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Real-Time Landslide Detection Through Edge AI Solution

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Abstract— Outlines an innovative approach that harnesses the power of edge computing and AI to enhance the efficiency and accuracy of landslide detection. This system deploys a network of edge devices equipped with accelerometer sensor to continuously monitor environmental conditions such as soil moisture, seismic activity, and atmospheric parameters in real-time. By processing data locally on these edge devices, the system significantly reduces the latency typically associated with cloud-based solutions, enabling immediate analysis and rapid response to potential landslide threats. Advanced AI algorithms are utilized to analyzed data and identify early warning signs of landslides and providing timely alerts that can facilitate preventive measures and emergency response. This approach not only ensures a high level of data security and reduces bandwidth. The integration of Edge AI in landslide detection represents a significant advancement in natural disaster monitoring, offering a scalable and effective solution to mitigate the impacts of landslides and enhance community safety.

Index Terms- Edge AI computing, STM32CubeIDE, Nano Edge AI, Anamoly classification, Motion detection.

I. INTRODUCTION

Detecting landslides using Edge AI involves a transformative approach that combines the power of edge computing and artificial intelligence to create a real-time, efficient, and scalable landslide monitoring system. This method utilizes an accelerometer sensor strategically placed in landslide-prone areas to collect critical environmental data such as soil moisture, ground movement, and weather conditions. This sensor is connected to edge devices that process data locally, significantly reducing the need for data transmission to central servers. By harnessing advanced AI algorithms on these edge devices, the system can analyze data on-site to detect patterns and anomalies indicative of potential landslides. This local processing capability enables immediate analysis, leading to timely detection and early warning alerts without the delays associated with traditional centralized systems, thereby enabling real-time analysis and rapid detection of potential landslide events. The use of AI algorithms trained on extensive datasets in NANO EDGE AI enhances the system's ability to accurately predict and identify early warning signs of landslides, facilitating timely alerts and responses. This method utilizes an accelerometer sensor strategically placed in landslide-prone areas to collect critical environmental data such as soil moisture, ground movement, and weather conditions. This sensor are connected to edge devices as STM32 NUCLEO L476RG board that process data locally, significantly reducing the need for data transmission to central servers The system can analyze data on-site to detect patterns and anomalies indicative of potential landslides This approach not only improves the accuracy and efficiency of landslide detection but also offers scalability and flexibility for deployment in remote or difficult-to-access areas. The integration of Nano Edge AI into landslide detection systems represents a significant advancement in disaster prevention, offering a proactive solution to mitigate the impacts of such natural hazard.

Moreover, it provides a flexible and scalable solution that can be adapted to various geographic locations and environmental conditions, ensuring comprehensive coverage and continuous monitoring even the most remote areas. By offering rapid, accurate, and localized landslide detection, Edge AI technology significantly improves disaster management and response, ultimately contributing to better risk management and community safety.

II. LITERATURE SURVEY

An automated approach for tracking and detecting landside conditions was suggested by the early warning and monitoring system. A motion sensor serves as a barrier to identify movement and criminal activity. There are two security systems using motion sensors in this project. The first security system stage operates outdoors, with a sensor that detects motion and lights up a lightbulb. A user-controlled alarm call is sent by an indoor second-stage security system when a motion sensor detects it [1]. This activates the GSM's dial speed key. An alarm system's ability to detect intrusions accurately and effectively is now essential due to the increasing frequency and prevalence of burglaries. In this study, the suggested approach is applied to sensitive and hidden locations that require a reliable human motion-detection-based surveillance system. The method can safeguard libraries with rare historical books and institutions with important historical artifacts. For the safety of banks, the security alert system is extremely crucial. The system leverages AForge.NET to facilitate motion detection using a two-frame difference technique and a straightforward backdrop modeling algorithm. The system uses YOLO to analyze the frames of motion whenever it detects motion and determines whether the motion is human. When it detects human movement, the security alert system triggers the notifications, such as sending [2]. Considering that it can be utilized to improve home security systems that currently exist, such as motion sensor lighting and indoor and outdoor security cameras, motion detection has emerged as one of the most crucial aspects. Artificial intelligence-powered motion detection systems are essential for enhancing the security of our homes, offices, and public spaces. We are working on a project to detect motion that will support the current home security system while taking this into consideration. To accomplish our aim, we will use the open CV module. A scene's background is subtracted, leaving the foreground as the frame under analysis. Consequently, we have a backdrop from which the distinct frames are being subtracted [3]. Since smartphones are the most popular smart device, they can serve as security alert systems. Recently, there has also been a notable surge in the adoption of smart IoT devices with AI embedded into them. We created a smart IoT security solution for smart homes in this study. Where in a NoIR Pi Camera Module is used to record videos and take pictures, and a Raspberry Pi serves as a security system. Motion is also detected using a Passive Infrared (PIR) Motion Sensor. Our created method will be used with a face recognition classification technique to predict a security danger based on motion sensor data and images captured by the NoIR Pi Camera Module. With of 91% and accuracy of 95.5%, the suggested system is capable of identifying any security threat [4]. An essential requirement due to the increasing frequency and prevalence of burglaries is an effective and reliable intrusion detection system coupled with an alarm system. There are more and more attacks on houses, workplaces, companies, banks, etc. Motion can now be identified thanks to technological advancements by calculating changes in an object's speed or vector inside the field of view. Electronic devices that quantify and measure changes in the specified environment, or mechanical devices that directly interact with the field, can do this. A home automation system, an energy-efficient system, and other systems are just a few of the numerous uses for motion detectors outside of intruder alarms. An embedded microcontroller system with motion detection capabilities is used in the construction of this setup. In order to detect movements of an intruder in a restricted area and activate an alarm or motion detector system, an embedded microcontroller system was used in the construction of this project. Nevertheless, a passive infrared sensor used the body heat of the subject to detect motion. The project's motion detector, a passive infrared (PIR) sensor, is connected to a microcontroller, which notifies the homeowner by turning on the alarm system and any other connected output devices. According to preliminary testing, the design functioned as anticipated [5].

III. SOFTWARE REUIREMENTS

- STM32 CUBEIDE

With peripheral configuration, code generation, code compilation, and debugging tools for STM32 microcontrollers and microprocessors, STM32CubeIDE is a powerful C/C++ development platform. STM32CubeIDE offers an all-in-one tool experience and reduces installation and development time by integrating STM32 configuration and project creation features with STM32CubeMX

- NANO EDGE AI STUDIO

Nano Edge AI Studio, also called the Studio, is a PC-based push-button development studio for developers. One of its significant advantages is that Nano Edge AI Studio requires no advanced data science skills. Any software developer using the Studio can create optimal tiny ML libraries from its user-friendly environment with no artificial intelligence (AI) skills. Anomaly detection, outlier detection, classification, and regression libraries are the four types of libraries that the Studio can produce.

IV. PROPOSED WORK

The proposed work for detecting landslides using Edge AI focuses on developing a comprehensive system that integrates edge computing and artificial intelligence to provide real-time, accurate, and efficient landslide monitoring. The system will be designed to operate with a network of accelerometer sensor installed in landslide-prone areas to continuously collect data on critical environmental factors such as soil moisture, slope stability, ground vibrations, and weather conditions. This sensors will transmit data to edge devices equipped with AI models capable of processing and analyzing the information locally, thus ensuring immediate detection of anomalies that may indicate an impending landslide. The edge devices will utilize advanced machine learning algorithms trained on historical and real-time data to identify patterns and predict potential landslide occurrences.

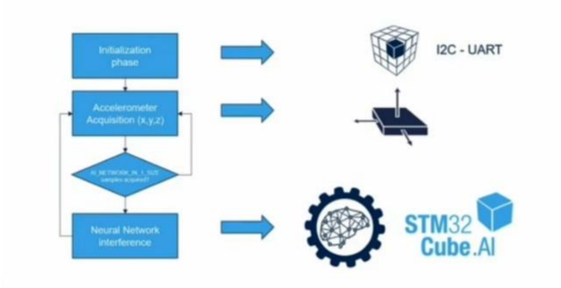

Fig 1: overview of proposed system

BLOCK DIAGRAM OF LANDSLIDE DETECTION

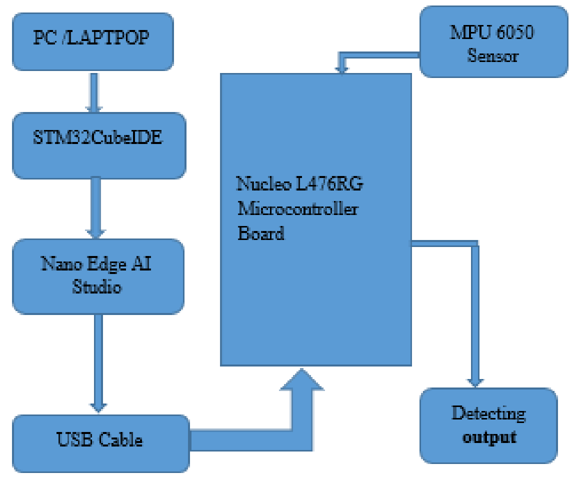

Fig 2: The block diagram of Landslide detection

V. WORKING OF PROPOSED SYSTEM

In this proposed system, the generated code in the STM32cubelDE is fetch to the Nucleo-1476RG microcontroller board using the USB cable which interface the STM32cubelDE, I^2C and accelerometer sensor. Connections are made in the board, as given below in the pin circuit. Next, generate the code for the motion detection, debug the code and console it to the board. When, disturbances are generated, it starts to obtain the abnormal signals and it observe the signals and analyze the waves based on the trained model. The motion data is trained in the NANO EDGE software tool then the model is calibrated using the benchmark for more accuracy. It shows the score of the model based on the accuracy level, whether it is RF, SVM or MLP model. The NANO EDGE Al shows the graph of the trained model and the signal is added and validated. In the emulator part, the detection of the data is made which is accurately matches the data trained finally in the STM32cubelDE tool shows the output the console part and it gives.

Initial Setup: The system is installed in the desired location with sensors positioned for optimal coverage. The MPU 6050 sensor is configured with the necessary AI models.

Motion Detection: The MPU 6050 sensor detects a change in infrared radiation and sends a signal to the Nucleo L476RG.Simultaneously, the accelerometer sensor measures the distance change, and the radar sensor detects the movement speed.

Data Analysis: The Nucleo L476RG receives data from all sensors. Edge AI algorithms process the data, confirming the presence of a moving object and ruling out false positives like environmental changes.

Local Action and Alert: The system triggers an alarm and turns on a security light. A notification is sent to the user's mobile application, alerting them of detected motion.

Start the STM32CubeIDE, and create a new STM32 project: File > New > STM32 Project as shown in figure 3.

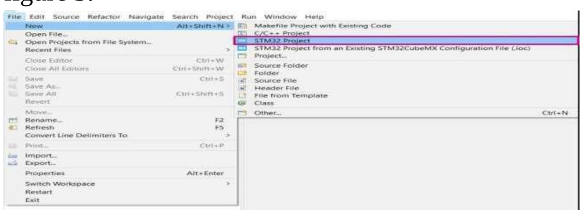

Fig 3: create a project

Select the board NUCLEO-L476RG.Configure the I2C bus interface as shown in figure 4.

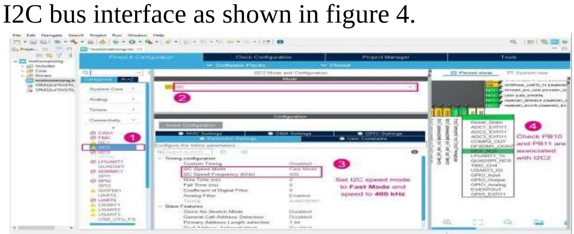

Fig 4: Configure the I2C

Under the GPIO settings tab, associate the D14 and D15 pins with the I2C interface as shown in figure 5.

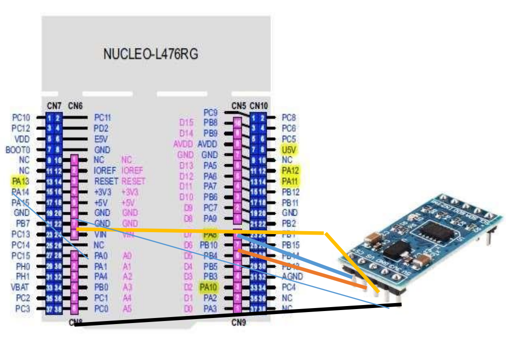

Fig 5: pin circuit of accelerometer sensor

Set up the communication interface for UART. Make the main.c code bootstrapped. Examine the accelerometer's data. Construct an STM32Cube.AI program utilizing X-CUBE-AI Put STM32Cube headers in there AI.

```
/* USER CODE BEGIN Header */
/**
  ******************************************
  ******************************************
  *******************
  * @file           : main.c
  * @brief          : Main program
body
  ******************************************
  ******************************************
  *******************
  * @attention
  *
  * Copyright (c) 2024
STMicroelectronics.
  * All rights reserved.
```

Fig 6: accelerometer code of main.c

We must train a dataset using Nano Edge AI in our suggested study. Click CREATE NEW PROJECT after choosing your preferred project type from the project creation column on the home screen. Project settings: to establish the overall project specifications signals, to import signals (both abnormal and regular) that are used to pick libraries. Optimize and Benchmark: To test the potential libraries prior to embedding them into the microcontroller, the best Nano Edge AI Library is automatically picked and optimized through an emulator. verification of the project benchmarks' overview (statistics, performance, flows).The best library will be compiled and downloaded during deployment, together with any necessary header files, so that the main.c code can link to it. Concatenating all signal instances is the general rule for anomaly identification, when everything is functioning as expected as shown in figure 7.

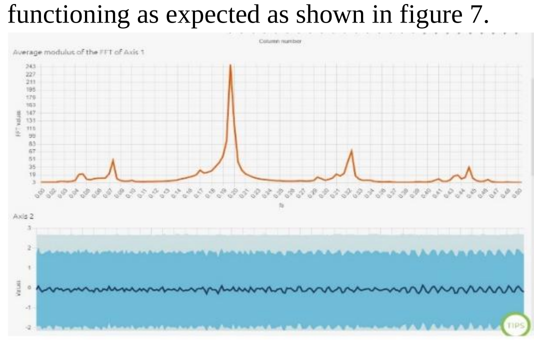

Fig 7: Regular signals

According to data collected by sensors during an anomaly period, the abnormal signals correlate to abnormal machine behavior. According to data collected by sensors during an anomaly period, the abnormal signals correlate to abnormal machine behavior as shown in figure 8.

Fig 8: Abnormal signals

Benchmark graph:
For further information, see the list of secondary indicators used to calculate the "Score" below. In an analysis during the benchmark, all libraries are ranked according to a single primary performance indicator known as "Score." A graph displays the position of imported signals (data points) in real time, as seen in figure 9. Numerous data collectors are dealt with by it. With a 97.45% score.

Fig 9: Benchmark score

VI. RESULTS AND DISCUSSION

Using a hardware floating-point unit, Nano Edge AI Studio enables the estimation of execution time for every library encountered throughout the test using the STM32F411 simulator from ARM. The estimate is derived from averaging several calls to the tested Nano Edge AI library functions. Instead of using user data directly, the tool estimates using data from a comparable range. Although this estimate approximates actual hardware circumstances, it should be regarded as such, and differences in the precise signal may affect execution time. Remember that switching to a different piece of hardware may result in noticeable variations in execution time.

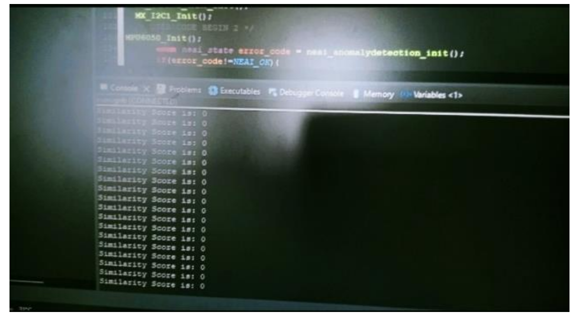

Fig 10: Output of empty space

Normal signals during lack of distraction in environment as shown in figure 10. The AI algorithms trained on datasets in NANO EDGE AI enhances the system's ability to accurately predict and identify early warning signs of landslides, facilitating timely alerts and responses as shown in figure 11.

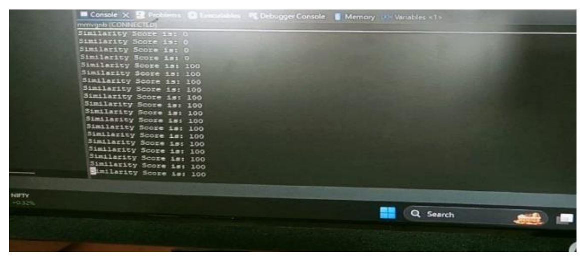

Fig 11: Output of landslide detection

CONCLUSION

Monitoring and responding to natural disasters has changed dramatically with the introduction of Edge AI for real-time landslide detection. This approach eliminates the latency issues that come with conventional cloud-based systems by utilizing local data processing and a network of edge devices that are equipped with accelerometers. Advanced artificial intelligence algorithms in conjunction with real-time monitoring of soil moisture, seismic activity, and climatic conditions allow for the early detection of probable landslides and prompt alerting. As a result, community safety and perseverance are greatly increased. This also increases detection accuracy and guarantees prompt action and efficient preventive actions. Edge AI is positioned as a critical development in reducing the effects of landslides and protecting susceptible areas, and its emphasis on data security and low bandwidth use highlights the system's usefulness and scalability.

FUTURE WORK

Future work will also emphasize the development of more energy-efficient and robust edge devices that can operate autonomously in extreme conditions and require minimal maintenance. Enhancing the data fusion capabilities to integrate information from various sources, such as UAVs (drones) and IoT devices, will provide a more holistic view of potential landslide risks. Furthermore, efforts will be directed toward improving the real-time data processing capabilities of edge devices to support more complex analytical tasks and decision-making processes at the edge.

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