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LoRaWAN-Based Artificial Intelligence Analytics for Forecasting Cyclone-Induced Floods on Urban Roads

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Abstract

On urban roads, frequently severe floods were caused by monsoon or tropical cyclones, and oceans or several lakes and rivers overflowed. These cyclone-induced floods had massive loss and damage to road infrastructure, vehicles, and human life. In addition, many homes and businesses were destroyed, transportation disruption, power outages, and the spread of waterborne diseases such as dengue and malaria. This research proposes LoRaWAN-based artificial intelligence (AI) analytics for forecasting cyclone-induced floods to address the abovementioned destructions. The LoRaWAN network uses sensor devices in flood-prone areas to extract hydrological and weather conditions. The proposed analytics compares the sensor-measured data with past pre, during, and post-flood conditions and forecasts for future flood disasters. NVIDIA Jetson platform is used for performing image analytics and other factor inferences. Hyper-heuristic-based Convolution Encoder-Decoder using Gated Recurrent Units with attention mechanism (ConvED-GRUAT) is used to intelligently analyze satellite imagery and hydrological and meteorological factors to detect changes indicative of flooding. The proposed prediction model is trained on historical flood data to identify patterns and predict the likely impacts of a future flood event. The prediction model may look for rapid changes in water level or changes in the conductivity of the water. Once a flood is forecasted, the model can also be used to predict the severity of the flood, which can help to take preventative action and vehicle rerouting. Overall, the proposed solution accurately and timely estimates the climate and hydrological changes indicative of flooding and forecasts future flood tragedies, which can help to mitigate the effects of floods. Radiofrequency (RF) channel quality of service parameters such as RSSI, SNR, CR, and SF are considered to guarantee flood forecasting reliability and accuracy.

***Keywords**: Urban; Floods; LoRaWAN; Jetson; IoT sensors; Attention mechanism.*

1. Introduction

The floods on urban roads had several impacts on road infrastructure, transportation, economic loss, and human life [1]. The annual monsoon or tropical rainfall was much higher than the seasonal average. It caused water levels to rise rapidly in the oceans, lakes, rivers, and dams. This led to flooding in low-lying areas of cities [2]. The drainage system could not handle the high volume of water, leading to waterlogging on the urban road network. There are several reasons for the frequent floods in urban areas [3]. 1. Heavy rainfall: Urban areas receive significant rain during the annual monsoon season, which usually starts in October and lasts until December. The heavy rain often exceeds the drainage system's capacity, leading to flooding. 2. Anthropogenic factor: The rapid urbanization and unplanned construction of buildings and roads have resulted in the loss of natural water retention areas, such as wetlands and lakes. This has reduced the capacity of the land to absorb water, leading to an increased risk of flooding. 3. Poor drainage system:

The drainage system is outdated and inadequate to handle heavy rainfall. This often results in waterlogging and flooding in low-lying urban areas. 4. Encroachment of water bodies: The encroachment of water bodies and natural waterways in and around urban areas has further reduced the capacity of the land to absorb water. This has increased the risk of flooding during heavy rainfall. In most coastal cities, many roads and bridges were in poor condition, making it difficult for emergency vehicles and relief efforts to reach affected areas [4]- [5]. Some of the major impacts of floods are 1. Damage to infrastructure: The floods caused significant damage to the city's infrastructure, including roads, bridges, and buildings. Many roads and bridges were washed away, making transportation difficult or impossible in some areas. 2. Loss of livelihood: The floods led to job losses and a loss of income for many people, particularly those working in the informal sector. 3. Health concerns: The floods increased the spread of waterborne diseases such as dengue and malaria. 4. Displacement of residents: Many residents were forced to evacuate and move to temporary shelters during the floods. This displacement can have long-term effects on mental and emotional health, as well as on economic stability. 5. Environmental impacts: The floods also released pollutants and waste into the waterways and surrounding areas. This can have long-term effects on the local ecosystem and wildlife. Conventional sensor-based systems need stronger scalability, reliability, and processing speed, hard to set, low coverage, and high cost for flood prediction. This poses a requirement for a large-scale, low-cost, ultra-low-power-consuming network. The most prominent network choices are LoRaWAN (Long-Range Wide Area Network) and NB-IoT (NarrowBand-Internet of Things). NB-IoT is preferred because of its low cost, coverage area improvement, power consumption, and latency [6]. LoRaWAN is an open-source technology, and it is a low-cost one [7]. LoRaWAN is a low-power, long-range wireless communication protocol that connects low-cost, battery-operated sensor devices. LoRaWAN technology is based on the LoRa modulation technique, which enables long-range communication with a low power consumption over several kilometers. This makes it ideal for IoT applications that require battery-operated devices to communicate with a central network. LoRaWAN operates in the unlicensed Industrial, Scientific, and Medical (ISM) bands, which makes it available for anyone to use without requiring a license. Some amazing features make LoRaWAN unique and more potent for flood forecasting than other technologies. It has deep indoor penetration, firmware auto-updates over the air, end-to-end security, geolocation, and a larger ecosystem. LoRaWAN is used in various applications, including smart cities, health, agriculture, metering (air quality, pollution, weather, gas, electricity, and water), natural disaster detection and prevention, supply chain logistics, asset tracking & quality management. In recent years, some reasonable use cases [8]-[12] have been deployed for real-time flood forecasting using LoRaWAN technology. However, these case studies lack comprehensive coverage of all the flooding sources, more reliability, and artificial intelligence analytics. This motivated us to propose a graphics processing unit (GPU)-based LoRaWAN Internet of Things (IoT) network for accurately collecting cyclone-induced flooding factors to forecast future floods. **The following are the major contributions of the proposal.**

- To develop a LoRaWAN-based artificial intelligent analytics for forecasting cyclone-induced floods.
- To install Dragino LoRaWAN-based ultrasonic level gauge, rain gauge, wind direction and wind speed, humidity, temperature, pressure, and other required sensors in flood-prone areas to capture and send meteorological and hydrological data to the gateways.
- Configure and place the outdoor LoRaWAN gateways at the appropriate distance between end sensors and network servers for reliable data communication.

- To collect historical pre-flood, during-flood, and post-flood satellite imagery and National hydrological and meteorological data sets for training the ConvED-GRUAT prediction model.
- To implement a convolution encoder-decoder using gated recurrent units with an attention mechanism for analyzing and detecting changes indicative of flooding based on historical data and current conditions.
- To use a powerful GPUs-based NVIDIA Jetson platform to run the ConvED-GRUAT flood prediction model.
- The proposed model can also be used to predict the extent and vulnerabilities of the flood, which can help emergency responders to allocate resources and plan evacuations and vehicle rerouting.
- RF channel quality of service parameters such as coding rate (CR), signal-to-noise ratio (SNR), spreading factors (SF), and received signal strength indicator (RSSI) are considered to guarantee flood forecasting reliability and accuracy.

Further organization of our article is divided into sections. Section 1 discusses the recent and more relevant existing literature/ case studies. Section 2 elaborates on the proposed methodology. Section 3 demonstrates the performance analysis. Section 4 summarizes the conclusion and future research direction.

2. Literature Study

This section discusses the recent and more relevant existing case studies and literature. Since flood forecasting is dynamic with hydrological and meteorological changes, a LoRaWAN-powered sensor network must capture such changes accurately. Table 1 presents recent LoRaWAN-based flood prediction and warning case studies. In [8], the LoRaWAN-based flood prevention use case is deployed using Libelium Plug & Sense device. This deployment measures the wind direction and wind speed, humidity, temperature, pressure, and water level of the Basin River in Argentina. An all-in-one sensor device called Libelium's Waspmote Plug & Sense captures and visualizes the data in the Sense2Cloud software platform. A LoRaWAN-based flood monitoring solution is deployed for Chorinsky-Klause Dam, Austria, to monitor upstream and downstream water levels [9]. The Things Network platform is used to visualize and analyze the EM500-SWL and EM500-UDL sensors data. In [10], the Advantech LoRaWAN solution is investigated for measuring flood inductive water levels, rainfall, and ground saturation. Message queuing-telemetry transport protocol transmits the data to the supervisory control and data acquisition for analysis.

Table 1 LoRaWAN-based flood forecasting use cases

Parameters	End-Sensors	Contribution	Ref.
River level & weather data	Libelium's Waspmote Plug & Sense!	Flood prevention	[8]
Dam level and rainfall	EM500-SWL and EM500-UDL	Flood monitoring	[9]
Rainfall, water level, and ground saturation	Wzzard LRPv edge nodes (BB-WSW2C42100)	Flood monitoring and warning	[10]

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River level and weather data	Elsys sonar, rain, weather sensors	Monitor metrological changes	[11]
Groundwater level	Elsys sonar sensors	Flood alert	[12]

Scott Andrews [11] deployed a LoRaWAN sensor network for Nant Barrog River flood detection. This network uses Elsys sonar, rain, and weather sensors to monitor water level, atmosphere pressure, temperature, and humidity. The Things Network platform visualizes and analyses the Elsys sonar, rain, and weather sensor data. In [12], a LoRaWAN-based flood alert network is deployed in Calderdale, England. This deployment uses Elsys sonar sensors to measure groundwater levels using The Things Network platform. However, these case studies presented above [8]-[12] need a reliable deep-learning model to analyze the flood-causing parameters. Since the LoRaWAN IoT networks enable various hydrological and weather data extraction sensors, an accurate prediction model is needed to fuse and infer the appropriate decisions efficiently. In recent years, deep learning models have become popular in enhancing long/short-term predictions of various applications. In [13], Fernandes F.E. et al. proposed a deep neural network for river flood forecasting in Brazil based on off-the-shelf camera image analysis. D. Liu et al. employed a steam-flow prediction case study to detect the Yangtze River flood [14]. This case study uses an encoder-decoder long short-term memory (ED-LSTM) model for long-term flood predictions using Hankou Hydrological Station streamflow data [14]. Xu G. et al. [15] presented Convolution Gated Recurrent Units with an attention mechanism (ConvGRU-AM) to predict the typhoon path. This model uses the EAR-Interim and China Meteorological Administration datasets to forecast real-time typhoons. Mandeep Kaur et al. [16] presented a Bayesian belief network (BBN) using a grasshopper optimization algorithm (GOA) to detect floods. The authors also proposed fuzzy inferences for flood vulnerability analysis.

Table 2 Deep Learning Models for Flood Prediction

Parameters	Methodology	Contribution	Ref.
River water level	Deep Neural Network	River Flood Forecasting	[13]
River streamflow	ED-LSTM	Long-term Flood prediction	[14]
3D weather features	ConvGRU-AM	Typhoon path prediction	[15]
River level and weather data	BBN with GOA, Fuzzy inferences	Flood detection and vulnerability study	[16]
Rain, pressure, temp. and humidity	Support vector machine	Flood Detection	[17]

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Rainfall datasets and EO images	Change detection and statistical-based techniques	Mapping Kerala floods 2018 from EO images	[18]
Weather radar data	ML regression methods	Nowcasting heavy rainfall	[19]

Al Qundus et al. [17] proposed a support vector machine for detecting flood disasters using onboard sensors data (i.e., wind speed, rain, air pressure, temperature, and humidity) and Google API data (i.e., sea rainfall and air pressure). To map the floods 2018 in Kerala, India, from earth observation (EO) images, V. S. K. Vanama et al. [18] proposed change detection techniques and statistical-based thresholding methods. Y. V. Wang et al. [19] adopted machine learning (ML) regression methods based on weather radar data to nowcast heavy rainfall. However, the deep learning solutions presented in Table 2 [13]-[19] need GPU accelerators to improve reliability and accuracy. This research is the first to configure a GPU-based LoRaWAN IoT network with attention-based deep learning (DL) accelerators to capture and learn appropriate hydrological and weather factors accurately. We adopt hyper-heuristic-based ConvGRU with a soft attention mechanism for future flood forecasting to overcome the limitations posed by existing models. Weather radar data ML regression methods Nowcasting heavy rainfall [19]

3. Proposed Methodology for Flood Forecasting

The early prediction of flood events is essential for timely response and mitigation of their impact on human lives and infrastructure. A network of IoT sensors can be installed in critical areas prone to flooding, such as oceans, rivers, lakes, and stormwater drains as shown in Figure 1. These sensors can measure water levels, flow rates, rainfall, pressure, temperature, and other weather patterns that may lead to flooding. The data collected by IoT sensors can be transmitted in real-time to a GPU-based software platform. It can be analyzed using deep learning analytics to forecast future flood events. LoRaWAN IoT networks typically consist of gateways that receive radiofrequency signals from end-sensor devices and forward them to a central network server. The network server then processes the data and makes it available to an application server to perform analytics, generate reports, or trigger actions based on the data.

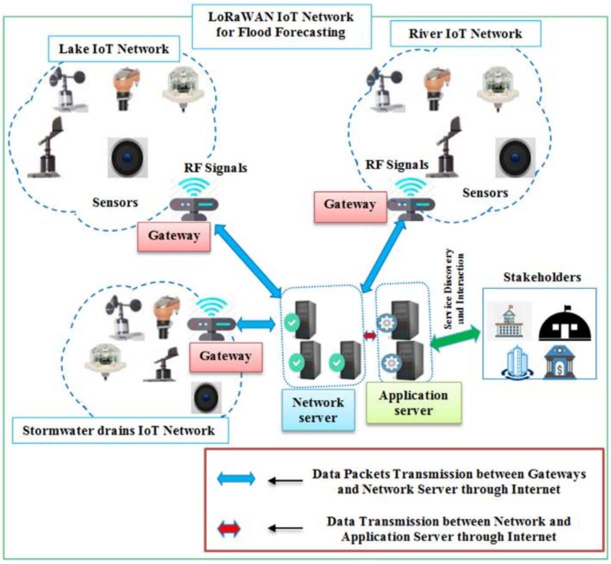

Figure 1 **Lorawan IoT Network for Flood Forecasting**

Figure 1 illustrates the LoRaWAN IoT network proposed for flood remote monitoring and forecasting. This systematic network captures hydrological data and weather factors. In this network, we use ultrasonic level gauge sensors, rain gauge sensors, wind speed and direction sensors, humidity, temperature, pressure, and other required sensors in flood-prone areas such as lakes, rivers, drainages, etc., to capture and send weather and hydrological data to the gateways. The outdoor LoRaWAN gateways are placed at the appropriate distance between end sensors and IoT network

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servers for reliable data transmission. The gateway receives RF packets that the sensors send and forwards the same to a network server through the internet. As shown in Figure 2, the network server identifies the sensor node and communicates through security and network management parameters. After successful authentication, the end devices send data to the application server. The application server filters duplicate packets and perform the necessary error detection and correction mechanism. The security and network management parameters are sensor ID, Name, DevEUI, JoinEUI, DevAddress, AppKey, and session information. DevAddress (Device address) is the unique address assigned to the sensor nodes. The end device's manufacturer sets the DevEUI. JoinEUI is awarded to the application server.

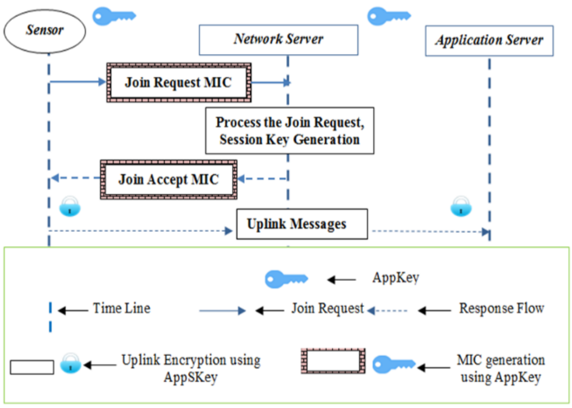

Figure 2 Lorawan IoT Network Security

The main goal of the network session key (NwkSKey) is to prevent message tampering. Payload data encryption and decryption will be performed using the application session key (AppSKey). AppSKey and NwkSKey are unique throughout the session. SNwkSIntKey guarantees the integrity of data for both uplink and downlink. The uplink and downlink payload is encrypted and decrypted with NwkSEncKey. Middle of Figure 1 is the Things Mate platform [19] to manage all the LoRaWAN end devices, gateways, network servers, and applications through secure routing. Things Mate supports all kinds of LoRaWAN versions. In the Things Mate-based application dashboard, the user has a high degree of customization, like adding and removing widgets and other entities. It also provides data visualization features like bar charts, line charts, pie charts, etc. The sensor values are stored in .csv and .xlsx formats for analysis purposes. Hyper-heuristic-based ConvED-GRUAT artificial intelligence analytics is used for satellite imagery pattern identification, data inference, early flood detection, and prevention. Figure 3 presents the outline of the proposed hyper-heuristic-based ConvED-GRUAT model. Hyper-heuristic-based ConvED-GRUAT deep learning has been used to develop a model for flood detection, which can help to mitigate the effects of floods and improve emergency response [20].

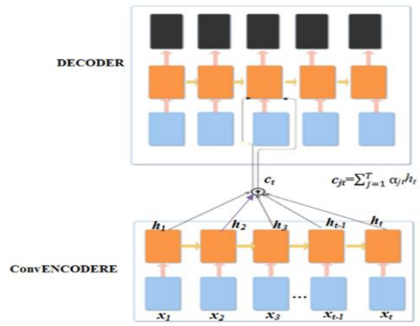

Figure 3 Conved-Gruat Deep Learning Model

One approach is to use remote sensing data, such as satellite imagery, to monitor changes in water levels and identify areas at risk of flooding. The proposed model is trained to analyze this data and identify patterns indicative of flooding. For example, the model may look for changes in water level over time. Another approach is to use sensors placed in flood-prone areas to monitor water levels and other environmental factors. The convED-GRUAT model presented in Figure 3 is trained to analyze the data from these sensors and detect changes indicative of flooding. For example, the model may look for rapid changes in water level or changes in the conductivity of the water. The proposed model also trained on historical flood data to identify patterns and make predictions about the likely impacts of a current flood event.

4. Case Study

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NVIDIA Jetson is a family of embedded boards designed for AI and edge computing applications. These small form factor boards feature powerful NVIDIA GPUs and are optimized for running deep learning models and other AI workloads. NVIDIA Jetson boards are well-suited for image analytics and computer vision applications due to their powerful GPUs and optimized software libraries. Jetson boards can be used to perform a variety of image analytics and big data inferences. The JetPack SDK includes several software packages that are specifically designed for image analytics, such as NVIDIA TensorRT, cuDNN, and OpenCV. These libraries provide optimized performance for the proposed deep learning model and enable them to accelerate their image analytics workloads on the Jetson platform. Jetson boards can also be used for past flood satellite imagery segmentation, which involves dividing an image into regions based on its content. Hence, NVIDIA Jetson boards provide a powerful and efficient platform for performing imagery and sensor-measured data analytics.

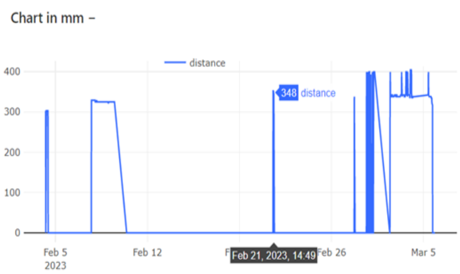

Figure 4 Ultrasonic Sensor Water Level

IoT Enabled Smart Ultrasonic Sensor - lst25406025 water level measurement from 5th February 2023 to 5th March 2023 is illustrated in Figure 4. The corresponding RSSI, SNR, and SF values are depicted in Figures 5, 6, and 7, respectively. Wind direction and speed indicated in Figures 8 and 9 are measured using a WSS-02 sensor. LHT65S sensor is used to measure atmospheric pressure, temperature, and humidity, as presented in Figures 10 and 11, respectively.

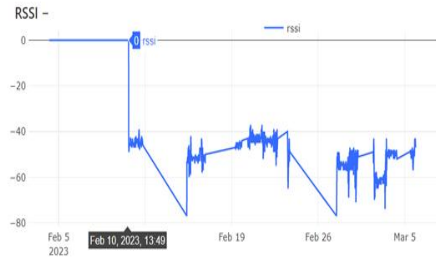

Figure 5 Ultrasonic Sensor RSSI

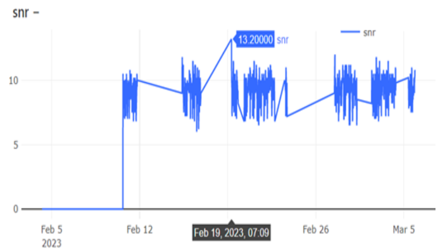

Figure 6 Ultrasonic Sensor SNR

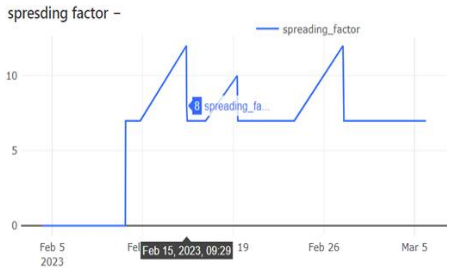

Figure 7 Ultrasonic Sensor Spreading Factor

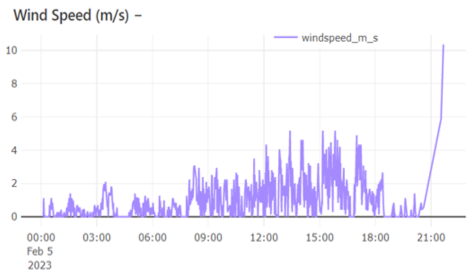

Figure 8 WSS-02 Sensor Wind Speed

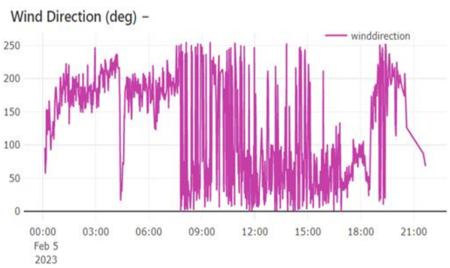

Figure 9 WSS-02 Sensor Wind Direction

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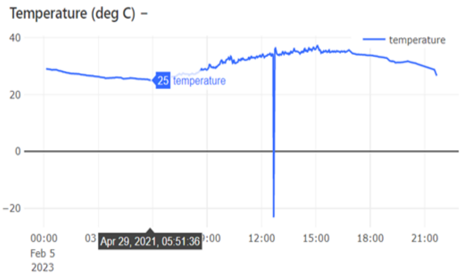

Figure 10 **LHT65S Sensor Temperature**

Figure 11 **LHT65S Sensor Humidity**

Conclusion

This research presented a LoRaWAN IoT network to capture cyclone-induced hydrological and weather parameters. IoT sensors are installed to measure water level, atmosphere pressure, temperature, humidity, and other weather parameters that may lead to flooding on urban road networks. We have accurately forecasted future floods using a hyper-heuristic-based ED-GRU with a soft attention mechanism. The proposed artificial intelligence analytics is trained based on historical and sensor-measured data. Prediction accuracy is improved by paying appropriate attention to hydrological and weather parameter thresholds. Radiofrequency channel RSSI, SNR, CR, and SF parameters are considered to guarantee LoRaWAN quality of service. In the future, we will propose a proactive vehicle rerouting approach to analyze the distance, future traffic load, number of intersections, flood-prone areas, air quality, and travel times on k-shortest paths.

Declarations

Conflicts of Interest The authors declare that they have no conflicts of interest.

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