i) the 395 size of the training dataset, (ii) the algorithm specific parameters(e.g., contamination factor for 396 Isolation Forest). Figure 7 illustrates the model training phase. 397



Figure 6: Illustrates data ingestion phase. The data preprocessing can be done on all platforms. However, due to the limited computing power of edge and fog devices, we prefer to utilize the cloud. In addition, if more than one edge device is connected to the fog device, data preprocessing can be done on the fog device to identify the edge devices.



Figure 7: Demonstrates the model training phase. Currently, the built-in algorithms within the AnoML.py are RNN, CNN, isolation forest, and One-class SVM. Multiple datasets can be utilized at the same. The storage place of these models depends on the preferences of the user. During our evaluation we used Google Drive [71] to store our models as it can be easily integrated into Google Colab [72]. Another option would be running an FTP server. The user also can utilize both at the same time.



Figure 8: Illustrates the model deployment phase. SetupAnoML is an executable Linux shell script that does the followings in order: (i) fetches generated ML models from Google Drive or FTP server, (ii) installs required libraries and packages, (iii) deploys models over HTTP. The deployment to edge should be handled manually. We are considering to provide automated edge ML deployment function via over-the-air (OTA) transmission in the future versions of AnoML-IoT.

398 4.3. Model Deployment

The next step after training the model is model deployment. Here we provide an executable 399 shell script SetupAnoML.sh that facilitates the model deployment phase by automating several 400 key tasks. The user should provide the following inputs to the script: (i) the platform (edge 401 or cloud) where the anomaly detection technique will be deployed, (ii) the details of the place 402 where the model is stored (e.g., server, username, password, and port names for an FTP server, 403 Google Drive token or Google Drive). After these inputs are given, the script will automatically 404 download, install, and configure all the required software packages (e.g., libraries, models, con-405 figurations). Then the script automatically will deploy the models to cloud, fog, or both cloud 406 and fog platforms. The user can deploy multiple models at the same time to different platforms. 407 Figure 8 demonstrates the model deployment process. 408



Figure 9: Illustrates the possible scenarios that can be generated within the AnoML-IoT pipeline. We allow the use of various topologies, wireless communication protocols, and execution of use case scenarios shaped around the decision of anomaly detection platform.

409 4.4. Inference and Maintaining

Successful deployment results in inferring all models on each type of platform. We developed an end-to-end pipeline which allows a user to generate ML models for anomaly detection from sensor data at all platforms. We developed a performance monitor which can present visualization of performance and accuracy of all type platforms, ML models, data-points and normalization/reduction techniques. Maintenance of data is a key aspect for evolution, we recommend that user should make it a practice to visualize performance comparison as a process of decision making in order to enhance performance and accuracy on all platforms.

417 5. Evaluation

In this section, we present the evaluations that are done to measure the efficiency of the pipeline with various configurations enabled. A data science pipeline evaluation is not a trivial task if the environment is heterogeneous such as IoT. Figure 9 demonstrates possible scenarios available within our pipeline where different sensors and wireless communication protocols are used.

423 5.1. Wireless Protocol Comparison

The decision on the wireless protocol selection depends on the application domain as each protocol has its benefits and disadvantages. There are several important features to be considered

Table 3: Wireless Protocol Comparison

		Latency	y (ms)		Power Consumption	Topology*
	Edge to Edge	Edge to Fog	Fog to Fog	Fog to Cloud	rower consumption	Topology
Wi-Fi	18.24	14.566	17.25	21.23	High	Star
Bluetooth Classic	195.13	171.15	187.15	NA	Medium	Point-to-Point
BLE	11.23	13.45	13.21	NA	Low	Mesh
Zigbee	18.56	16.66	14.56	NA	Low	Mesh

NA: Not Applicable. *****: The most common topology is given.

⁴²⁶ when designing an anomaly detection pipeline for the IoT environments:

Latency. The time that takes for one network package to be transmitted from the transmitting endpoint to the receiving endpoint. Latency optimization is very significant to achieve near real-time processing and inference. It is one of the significant features that determine the anomaly detection time. Low latency is aimed for the applications (e.g., industrial) where the anomaly detection time is critical [73].

Power consumption. IoT is a resource-constraint environment, hence power consumption
 is one of the significant features to be considered.

Network Topology. The data circulation and the system design depend on the network topology. While there are many topologies (e.g., star, mesh, ring) offered by the current communication protocols, the mesh, and star networks are the most common ones that are established in IoT environments.

Table 3 compares the wireless communication protocols utilized in the proposed pipeline 438 based on the aforementioned features. We measured the latency by taking the mean of the passed 439 time for the 1000 transmitted packages. Edge and fog devices were placed next to each other 440 441 during the tests hence there was no physical barrier between the devices. No packet drop is observed. While we observed similar latency for the BLE, Wi-Fi, and Zigbee, the Bluetooth 442 Classic had the highest latency. However, it is challenging to have a conclusion as many factors 443 that might affect the latency. Hence, to get the most realistic results, the tests should run in a real 444 environment where anomaly detection takes place. 445

446 5.2. Dataset and Testbed

Realistic datasets and testbeds are required to achieve the most promising results. To evaluate the efficiency of the pipeline, we built a testbed that contains components that are low-cost and accessible to most of the IoT community. When designing the IoT testbed, the sensor selection is the initial task that shapes the main futures of the testbed. In cyber-physical environments, there are several behaviors (e.g., temperature, noise, humidity) that can be considered as common. Hence, we observe these common behaviors via our testbed and generate a dataset. Table 4 demonstrates the components utilized during the evaluation.

We recorded the temperature, humidity, light, loudness, air quality data for around two days. We observed the data at the beginning to form an initial opinion about physical behavioral changes in the test environment. We realized the only temperature and humidity sensors are working as expected and let us creating anomalous behaviors. Hence, we only utilize these two data during the evaluation. Figure 10 provides visualization of the generated dataset. Arduino

	L L
Sensors	Grove - Temperature & Humidity Sensor (High-Accuracy & Mini) v1.0 Grove - Light Sensor Grove - Loudness Sensor Grove - Air Quality Sensor v1.3 Grove - UART Wifi V2 Digi XBee 3 Zigbee 3 RF Module
Microcontrollers	Arduino Nano 33 BLE Sense Raspberry Pi Pico Arduino Nano RP2040 Connect
Shields	Grove - Bee Socket Grove Shield for Pi Pico V1.0 Arduino Tiny Machine Learning Shield
Single-board Computer	Raspberry Pi 4 Model B
Software Tools	Putty Raspberry Pi Imager Node-RED Arduino IDE 1.8.15 Visual Studio Code Google Colab

Table 4: Testbed Components

Table 5: Comparison of Datasets

Features	WADI [8]	AnoML [7]
Amount of Data	122,543,744	45,906
Number of Rows	957,374	6,559
Number of Columns	129	7
Number of Sensors & Actuators	123	5
Time-Series	✓	✓
Labelled	✓	✓
File Size	588,906 KB	265 KB

Nano RP2040 Connect, Grove sensors, and Putty is used to generate the dataset which is pub-459 lished on Kaggle [7] where more details are also provided regarding the testing environment. 460 In addition, we utilize the WADI [8] dataset during the evaluation to analyze how the key ML 461 parameters such as accuracy, F1-score, and prediction time differ according to the ML platform. 462 The dataset contains data from 123 sensors and actuators from a water distribution testbed that 463 had non-stop run for 16 days while being attacked during the last two days. Table 5 demon-464 strates the differences between two utilized datasets. By using these datasets, we also evaluate 465 the relationship between the power consumption and data volume. 466

467 5.3. Anomaly Detection Methods

We tested the anomaly detection algorithms mentioned in Section 2 on WADI and AnoML datasets, as well as edge, fog, and cloud platforms by applying several scaling/reduction techniques. During the evaluations, we only used the baseline version of anomaly detection algorithms, hence we did not tune the algorithms to get better results to demonstrate the performance



Figure 10: Demonstrates the behaviour per data type. The controlled anomalies for temperature and humidity data are identifiable. The anomalies in temperature and humidity are created via hair dryer. The air quality, light, and loudness can be considered as faulty due to not responding to our anomaly creation attempts. There might be two reasons for the occurrence of faulty data: (i) the sensors are cheap quality, (ii) these sensors are designed for the AVR[74] architecture. However, during the evaluation we used ARM-based microcontrollers.

[75].

of baseline versions. We evaluate the following parameters as they are the core elements that de-472 termine the efficiency of an anomaly detection algorithm. Accuracy [76] determines the overall 473 correct prediction ratio. Precision [77] defines how close the predictions are. Recall [77] demon-474 strates how the anomaly detection algorithm is successful at detecting normal data. F1-Score 475 [76] is an evaluation metric that takes class distribution into considering. It might be preferred 476 as the main metric when false detections matter (e.g., industrial environments). True positive 477 (TP). The normal data is detected as normal. True negative (TN). The anomalous data is detected 478 as anomalous. False positive (FP). The normal data is detected as anomalous. False negative 479 (FN). The anomalous data is detected as normal. The following equations demonstrate how these 480 parameters are calculated: 481

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$F1 - S core = \frac{2 * TP}{2 * TP + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

The TensorFlow has three different APIs. The main API (TensorFlow) contains all the available methods and utilizes high-level API Keras [78] to build neural networks. TensorFlow Lite [43] which is the lightweight version of TensorFlow that is specifically designed for mobile/IoT devices is generated via the main TensorFlow API. TensorFlow Lite for Microcontrollers [79] only allows a subset of TensorFlow operations to be run on 32-bit microcontrollers. Hence, currently only CNN is supported. TensorFlow Lite models are converted into micro models via
 TensorFlow Lite converter Python API [80]. Then, inference is possible at the edge.

Table 6 and Table 7 demonstrates the results of anomaly detection tests. We see that baseline 489 CNN at the edge achieves 77% accuracy and 86% F1-score. We did not observe any significant 490 differences regarding accuracy and F1-Score. We also see those reduction methods help to reduce 491 the inference time. If we compare scikit-learn methods and TensorFlow methods, we see that 492 scikit-learn performs better when there is more computing power, but TensorFlow might generate 493 better results on fog rather than the cloud. If we use CNN-AE, we see that the accuracy is higher 494 when the standard deviation is applied, but for one-class SVM, we see that skew performs better 495 than the standard deviation. Also, we see that the TF Lite models are significantly less in size 496 than TF models. During the evaluation of the Isolation Forest, the whole dataset must be fit at 497 once, due to nature algorithm. The Raspberry Pi 4B with 4 GB RAM fails due to high RAM 498 usage that occurs because of fitting the whole dataset at once. Hence, we utilized the 64-bit 8 499 GB version of Raspberry Pi to evaluate the performance of Isolation Forest. 500

501 **6. Lessons Learned**

IoT infrastructures are expanding thanks to the benefits of ubiquitous computing. The rapid 502 developments in lightweight edge mechanisms made them desirable for labor-intensive tasks 503 such as anomaly detection. The increasing variety of 32-bit microcontrollers allows us to choose 504 a specific device with desired features (e.g., relatively high RAM) that can run ML algorithms. 505 In the edge environment where these microcontrollers are utilized, while ML-based tasks such 506 507 as keyword spotting, natural language processing, image processing have proven to be promising, anomaly detection is still in a very early phase [81]. Machine learning pipelines are the 508 key elements that let us evaluate these edge ML algorithms. Thus, we develop an end-to-end 509 ML pipeline that facilities developing anomaly detection systems where the detection can be 510 done on different layers (edge, fog, and cloud). We make the following observations based 511 on our findings: (i) lack of complete multi-protocol edge anomaly detection frameworks, (ii) 512 the lack of control over converted ML models, (iii) there is a lack of sensor data terminology, 513 (iv) manufacturers/developers provide platform-specific support, (vi) there is lack of support for 514 multi-language/protocol development frameworks, (vii) automated is actually not automated. 515

Lack of complete multi-protocol edge anomaly detection frameworks. The two tasks that 516 are executed within anomaly detection pipelines are: (i) data gathering/ingestion, (ii) anomaly 517 detection model development. While these tasks are different by nature, they are essential to 518 implement a complete IoT anomaly detection mechanism. During the evaluations, we see that 519 the required tools are very diverse and no ML framework offers a complete solution. For data 520 ingestion, flexibility and scalability are the most desired features. Hence, microcontrollers are 521 the primary elements that are deployed in IoT environments to gather data. Due to the resource 522 constraints of these environments, we need low power-consuming communication protocols. 523 This is one of the main reasons that why BLE [58] is invented. In the edge, during the evaluations 524 we see that there are three conditions needed for data acquiring: (i) sensors should be compatible 525 with the microcontroller, (ii) communication protocol libraries should be available to establish 526 a network both for the edge and the fog, and (iii) configurable platform that provides visual 527 assistance is needed. As no framework ensures all three conditions, we had to use tools that 528 require different programming languages (e.g., Arduino, JavaScript, Python). 529

The lack of control over converted ML models. TensorFlow allows us to convert the neural network models that are generated via the main API to more lightweight models that can be

				F								OC-SVM					RNN-AE				RNN							CNN-AE				Algorithm	
StDev	Skew	SS	NS	MM	MAD	Kurtosis	Average	StDev	Skew	SS	NS	MM	MAD	Kurtosis	Average	SS	NS	MM	StDev	Skew	MAD	Kurtosis	Average	StDev	SS	Skew	NS	MM	MAD	Kurtosis	Average	SR	
SK	SK	SK	SK	SK	SK	SK	SK	SK	SK	SK	SK	SK	SK	SK	SK	ΤF	ΤF	TF	ΤF	ΤF	TF	TF	ΤF	ΤF	TF	TF	ΤF	TF	TF	ΤF	TF	API	
0.1884	0.1884	0.2119	0.1884	0.1978	0.1884	0.1884	0.1884	1.13791	0.545252	1.314422	0.680684	0.687799	0.512389	0.855004	0.894195	18.08283	17.90922	18.32667	8.09226	7.621182	8.014902	8.020618	8.164231	1.051563	440	1.001088	440	440.2933	1.025978	0.995147	1.01413	Fog	
0.2868	0.2868	0.3103	0.2868	0.3081	0.2868	0.2868	0.2868	0.469978	0.189985	0.576975	0.335778	0.367881	0.207312	0.341614	0.342938	49.55683	41.1471	40.9852	30.83805	29.82979	29.02	30.07291	29.9278	25.3799	106.2	24.6464	103.3094	96.6556	24.03	24.0796	23.3021	Cloud	
0.5519	0.6415	0.6951	0.6951	0.7155	0.4325	0.6433	0.5891	0.501338	0.493176	0.496702	0.5	0.5	0.500747	0.481406	0.491203	0.699284	0.5	0.470241	0.420087	0.448924	0.421892	0.515931	0.431887	0.497397	0.699918	0.361076	0.5	0.498538	0.448848	0.519019	0.418136	Fog	
0.5519	0.6415	0.6951	0.6951	0.7155	0.4325	0.6433	0.5891	0.501338	0.493176	0.496702	0.5	0.5	0.500747	0.481406	0.491203	0.699284	0.500252	0.470231	0.42009	0.448965	0.421892	0.515931	0.431887	0.497397	0.699918	0.361073	0.50022	0.498538	0.448848	0.519019	0.418136	Cloud	
0.7034	0.7036	0.8444	0.8444	0.8399	0.7123	0.7205	0.7152	0.7897	0.8383	0.8028	0.1501	0.1501	0.7141	0.8127	0.7086	0.671158	0.942253	0.166829	0.436152	0.544221	0.69089	0.433345	0.174428	0.929901	0.758349	0.261203	0.059669	0.18035	0.7072	0.728089	0.323962	Fog	
0.7034	0.7036	0.8220	0.8220	0.8399	0.7123	0.7205	0.7152	0.7897	0.8383	0.8028	0.1501	0.1501	0.7141	0.8127	0.7086	0.671158	0.05964	0.166811	0.436158	0.544209	0.69089	0.433345	0.174428	0.929901	0.758349	0.261197	0.059669	0.18035	0.7072	0.728089	0.323962	Cloud	
0.7066	0.7049	0.8247	0.8247	0.8426	0.7183	0.7221	0.7179	0.913402	0.986351	0.93411	0	0	0.805624	0.954818	0.801859	0.667486	-	0.127211	0.43825	0.556664	0.726014	0.422561	0.140811	0.986375	0.765979	0.248162	0.002144	0.138802	0.740935	0.755389	0.311666	Fog	
0.7066	0.7049	0.8247	0.8247	0.8426	0.7183	0.7221	0.7179	0.913402	0.986351	0.93411	0	0	0.805624	0.954818	0.801859	0.667486	0.002107	0.127192	0.438256	0.556646	0.726014	0.422561	0.140811	0.986375	0.765979	0.248156	0.002144	0.138802	0.740935	0.755389	0.311666	Cloud	
0.9910	0.9937	0.9944	0.9944	0.9948	0.9876	0.9936	0.9921	0.850274	0.848138	0.849	1	1	0.850137	0.84496	0.84711	0.975904	0.942253	0.917464	0.922818	0.932372	0.930689	0.946374	0.892397	0.941966	0.971539	0.885031	0.942253	0.941108	0.934799	0.945001	0.91451	Fog	
0.9910	0.9937	0.9944	0.9944	0.9948	0.9876	0.9936	0.9921	0.850274	0.848138	0.849	1	1	0.850137	0.84496	0.84711	0.975904	0.955432	0.917453	0.922819	0.93238	0.930689	0.946374	0.892397	0.941966	0.971539	0.885028	0.953552	0.941108	0.934799	0.945001	0.91451	Cloud	
0.8250	0.8247	0.9016	0.9016	0.9124	0.8317	0.8364	0.8330	0.880708	0.912038	0.889524	0	0	0.827282	0.896536	0.823864	0.792754	0.970268	0.22344	0.594276	0.697119	0.815708	0.584251	0.243241	0.963659	0.856599	0.387632	0.004278	0.241923	0.826653	0.839623	0.464895	Fog	
0.8250	0.8247	0.9016	0.9016	0.9124	0.8317	0.8364	0.8330	0.880708	0.912038	0.889524	0	0	0.827282	0.896536	0.823864	0.792754	0.004205	0.223411	0.594282	0.697107	0.815708	0.584251	0.243241	0.963659	0.856599	0.387624	0.004278	0.241923	0.826653	0.839623	0.464895	Cloud	
20.04371	69.34095	0.814415	133.64	1.433161	72.07326	67.18984	6.88913	20.04371	69.34095	0.814415	NA	1.433161	72.07326	67.18984	6.88913	3.304777	NA	1.330966	20.04073	69.21164	71.88432	67.16076	6.911079	20.04371	0.814415	69.34095	NA	1.433161	72.07326	67.18984	6.88913	Fog	
3.039728	34.05004	0.790764	133.64	0.481541	21.63906	23.71106	1.416631	3.039728	34.05004	0.790764	NA	0.481541	21.63906	23.71106	1.416631	1.005414	NA	0.328342	3.640271	31.53431	19.5469	22.99305	1.273132	3.039728	0.790764	34.05004	NA	0.481541	21.63906	23.71106	1.416631	Cloud	
765.32	761.20	944.20	NA	952.58	634.68	775.20	962.10	92.62793	10.2168	1442.616	395.542	407.5889	8.673828	50.1582	56.62305	1414.512	1410.465	1414.535	797.8203	797.8125	797.8164	797.8047	797.8203	34.64844	397203.6	34.60938	397194.2	397203.7	34.64844	34.60938	34.64844	Fog	
765.32	761.20	944.20	NA	952.58	634.68	775.20	962.10	92.62793	10.2168	1442.616	395.542	407.5889	8.673828	50.1582	56.62305	10378.48	10386.67	10386.43	4045.537	4044.202	4044.854	4042.888	4045.537	291.4189	1191796	291.0166	1191799	1191798	291.4189	291.0166	291.4189	Cloud	

Table 6: Evaluation Results of WADI Dataset

Table 7: Evaluation Results of AnoML Dataset

M	odel Details		Infer	ence Time	(ms)		Accuracy	F1 Score			2	AUC			Recall			Precision			Scale 7	ime (s)	Model Size (KB)		
Model	SR	API	Edge	Fog	Cloud	Edge	Fog	Cloud	Edge	Fog	Cloud	Edge	Fog	Cloud	Edge	Fog	Cloud	Edge	Fog	Cloud	Fog	Cloud	Edge	Fog	Cloud
	StDev	TF	174.24	1.95	32.22	0.258	0.251	0.251	0.000	0	0	0.4991	0.485	0.485	0.000	0	0	0.000	0	0	0.716	0.12	19.62	3.172	80
	Average	TF	172.05	1.13	32.63	0.769	0.871	0.871	0.862	0.91	0.91	0.5738	0.867	0.867	0.979	0.876	0.876	0.770	0.946	0.946	0.241	0.04	19.50	3.152	80
CNN	Skew	TF	NA	8E-15	32.20	NA	0.475	0.475	NA	0.57	0.57	NA	0.474	0.474	NA	0.476	0.476	NA	0.72	0.72	2.487	0.8	19.52	3.156	80
	Kurtosis	TF	NA	2E-07	32.04	NA	0.259	0.259	NA	0	0	NA	0.5	0.5	NA	0	0	NA	1	1	2.425	0.57	19.50	3.152	80
	MAD	TF	NA	1.81	32.16	NA	0.576	0.576	NA	0.60	0.60	NA	0.702	0.702	NA	0.441	0.441	NA	0.972	0.972	2.558	0.88	19.52	3.156	80
NA: Not	A: Not applied MAD: Median Absolute Deviation StDev: Standard Deviation IF: Isolation Forest TF: TensorFlow																								

Tabl	e 81	Data	Format
raor	U U.	Data	1 Ormai

Categories		Sen	sor Type				Protocols			Others				
Features	Temperature	Humidity	Air Quality	Light	Sound	WiFi	Bluetooth Classic	BLE	Zigbee	Location ID	Sensor ID	Microcontroller ID		
Identifiers	TH	HU	AQ	LI	SO	WF	BC	BL	ZB	Numbers	Numbers	Numbers		
Example Data	24.45	44.31	75	255	644	NA	NA	NA	NA	01	001	1		
NA: Not Applic	JA: Not Applicable.													

deployed to edge and fog. However it offers zero control over the model conversion. During 532 the evaluations, we realized that some lite models perform better than their main peers which 533 were unexpected as there is a known trade-off between model accuracy and power consumption. 534 Due to not having any control over this conversion, the only way to compare these models is 535 by running inference. Also, scikit-learn models do not have a lite version. Pickle [82] library is 536 used to pack and deploy the same model to another platform. Hence deploying these models to 537 microcontrollers is currently not possible. This is why during the evaluations we did not observe 538 any differences rather than inference time when running scikit-learn models. 539

Lack of unified IoT sensor data terminology. In an IoT environment, the sensors generate data 540 in a similar format. Showing such similarities might be confusing if the data are not identified 541 with certain terms/identifiers especially where big data are present. Hence, we apply further pro-542 cessing to identify the data context. However, there is no sensor terminology that explicitly states 543 the sensor data format. Thus, we designed ECCG in a way that it generates a code that provides 544 all required information such as the location of the sensor, sensor type, and the microcontroller 545 model. Also, another important point to consider regarding IoT sensor data terminology is the 546 data with floating points. While WiFi, Zigbee, and Bluetooth Classic have no issues when send-547 ing floating-point data, BLE by nature designed to send buffer (byte array) as it provides power 548 optimization. Hence, when sending data over BLE we might require further indicators such as 549 "F" for floats or "I" for integers to correctly identify the data. Table 8 presents the data for-550 mat that is generated via ECCG. We set the number IDs in different lengths to prevent possible 551 confusion. 552

553 We evaluated our AnoML pipeline with two datasets, WADI and AnoML. WADI dataset has data from 127 different sensors, which is not possible to be replayed on edge devices due to 554 limited computing power. WADI dataset was only evaluated on fog and cloud. We used a pri-555 vate machine with NVidia Tesla GPU and TensorFlow-GPU library version 2.4.1 for ML model 556 training. AnoML dataset has data from five environmental sensors but two of them (temperature 557 and humidity) were used to build and evaluate models on edge, fog, and cloud. We used Google 558 Colab with GPU support to build models for the AnoML dataset with TensorFlow-GPU library 559 version 2.1.1. AnoML dataset was transformed using reduction techniques only, to convert it 560 into univariate. 561

In terms of accuracy, F1-score, precision, recall, and Area Under Curve (AUC), there was no significant difference recorded when comparing fog and cloud inferences in all types of models for the WADI Dataset. It was also observed that batch processing (all at once) in TensorFlow on the cloud does not affect the efficiency of the pipeline. Figure 11 shows the comparison of each metric for all models for the WADI Dataset. Regarding fog and cloud, we observed a similar
 trend for the AnoML Dataset. However, we noticed that edge results were comparatively less
 efficient.

We noticed that inference on fog takes distinctly less time as compared to inference on the 569 cloud. But, we observed the opposite results for CNN-AE when doing multivariate analysis 570 where we recorded that cloud inference was faster than fog. Figure 11a provides a visual com-571 parison between inference times of fog and cloud. We also experienced that when using batch 572 prediction in the cloud (all rows at once), the average prediction time was extremely faster. But, 573 this is not applicable in the real-world scenario where data is being streamed. Both scaling and 574 reduction techniques were faster on cloud (using batch-prediction) when compared to fog as seen 575 in Figure 11g. Inference time trends were also identical in ML models for the AnoML dataset 576 as fog inference time was less than cloud inference. The fog was more than 10 times faster than 577 cloud inference. Inference time on edge was extremely slow when compared to fog and cloud, it 578 was more than 100 times slower than the fog and almost 5 times slower than the cloud. 579

WADI Dataset is based on two sub-datasets recorded at different times, normal and attack, 580 as we discussed that normal dataset was used for ML model training thus we used the attack 581 dataset for testing. The attack dataset consists of 172800 rows which were then converted into 582 time-series data. As a result, the dimension of the data became (172770, 30, 127) for scale-based 583 and (172770, 30, 1) for reduction-based models. Reduction-based models took exceptionally 584 less time for training because of the univariate nature of the data. The size-on-disk of CNN-AE 585 scaled-based models is too big as compared to CNN-AE reduction-based models. For RNN-AE 586 models, the size-on-disk of reduction-based models are not significantly different from scale-587 based RNN models. The main reason for this was that we used LSTM layers for RNN. The 588 size-on-disk variation trend was identical in fog models as seen in Figure 11h. We also learned 589 that scikit-learn models maintain consistency over fog and cloud. The time-related results in 590 the fog were always slower due to the difference in computing power, but there was no change 591 observed in accuracy-related metrics. The obvious reason was that there was no platform/format 592 conversion done for scikit-learn models. 593

Models for the AnoML dataset were lightweight but there was a notable difference for the fog models in cloud model size-on-disk. We also observed that the size of edge models was significantly greater than fog models, even though these models were converted from them. The reason was that edge models were in plain-text (hex-dump) as they were a C-array, but fog models were flat-buffered-binary format.

599 7. Conclusion

The proposed system offers support to a data scientist with minimal IoT knowledge to deploy 600 a reconfigurable IoT anomaly detection infrastructure that utilizes a data science pipeline. The 601 proposed framework contains: edge nodes consist of microcontrollers, fog nodes consist of single 602 board computers and virtual cloud nodes. The communication between nodes is not limited 603 to edge node types but limited with protocol specifications (e.g., Bluetooth only allows seven 604 slaves/servers), hence allowing the implementation of different network topologies (e.g., bus, 605 tree, and star). The system also explicitly supports the four major phases of data processing: 606 gathering, training, deployment, and inference. We evaluated several combinations to measure 607 the scalability that is offered by the proposed framework. We observed that the proposed anomaly 608 detection pipeline reduces the required labor for building an IoT anomaly detection system. We 609







(a) Inference Time



(b) Accuracy



(e) Precision



Fog Cloud



(g) Scaling Time







identified the drawbacks of the proposed system including the reasons behind them. We believe
 our work encourages the future studies that aim to build open-source ML-based pipelines.

As future work, we are seeking to improve the ECCG web application by including more edge nodes, sensors, and protocol types. In addition, we envision converting required manual processes (e.g., deploying ML model to edge, uploading training data, deploying edge code) within the AnoML-IoT to automated.

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