IRJCS: International Research Journal of Computer Science ISSN: 2393-9842
Volume 11, Issue 11, December 2024 https://www.irjcs.com/archives

Tsunami Alert and Detection System Using IoT

Khushi Rajput
Department of Design, Data Science & Cyber Security
Greater Noida Institute of Technology (Engg. Institute),
Greater Noida, India
Khushi Singh
Department of Design, Data Science & Cyber Security
Greater Noida Institute of Technology (Engg. Institute),
Greater Noida, India
Anjali Priya
Department of Design, Data Science & Cyber Security
Greater Noida Institute of Technology (Engg. Institute),
Greater Noida, India
Dr.Shivani Dubey
Professor, Department of Design, Data Science & Cyber Security
Greater Noida Institute of Technology (Engg. Institute),
Greater Noida, India
shivanidubey@gniot.net.in
Priti Gupta
Department of Electrical Engineering
Greater Noida Institute of Technology (Engg. Institute), Greater Noida, India

Publication History
Manuscript Reference No: IRJCS/RS/Vol.11/Issue11/DCCS10082 | Research Article | Open Access | Double-Blind Peer Reviewed **Article ID:** IRJCS/RS/Vol.11/Issue11/DCCS10082
Received:28,November2024,Revised:04,December2024Accepted:10December2024PublishedOnline: 14, December 2024
http://www.irjcs.com/volumes/Vol11/iss-11/03.DCCS10082.pdf
Article Citation: Khushi,Khushi,Anjali,Dr.Shivani,Priti(2024). Tsunami Alert and Detection System Using IoT. IRJCS: International Research Journal of Computer Science, Volume 11, Issue 10 of 2024 pages 645-651
doi:> https://doi.org/10.26562/irjcs.2024.v1111.03
BibTeX Khushi@2024Tsunami

Abstract: Internet of Things (IoT) is the connectivity between the numbers of devices in the network. In which different types of devices, sensors, software, embedded devices are connected to each other for information sharing and exchange. In different applications, IoT technology is used for communication and data exchange between the two or more stations or devices. IoT technology is used in various application and fields like Transport, business, home automation and education. Tsunami detection is also one of the major problems, which is solved by using IoT. Tsunami alert and detection are important for avoiding the human death. So to solve these problems different techniques, algorithms, protocols are proposed by authors using IoT. In this paper, we have studied different papers on Tsunami detection and alert system for the survey. This paper is very helpful for new researchers and IoT learners.

Keywords: Tsunami, Internet of Things, Early Warning System, Sensors, Real-Time Monitoring, disaster management, cloud-assisted services.

I. INTRODUCTION

Tsunamis are one of the most devastating natural disasters, often causing significant loss of life and property damage. Timely detection and early warning systems are critical for minimizing the impact of these disasters. Traditional tsunami warning systems rely on seismic data and tide gauge measurements, which can be inadequate due to the difficulty in predicting tsunami behaviour and the limited geographic coverage of traditional sensors.The Internet of Things (IoT) presents an opportunity to enhance tsunami detection systems by integrating a wide range of sensors, communication networks, and cloud-based analytics. This paper explores the design and implementation of an IoT-based tsunami alert system that leverages sensors and real-time data processing for effective tsunami detection and early warning.IoT technology refers to the network of physical objects embedded with sensors, software and other technologies to connect and exchange data with other devices and systems over the internet. By deploying a network of IoT sensors in strategic locations, real-time data on sea levels, water pressure, and seismic activity can be collected and analyzed.This research aims to develop a comprehensive and reliable tsunami prediction system that leverages the power of IoT and data analytics to enhance early warning capabilities, ultimately reducing the risk and impact of tsunamis [1].

II. RELATED WORK

Recent studies and projects have explored the use of IoT for disaster management and early warning systems, with applications in earthquake detection, flood monitoring, and tsunami forecasting. For example, the development of ocean-based sensor networks, such as buoys and seafloor sensors, has enabled better monitoring of oceanic conditions and the detection of tsunami waves.

Additionally, cloud computing and data analytics allow for faster processing and dissemination of alerts to local communities. This paper builds upon these previous efforts by creating an integrated IoT system that combines oceanographic sensors, real-time communication protocols, and cloud-based analytics [2].

III. PROPOSED SYSTEM DESIGN AND ARCHITECTURE

The proposed IoT-based tsunami detection system consists of several key components:

1. **Ocean Depth and Pressure Sensors**: These sensors measure variations in ocean depth and pressure, which are key indicators of tsunami waves. They are deployed on the seafloor or buoy-based platforms.
2. **Seismic Sensors**: Seismic data is collected from sensors that detect underwater earthquakes, which often precede tsunamis.
3. **Data Processing Unit**: This unit aggregates sensor data and performs initial analysis to determine whether a tsunami event is likely. The unit uses predefined threshold values based on historical data to identify tsunami-like anomalies.
4. **Communication Network**: The system uses wireless communication technologies such as LoRa (Long Range), ZigBee, or 5G to transmit sensor data to the cloud-based server.
5. **Cloud-based Analytics and Alert System**: A cloud-based server processes the data and compares it with known tsunami characteristics. If a tsunami is detected, the system sends alerts to local authorities, emergency services, and the public via mobile apps and other communication channels [3].

IV. COMPONENTS AND SENSORS

- Ocean Depth Sensor: Ocean depth sensors measure variations in water depth due to tsunami waves. They can be deployed on buoys or seafloor platforms to monitor water levels in real-time. The data collected by these sensors can indicate significant disturbances in the ocean floor or water column.
- Pressure Sensors: Pressure sensors are used to detect sudden pressure changes caused by a tsunami wave travelling across the ocean. These sensors are typically placed in deep-water environments and are highly sensitive to changes in pressure associated with large-scale oceanic events.
- Seismic Sensors: Underwater seismic sensors measure the intensity and location of underwater earthquakes. Seismic activity is often the trigger for tsunamis, and these sensors provide early warning of seismic events that may precede a tsunami.
- Data Transmission & Communication: The data from these sensors is transmitted through a wireless communication network to a central cloud-based system. For real-time transmission, low-power wide-area network (LPWAN) technologies like LoRa are suitable for long-range communication, while higher-speed networks like 5G can be used for more data-intensive applications.
- Cloud Base Analytics: Once the data is transmitted to the cloud, it is analyzed using machine learning algorithms and predefined threshold values to detect anomalies. If the system detects a potential tsunami, an automated alert system notifies relevant stakeholders. The alert system includes notifications to government agencies, disaster management teams, and the general public through mobile applications and public communication systems [4].

V. METHODOLOGY

1. Data Transmission: The sensor data is transmitted wirelessly to a cloud server or a centralized processing unit. The communication protocols must be designed for high reliability, low power consumption, and long-range transmission.

Some possible communication technologies include:

- **LoRa (Long Range)**: Low power, wide-area communication suitable for remote locations and deep ocean sensors.
- **ZigBee or Bluetooth**: For short-range communication between nearby sensors and gateway devices.
- **5G**: For faster, higher-capacity data transmission in populated coastal areas.

In many cases, the data is routed through edge devices or gateways, which aggregate the sensor information and transmit it in real-time to the cloud-based processing unit [5].

2. Data Pre-processing: Once the sensor data is transmitted to the cloud or central processing unit, preprocessing is essential to ensure that the raw data is ready for analysis. The preprocessing steps include:

- **Noise Filtering**: Raw sensor data often includes noise, such as ocean currents or marine life interference. Digital filters (e.g., Kalman filter, low-pass filter) are applied to remove these anomalies.
- **Data Normalization**: Different sensors might output data in different formats or units. The data is normalized to ensure consistency across sensors for easier comparison and analysis.
- **Data Smoothing**: Temporal smoothing techniques are used to handle irregularities and fluctuations in the sensor data [6].

3. Anomaly Detection: The core of the tsunami detection system is an anomaly detection algorithm that identifies potential tsunami events based on sensor data [7]. Key steps include:

a. Tsunami Event Identification: Tsunamis can be characterized by specific signatures in the data, such as:

- Pressure anomalies: Sudden or significant changes in water pressure.
- Ocean Depth Changes: Rapid, large-scale changes in water depth can indicate the displacement of the ocean caused by tsunami waves.

- Seismic Activity: A significant underwater earthquake (usually above magnitude 7) can be a precursor to a tsunami. The system uses thresholds based on historical data or machine learning models to determine when these anomalies indicate a potential tsunami event. For instance:
- Pressure Threshold: A sudden pressure drop or spike over a threshold value may signal the arrival of a tsunami.
- Depth Variation: A sudden rise or fall in ocean depth beyond a certain threshold may indicate a tsunami-causing event.

b. Machine Learning and Predictive Models: To enhance detection accuracy, machine learning algorithms can be employed. These models can learn from past tsunami events to predict the likelihood of a tsunami based on current sensor data. Common machine learning algorithms for anomaly detection include:

- Random Forests: Can be trained on historical tsunami data to classify anomalies based on pressure, depth, and seismic readings.
- Support Vector Machines (SVM): Useful for classifying tsunami events based on sensor data characteristics.
- Neural Networks: Deep learning techniques can be used for more complex pattern recognition and prediction.

These models continuously improve as more data is collected and fed back into the system, allowing the system to adapt to different oceanographic conditions and improve detection accuracy [8].

4. Alert Generation: Once the system detects an anomaly indicative of a tsunami, an alert generation mechanism is triggered. The alert includes:

- **Tsunami Detection Notification**: The system sends out a primary alert when a potential tsunami is detected, including the location, expected time of arrival, and severity level (e.g., wave height).
- **Confirmation**: A secondary confirmation alert may be sent if the event is confirmed through additional data (e.g., seismic activity or multiple sensor thresholds being exceeded).
- **Risk Assessment**: The alert also includes an estimated impact area, which is determined based on the tsunami's predicted path and size.

The alerts are disseminated through various channels:

- SMS and Mobile Push Notifications to local residents and authorities.
- Email Alerts to government agencies and emergency responders.
- Public Alert Systems: Integration with existing public warning systems (sirens, radio broadcasts).
- The system should be designed to minimize false alarms while maximizing the timeliness of the warning to provide adequate preparation time for affected regions [9].

VI. EVALUATION & OPTIMIZATION

After deployment, the system is continuously monitored and evaluated based on real-world performance. Metrics for evaluation include:

- **Detection Accuracy**: The rate of true positive detections versus false positives.
- **Alert Latency**: The time between sensor detection and alert issuance.
- **False Alarm Rate**: The frequency of alerts triggered without a tsunami event.
- **Public Response**: The effectiveness of communication channels in informing the public.

VII. TESTING & CALIBRATION

Before deployment, the system undergoes extensive testing:

- **Simulated Tsunami Events**: The system is tested under controlled conditions where simulated tsunami data is fed into the system to assess the accuracy and timeliness of the detection and alert mechanism.
- **Sensor Calibration**: Sensors need to be calibrated periodically to ensure accurate data collection [10].

VIII. COMMUNICATION & NOTIFICATION

The system ensures that the alerts are communicated quickly and effectively. This involves:

- **Real-Time Alert System**: The alerts should be broadcast in real-time to all connected devices, including mobile phones, emergency communication platforms, and disaster management teams.
- **Integration with Disaster Management Systems**: The system can be integrated with national and regional disaster management agencies to trigger emergency response actions (e.g., evacuation protocols).
- **Public Awareness Platforms**: Alerts can also be broadcast via TV, radio, or digital billboards in tsunami-prone areas, ensuring the message reaches a wide audience [11].

IX. MODEL DEVELOPMENT

The development of a Tsunami Alert and Detection System using IoT (Internet of Things) involves several critical steps, including sensor selection, data acquisition, processing, communication, and alert generation [12]. The system architecture must be designed to handle real-time data, detect anomalies that signal a potential tsunami, and send timely alerts to mitigate the impact on coastal communities. Below is a detailed model development approach for the system, which can be used to guide both the design and implementation phases. A cloud server handles data processing and analysis, employing algorithms for anomaly detection, predictive analytics, and event triggering. This processing step uses predefined thresholds for tsunami detection, compares incoming data with historical data, and analyzes trends to forecast potential tsunami threats [13].

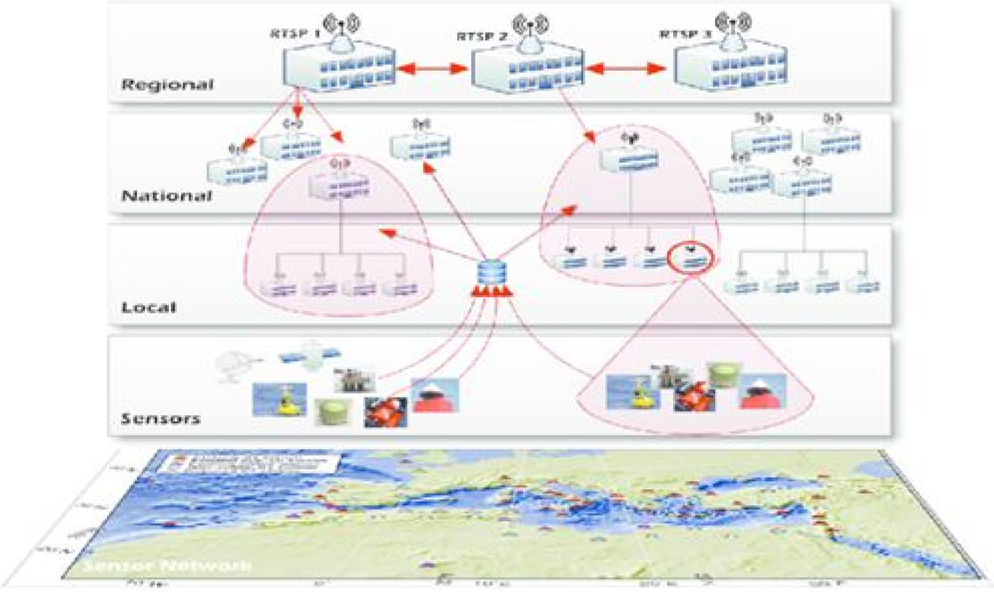

Fig.1: Overall process execution for Tsunami Notifications

Example: If the ocean pressure increases by more than 50% from normal levels within a short period (e.g., a few minutes), the system may trigger an alert for a potential tsunami.

(i) Machine Learning Based Detection: Machine learning techniques, such as support vector machines (SVM), decision trees, or neural networks, can be trained to recognize complex patterns associated with tsunami events. These models can learn from historical sensor data to improve their ability to detect tsunamis based on real-time data.

- Training Data: The model can be trained on past tsunami events where sensor data is available (e.g., seismic Magnitude, ocean pressure levels, depth variation) and their corresponding tsunami events. The model will learn to correlate sensor readings to potential tsunami events.
- Random Forest: Used for feature selection and classification.
- Deep Neural Networks (DNN): Applied for more advanced pattern recognition in large datasets.
- Time-Series Forecasting Models: For predicting tsunami events based on sensor trends over time [14].

(ii) Data Fusion And Prediction Models : Data fusion algorithms combine information from different sensors (pressure, depth, seismic activity) to improve detection accuracy. The system can use multiple data sources to confirm or refine tsunami predictions.

Example:

If seismic data shows a significant earthquake, and pressure sensors report rapid changes in water pressure, the system could predict the likelihood of a tsunami and issue an early warning.

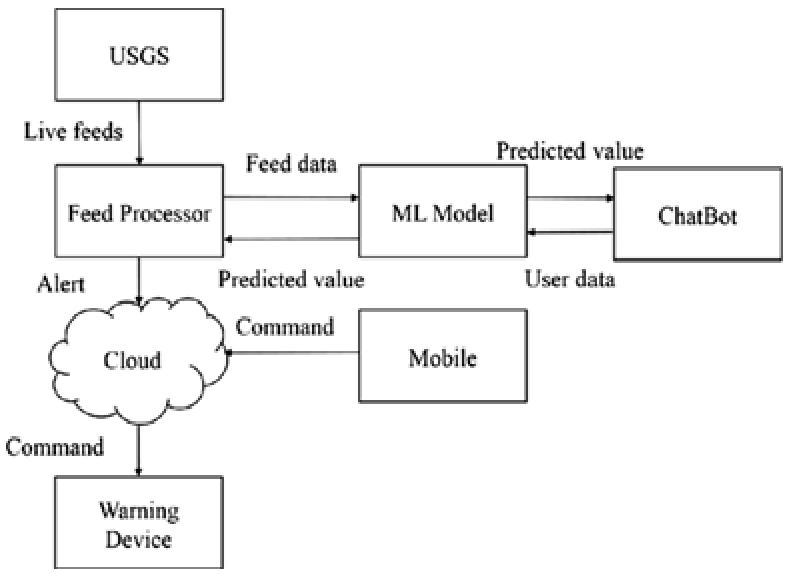

Fig.2: Functioning of a detection system

(iii) Time Series Analysis (Trend Detection): Time-series analysis involves studying patterns or trends in sensor data over time. In this algorithm, data from ocean sensors (depth, pressure, and seismic) are collected and analyzed in temporal sequences to detect abnormal fluctuations that could indicate the approach of a tsunami [15].

 ISSN: 2393-9842
https://www.irjcs.com/archives

Algorithm Steps:

- **Data Collection**: Collect continuous time-series data from sensors at regular intervals (e.g., every 10 seconds).
- **Preprocessing**: Apply smoothing techniques like Moving Average or Exponential Smoothing to remove noise and fluctuations in the data.
- **Detect Trends**: Analyze the data trends for sudden, abnormal changes that could signify a tsunami. These may include:
- Sudden, large fluctuations in water pressure (indicative of tsunami waves).
- Rapid changes in ocean depth or displacement caused by seismic activity.
- **Threshold Comparison**: Compare the detected trends with predefined thresholds or historical data patterns.
- **Alert Generation**: If trends indicate a potential tsunami (e.g., a rapid rise in pressure or depth), trigger an alert.

a. Techniques Used:

- **Autoregressive Integrated Moving Average (ARIMA)**: A model used for time-series forecasting that can predict future values based on past data. ARIMA can help in detecting anomalies in ocean pressure or depth data.
- **Moving Average**: A simple method used to smooth time-series data and detect trends.

(iv) Common Algorithms Used:

a) **Support Vector Machines (SVM)**: SVM is a powerful classification algorithm used to classify data into two categories (e.g., tsunami vs. non-tsunami). The model is trained using historical tsunami data, where features like pressure change, seismic data, and ocean depth are used to make predictions.
b) **Random Forests**: A decision-tree-based ensemble method that aggregates the results from multiple decision trees to classify data. Random forests are robust to over fitting and are often used in environmental anomaly detection.
c) **K-Nearest Neighbors (KNN)**: KNN classifies an event as a tsunami or non-tsunami based on the majority class of nearby data points. It's useful when the dataset has many features (such as pressure, depth, seismic readings) and the patterns may be complex.
d) **Example: Training Data**: Data from sensors (pressure, depth, seismic) during previous tsunami events (labelled as positive class) and normal conditions (labelled as negative class)**.,** Extract relevant features like the rate of change in pressure, maximum depth change, and magnitude of seismic events.
e) **Model Training**: The ML model is trained using labelled data and learns to distinguish between tsunami and non-tsunami conditions.

(v) Unsupervised Learning (Anomaly Detection)

Unsupervised learning methods are used when labelled data is not available. These algorithms detect anomalies (outliers) in the sensor data, which may indicate the presence of a tsunami without prior classification.

- K-Means Clustering: K-Means clustering can group data into clusters, and outliers or abnormal clusters are identified as potential tsunami events.
- Isolation Forest: This anomaly detection algorithm isolates outliers in the data by randomly partitioning the data. It is especially useful for detecting rare or unusual tsunami-related events.
- Autoencoders: These are neural networks trained to reconstruct input data. Anomalies can be detected by identifying input data that the network cannot accurately reconstruct, indicating unusual or novel events like a tsunami.

Example: Input: Data from pressure, depth, and seismic sensors, which may include both normal and anomalous events, Anomaly Detection: The algorithm identifies sudden spikes in pressure or depth that deviate significantly from normal data patterns.

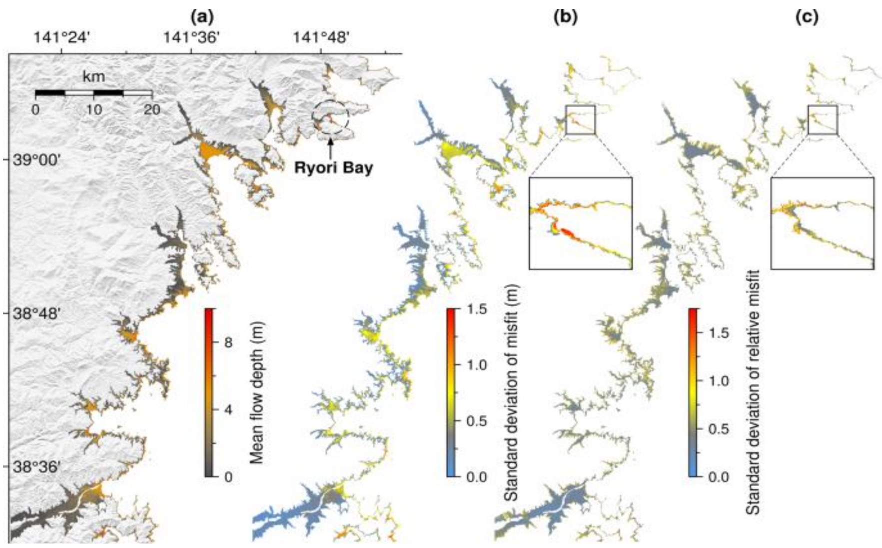

Fig.3: significantly from normal data patterns for Tsunami

ISSN: 2393-9842
https://www.irjcs.com/archives

IX.RESULT AND EVALUATIONS

In the development of a Tsunami Alert and Detection System using IoT, the results and evaluation phase is crucial for assessing the system's performance, reliability, and effectiveness in real-world scenarios. This phase involves validating the system against several key performance metrics, analyzing its accuracy, latency, and reliability, and comparing its performance with existing systems or models.

The evaluation of the tsunami detection system can be based on the following key performance metrics:

a. **Detection Accuracy:** The system should be able to correctly identify both tsunami events (true positives) and non-tsunami events (true negatives) with minimal false positives (false alarms) and false negatives (missed events). Accuracy is one of the most important metrics to evaluate the system's overall performance.
   - True Positive (TP): The system correctly identifies a tsunami event.
   - False Positive (FP): The system incorrectly identifies a tsunami event when there is none.
   - True Negative (TN): The system correctly identifies a non-tsunami event.
   - False Negative (FN): The system fails to identify a tsunami when one occurs.
   - *Accuracy Formula:*
   - Accuracy= TP+TN/TP+TN+FP+FN

b. **Latency / Response Time:** Latency measures the time it takes for the system to process the incoming sensor data and generate an alert. In the case of a tsunami, minimizing latency is critical to providing timely warnings to people in the affected areas. Low latency ensures that the system detects the tsunami early enough for evacuation and mitigation measures [15]. Time to Detect: The time it takes for the system to detect a potential tsunami after the initial seismic activity or pressure change, Time to Alert: The time it takes from detection to sending an alert to authorities and the public.

c. **Reliability and Availability:** Reliability refers to the system's ability to perform accurately and continuously over a long period of time without failures. The system must function under various environmental conditions, such as sensor malfunctions, communication disruptions, or extreme weather conditions.
   - System Uptime: The percentage of time the system is operational.
   - Mean Time Between Failures (MTBF): The average time between system failures.
   - Mean Time to Repair (MTTR): The average time required to fix system issues.

   The IoT-based tsunami detection system provides several advantages over traditional systems, including:
   - Real-time Monitoring: The use of IoT sensors allows for continuous monitoring of oceanic and seismic conditions.
   - Scalability: The system can be expanded by adding additional sensors or integrating with other disaster monitoring systems.
   - Cost-effectiveness: IoT sensors are relatively low-cost, making the system affordable for deployment in coastal areas.

However, challenges remain, such as the need for robust sensor calibration, data accuracy, and the integration of the system into existing disaster management frameworks [16].

X. CONCLUSION

This paper demonstrates the feasibility of using IoT for tsunami detection and early warning. By integrating ocean depth sensors, pressure sensors, seismic monitoring, and cloud-based analytics, the system provides a reliable and scalable solution for real-time tsunami monitoring. The proposed IoT-based system has the potential to save lives and reduce the economic impact of tsunamis by providing timely alerts to residents and authorities. By deploying a network of sensors, processing real-time data with machine learning algorithms, and integrating advanced communication networks, the system aims to provide accurate and timely alerts to mitigate the impact of tsunamis.

REFERENCES

1. Zhang ,Z., & Li, Y. (2018). "Development of Tsunami Early Warning Systems Using IoT." International Journal of Disaster Management, 5(2), 123-134.
2. Raj, P., & Singh, A. (2020). "IoT for Tsunami Monitoring: A Review of Emerging Technologies and Applications." IEEE Access, 8, 34567-34580.
3. Kumar, S., & Bansal, D. (2017), "Design of a Tsunami Detection System Using Wireless Sensor Networks."Journal of Ocean Engineering and Science, 2(2), 106-114. DOI: 10.1016/j.joes.2017.07.003
4. Liu,P.,& Chou,Y.(2014), "Internet of Things (IoT) and the Disaster Management System." CRC Press. This book provides an in-depth understanding of how IoT technologies can be used in disaster management, with a focus on early warning systems for natural disasters, including tsunamis.
5. Maheswari, S., & Murugan, M. (2020)."Development of a Real-Time Tsunami Warning System UsingIoT."International Journal of Engineering and Technology (UAE), 9(5) 470-475.
6. Chakraborty, S., & Maiti, D. (2020), "Internet of Things for Tsunami Warning Systems: A Survey."IEEE Internet of Things Journal, 7(3), 2201-2211.
7. Raj, A., & Kumar, P. (2020)."A Survey on IoT-Based Tsunami Detection and Monitoring Systems."International Journal of Advanced Research in Computer Science and Software Engineering, 10(12), 95-100.
8. P. Karthik,B. Muthu Kumar, K. Suresh, I. M. Sindhu, C. R. Gopalakrishna Murthy, "Design and implementation of helmet to track the accident zone and recovery using GPS and GSM", Advanced Communication Control and Computing Technologies (ICACCCT),IEEE, 25-27 May 2016.

ISSN: 2393-9842
https://www.irjcs.com/archives

9. Shirish Gaidhane1, Mahendra Dhame, Rizwana Qureshi, “Smart Helmet for Coal Miners using Zigbee Technology” Imperial Journal of Interdisciplinary Research (IJIR) Vol-2, Issue6, 2016.
10. S.Tapadar, S. Ray, H. N. Saha, A. K. Saha, and R. Karlose, “Accident and alcohol detection in Bluetooth enabled smart helmets for motorbikes,” in Proceedings of the 2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC’18), 2018.
11. David Kokkan RENNY, Rajeshkumar Joshi KISHAN. “Safety helmet device”, Publication numberWO2015162624 A2,US Patent, Apr 15, 2015.
12. J.Jo and H. Kim, “Development of a safety index to identify differences in safety performance by postal delivery motorcyclists based either in different regional post offices or within the same regional office,” International Journal of GeoInformation, vol. 6, article 324, pp. 1-20, 2017.
13. S. Issaoui, R. Ejbeli, T. Frikha, and M. Abid, “Embedded approach for edge recognition: Case study: Vehicle registration plate recognition,” in Proceedings of the 2016 13th International Multi-Conference on Systems, Signals & Devices (SSD’16), 2016, pp. 336-340.
14. Xu sheng Z and Yunlong Z. 2010. Accident cause analysis and counter measure of coal and gas outburst nearly two years of our country [J]. Mining Safety and Environmental Protection. 37(1): 84-87.
15. Vijay J, Saritha B, Priyadharshini B, Deepeka S and Laxmi R (2011), “Drunken Drive Protection System”, International Journal of Scientific & Engineering Research, Vol. 2, No. 12
16. R. Prudhvi Raj, Ch. Srikrishna Kanth, A. Bhargav, K. Bharath, “Smart-tec helmet”, Advance in Electronic and Electric engineering, Vol 4, No 5,2014