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An AI powered, Low-Cost, IoT Node Oriented to Flood Early Warning Systems †

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Abstract: The present study aims to design a low-cost smart AI powered node, to serve as a flood Early Warning System complete solution. The node is designed to predict forthcoming flood events by capturing and combining critical data related to such phenomena. Such data are the water level at rivers or other water discharge basins, rainfall, soil moisture, and material displacement at river slopes. The node will autonomously monitor the above quantities at a high frequency rate, and selectively upload them to a server only when verified conditions for a forthcoming flood will exist. These conditions will be evaluated by the local ML model. This will allow each node to reliable predict flood events and issue local and remote alarms. Combination of several nodes at an area of interest will form a robust and reliable Early Warning System.

Keywords: Early Warning Systems; floods; AI; low-cost; IoT; nodes; sensors; cellular network

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1. Introduction

Natural disaster management presents a challenging field of research and technology applications. Especially during the last decade the climate change has led to several occurrences of extreme weather events leading to severe natural disasters [1]. Researchers from various scientific fields target towards viable technological solutions to aid disaster management. One of the most critical natural disasters is the floods. Their extent and magnitude often cause huge social, economic, health and safety impact [2].

Flood management via precipitation prediction and hydraulic modeling was proved to be less effective to predict floods [3]. To aid the accuracy of the prediction several more measurements are required. At this scope, many attempts have been made in the past to employ the Internet of Things (IoT) technology [4], and several IoT aided Early Warning Systems related to floods have been designed and proposed [2,5–8]. The IoT can be roughly described as a system that incorporates small and remote electronic devices of low-power and usually low-cost that samples data and transmit them to an IoT server for further processing. At the case of EWS's, data from the nodes are used as the input data to several models of the disaster prediction.

Since the number of the IoT nodes presents a high growth that, it is reported that both the network communication latencies [9], and the time needed to process the vast amount of data in order to conclude on certain alarms and/or actions, is increased. Also, the increasing number of nodes stresses the wireless communication channels and this can also induce further communication latencies. The increasing latencies lead to delays on taking certain actions. Taking into consideration that the data usage can also be translated to cost, the need to locally process the collected data directly at the end devices has emerged.

While some actions can be triggered using simple threshold values of the received data, more complex decisions, such as those related to flood prediction, require sophisticated algorithms. According to the latest literature [4,9,10], the most popular method of applying such complex algorithms is the Artificial Intelligence (AI). When implemented directly on the IoT nodes, this technology is called Artificial Intelligence of Things (AIoT) [2]. AIoT requires more system resources such as computational power and memory, which are offered in modern embedded platforms and Microcontroller Units (MCU). In [7], the authors claim to have developed the first large-scale IoT-based real-time flood forecast system that has been enabled by AI and deployed in real world.

In the present study, a node capable to execute TinyML models and perform AI algorithms is designed. The node has all the specifications to serve as an IoT device. It is power autonomous, network connected, and interfaces with various sensors and actuators. The sensor suite employed matches the needs to serve as part of an EWS aimed for floods. Since major flood phenomena relate to river bank collapses, the design is also oriented towards this phenomenon. To the best of the authors' knowledge, this is the first study that utilizes accelerometer data at river related terrestrial locations to study the relation of river bank/slope movements to upcoming flood event. In all other flood related studies, the combination of accelerometer data mainly relate to civil infrastructure monitoring.

2. Materials and Methods

The proposed system is based on a system-level designed electronic device, referred to as the node. The node is completely custom designed, both in hardware and in software. The hardware design and the operating sequence of the device are described at the following subsections.

2.1. Hardware

The main parts and modules of the node are the Microcontroller unit (MCU), the power supply unit (PSU), and the data connectivity unit (modem). All circuitry was hosted in a custom designed printed circuit board (PCB), and within a commercial IP65 rated project box, in order to withstand external environmental conditions at the place of deployment. A short description of each main part of the node is presented at the following paragraphs.

The selected MCU is the Microchip ATmega2560 8-bit AVR controller. This MCU offers enough resources (20 MHz clock, 8 kB of SRAM, 256 kB Flash) to be able to run TinyML models, custom designed for 8-bit architectures. The MCU also has plenty onboard peripherals, supporting multiple serial communication protocols and Analog to Digital converters. The selected module hosting this MCU is the RobotDyn Mega 2560 PRO [11]. The module also offers USB to TTL converter to easily re-program the MCU, together with a flexible power management circuit and ultra-compact footprint.

The PSU is based on a single 3.7 V, 5 Ah, 26650 form factor, Li-Ion battery cell paired with a battery charger and protection circuit using the TP4056 Integrated Circuit (IC). The power source to charge the battery is a 6 V Solar Panel able to provide a maximum 1 W of charge power.

Data connectivity is provided via Simcom's SIM7600G modem [12]. The modem is fitted at an OEM breakout board, which also bears a power management circuit, a SIM card socket, antenna connectors, and all components needed for the modem's recommended operation. The modem provides LTE/GSM (4G/2G) connectivity.

The block diagram of the system is presented at Figure 1. The various peripherals communicate differently to the MCU. The modem occupies a hardware USART port. Regarding the sensors, the accelerometer uses the I2C line of the MCU, the analog output of the soil moisture sensor is read using one 10-bit ADC, while the rain gauge's output pulses are read by the MCU utilizing one external interrupt pin. The raw battery voltage output is used as the main Vcc powering all electronic modules, since each module has its own power management and voltage regulation circuitry. This was a primary voltage regulator is omitted.

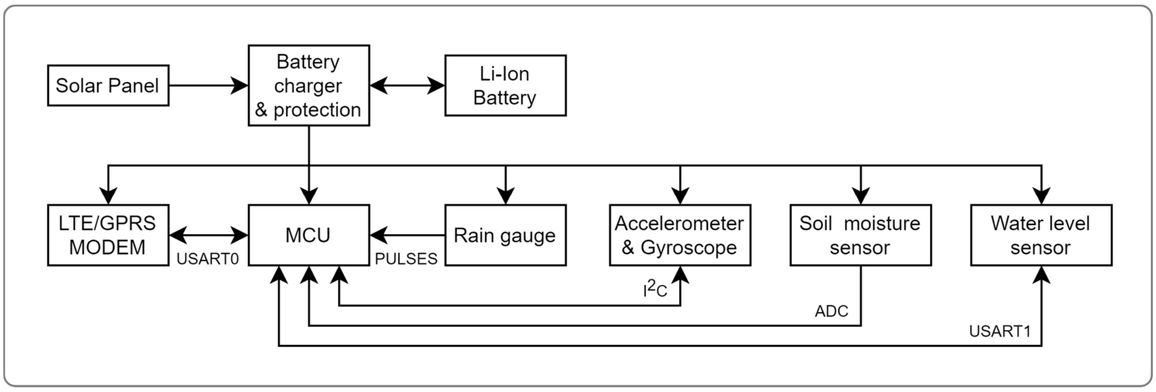

Figure 1. The block diagram of the node.

The various external sensors are cable connected to the node. The use of cable glands ensure the IP rating of the node's case, and reliefs any stress that may be applied to the cables. The sensors selected for this application are a soil moisture sensor (Truebner SMT50 [13]), an ultrasonic ranger used as a water level sensor (MaxBotix MB7066-100 [14]), an accelerometer and gyroscope sensor (Invensense MPU6050) hosted at an OEM breakout board, and a rain gauge sensor (DFRobot SEN0575 [15]). A photograph of a complete prototype and a map of the first deployment location are depicted in Figure 2.

Figure 2. A photograph of the complete prototype (**left**), and the first deployment location (**right**).

2.2. Operating Sequence

The second important part is the Firmware (FW) and the operating sequence of the device. The operating logic diagram is presented in Figure 3. When the node is first powered up, an initialization routine is run, to check that the system is fully functional. Then, the node proceeds to a periodic data acquisition from the sensors. Inertial measurement unit (IMU) data from the accelerometer are retrieved at a frequency of 4 Hz, and stored at a circular buffer that has a total length of 240 measurement sets. This provides the opportunity to recall a detailed IMU history of 60 s at any moment. Data from the soil moisture sensor, the water level meter, and the rain gauge are sampled at a period of 5 min, and stored a secondary circular buffer with total length of 288, providing a measurement history of 24 h.

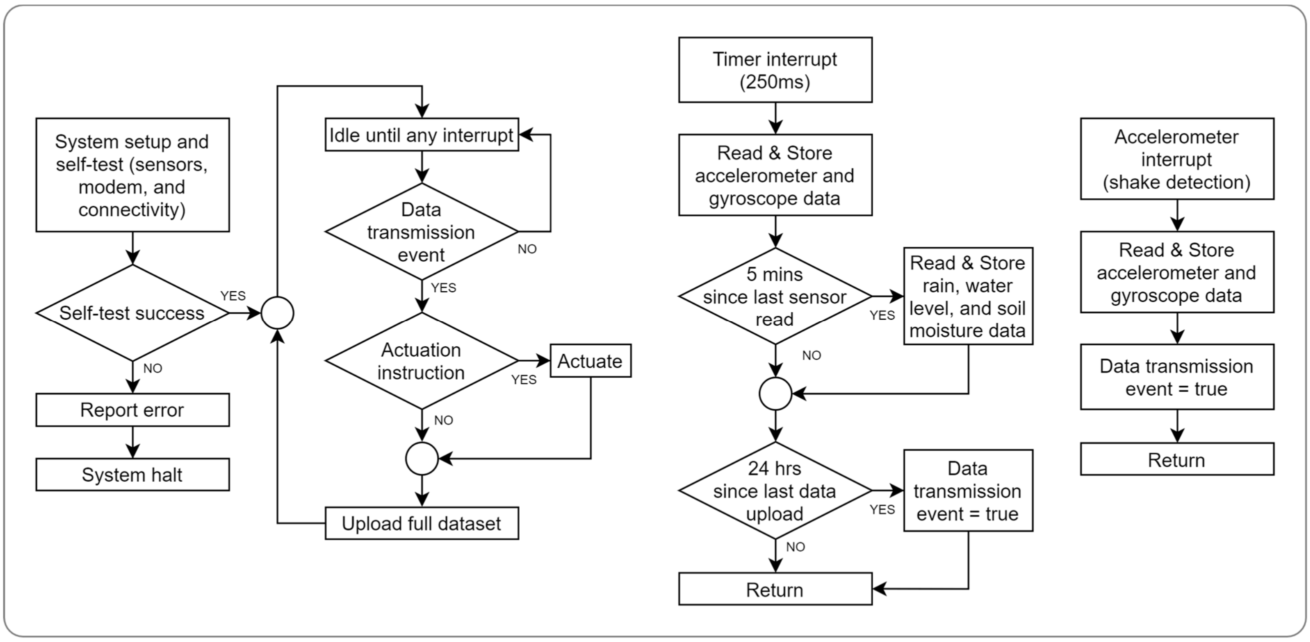

Figure 3. The logic diagram of the Firmware.

The secondary buffer is uploaded once per day to the server to keep record of the rain and the soil moisture. On the contrary, the one minute historic data of the accelerometer are uploaded only at certain occasions. These are the MPU6050 internal programmable interrupt at shake detection, or the existence of an event of angle change calculated according to the following equation [16]:

$$a_F = c \times a_G + (1 - c) \times a_A, \quad (1)$$

where:
a_F: the filtered angle,
c: filter tunable constant ($0 < c < 1$ in order to have a complementary filter that neither overshoots nor attenuates),
a_G: calculated angle using gyroscope data, and
a_A: calculated angle using accelerometer data.

This logic ensures that critical short-term historical data related to possible material displacement at river slopes will be retrieved. Each of these datasets will be matched to the actual physical phenomenon of flood or landslide at the river bank, if apparent, and thus be classified. These data will be used as the main training dataset for the tinyML model to detect floods and landslides at river banks. Alongside to the accelerometer data, precipitation, temperature/RH and soil moisture data will also be contributing to the model training.

The first version of the system will act mostly as a filtered critical data acquisition device, and when the TinyML models are developed, a new firmware will be uploaded to test the efficiency of the model. The Newton framework will be used to train and produce the TinyML model, customized for the 8-bit architecture of this system. Newton is a trusted high-level framework, perfectly fitted for applications requiring fast development avoiding an in-depth Neural Network optimization.

After loading the TinyML code to the node, when a node detects the risk of flood certain local actions can be taken, such as issuing an alarm sign or actuating electromechanical devices to engage a certain anti-flood infrastructure. Certainly both the data related to the detection of flood risk, and the actions applied by the end device will be uploaded to the IoT server for further processing and consequent management actions.

3. Results & Discussion

The overall system proved to be well designed. Operationally the node performed stable, and the sensor readings were consistent and reliable. Power-wise the node presented a moderate average current consumption of about 30 mA when acquiring data, and about 50 mA when in data transmission mode. The overall power autonomy is approx. 5–6 days on a fully charged battery. Although this battery life seems rather short, the real-time and continuous sampling of the sensors data actually justifies this performance.

FW logic in terms of data acquisition and upload worked seamlessly. Communication via cellular network proved to be very consistent, with short network registration and upload/download latencies. The customized data upload protocol reduced data usage to the extent that an inexpensive data plan is sufficient (i.e., 10 MB/month). The prototype node was manually triggered to upload five IMU datasets of 60 s duration each. Thus, a 300 s IMU signal was obtained, presented in Figure 4.

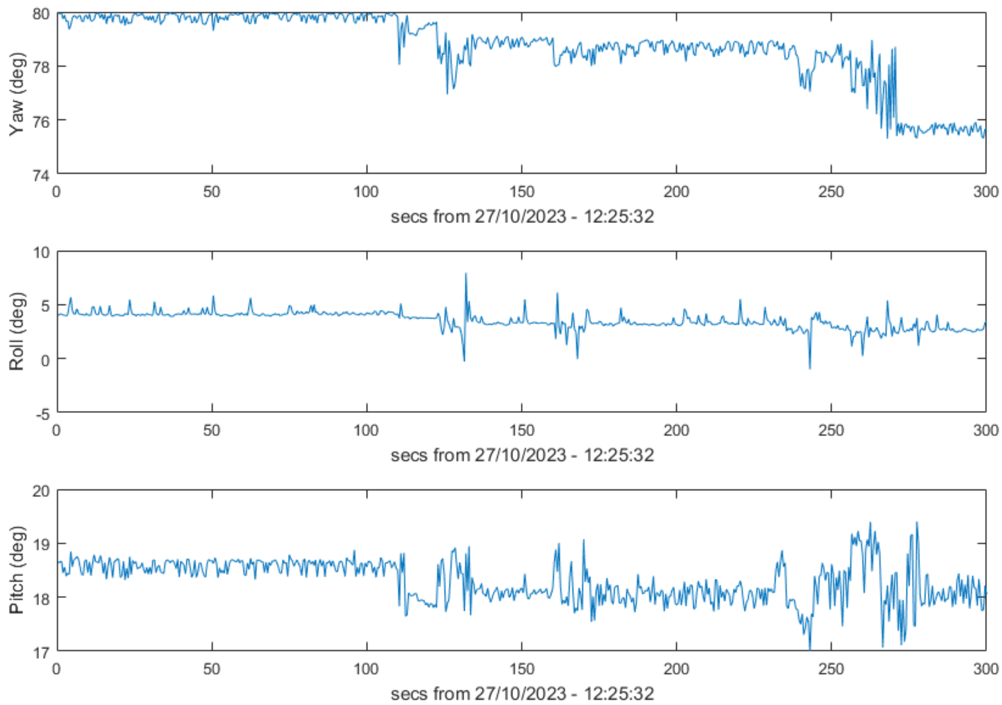

Figure 4. Sample IMU signals (yaw, roll, and pitch, top to bottom).

According to the project’s timeline, it is expected that the first training dataset will be ready by the end of Q2 2024, and that immediately after the TinyML models will be deployed. This way the proposed system will be tested in real world conditions during the wet season of 2024.

4. Conclusions

This research presented the concept, architecture, design and development of a low-cost AI powered IoT node aimed for flood Early Warning Systems. The node interfaces to several sensors, monitoring critical quantities related to floods, such as the water level at a riverbed, the precipitation, the soil moisture and the material displacement at river slopes. The first stage of the system, i.e., the development of the prototypes, is concluded. The nodes were tested thoroughly at a laboratory environment and proved to be ready for the next stage of this research. The second stage will be the deployment of a certain amount of nodes to the area of interest, the collection of the training dataset for the TinyML model, and the actual training of the model. Further on, the third stage will be upload of the model to the end nodes, the test of the model and the characterization of the accuracy for flood prevention. New datasets retrieved from the third stage may also be used for further training and improvement of the model. All findings are scheduled to be published when available.

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