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AI-Based Boat Alert Monitoring System using RSSI Technology

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***Abstract*— The problem of cross-border movement of illegal vessels carried out by fishing boats creates a significant problem for coastal security, regional stability, and global relations. In this regard, existing alert systems based on GPS signals and geo-fencing have some limitations due to pre-set thresholds. In this study, a hybrid Edge AI-based maritime boundary monitoring system is proposed, where two interconnected devices based on ESP32 technology will be utilized: one for the boat, serving as a transmitter, and another for the shore, serving as a receiver, along with a centralized analysis and decision layer based on a PC. Within this system, the boat device will be utilized for prediction of vessel trajectory in real-time, signal strength data filtering, and intelligent zone classification based on lightweight machine learning approaches within TinyML technology. At the same time, the shore device will be utilized for anomaly detection, probability of violation calculation, and retraining deeper machine learning approaches. The proposed system demonstrates high accuracy in intelligent zone classification, reaching 94.2%, reducing noise levels by 28%, providing low latency of less than 50 ms, and an enhanced early warning system of up to 25 seconds.**

***Keywords* — Edge AI, ESP32, LoRa, RSSI Filtering, Maritime Monitoring, TinyML, Distributed Intelligence, Anomaly Detection**

I. INTRODUCTION

The problem of maritime boundary violation through small fishing vessels is a worldwide issue. The traditional approach to monitoring these vessels, utilizing GPS and geo-fencing, is no longer adequate. The problem with this traditional approach is that, although GPS and geo-fencing can indicate the positions of the vessels, these technologies are not predictive, and prediction is a necessity in modern times. Additionally, these technologies are heavily network-centric, and this slows down the system and does not allow for timely intelligence regarding the vessels [16], [17].

The recent developments in IoT technologies and the concept of Edge Computing introduce a new paradigm for computing, where intelligence is pushed to the sensor level itself [1], [8]. The concept of Edge Computing is to move computing closer to the sources of data, eliminating the need for a network and allowing for timely decision-making [2], [12]. The need for timely decision-making is important for an alert system that can prevent violation.

Additionally, with the advent of lightweight Artificial Intelligence (AI) models and their integration into microcontrollers using TinyML, it has now become possible to use various machine learning algorithms with constrained devices such as ESP32 [5], [20]. Low Power Wide Area Network (LPWAN) technologies, such as LoRa (Long Range communication), have been identified as suitable technologies for maritime communication, considering their higher transmission capabilities, low power consumption, and cost-effectiveness [3], [14], [15]. Nevertheless, various issues, including multipath fading, atmospheric disturbances, and attenuation, arise during maritime communication, affecting the stability of the Received Signal Strength Indicator (RSSI) values. The accuracy of distance measurement using RSSI values, in the absence of proper filtering, cannot be guaranteed; therefore, there is a need for intelligent modeling and noise reduction [18].

Most existing frameworks and technologies employed in maritime monitoring systems only consider centralized analytics or basic threshold-based alerting. These technologies have three major limitations: (a) no support for predictive trajectory analysis, (b) post-event detection, and (c) high cost. A hybrid distributed intelligence approach needs to be considered, where decision-making takes place both onboard and centrally, along with retraining of models [2], [12].

II. BACKGROUND AND RELATED WORK

Maritime monitoring and boundary enforcement have gained significant importance due to the increasing concerns about unauthorized fishing, vessel intrusion, and maritime security issues. Maritime nations use sophisticated monitoring technologies to monitor vessel movement and adhere to maritime regulations. The conventional monitoring techniques mostly use satellite-based position determination technologies, such as the Global Positioning System (GPS), to monitor vessel movement [16], [17]. Although GPS technology offers precise geolocation information, the monitoring techniques mostly use static geofencing techniques, which might cause latency in decision-making.

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The rapid advancement of Internet of Things (IoT) technologies has led to the deployment of distributed sensor networks that are capable of collecting information regarding the environment and positions [1], [8]. The IoT-based monitoring systems allow the wireless communication of devices that are equipped with sensor technologies. The IoT-based tracking system, for instance, can be deployed on fishing boats to collect information regarding the coordinates, signal strength, and movement patterns. The information can then be analyzed to detect any unusual movements and potential violation of boundaries [18].

Among the different wireless communication technologies available for IoT applications, LoRa (Long Range Communication) technology is found to be a potential technology for wireless communication [3], [14], [15]. LoRa is a Low Power Wide Area Network (LPWAN) technology that is designed to allow for wireless communication over a long distance while maintaining low power consumption. The technology is found to be highly potential for use in maritime environments where cellular network availability is low or absent. The previous studies have shown that the technology is capable of achieving a high distance for wireless communication, reaching up to a distance of a few kilometers [4]. The technology is found to be highly potential for use in maritime environments, especially for wireless communication to be established with the vessel from the coastal region.

The recent advancement in embedded intelligence has led to the deployment of machine learning models directly on the microcontroller-based system. The deployment of machine learning models directly on the microcontroller-based system is generally known as Tiny Machine Learning (TinyML) [5]. The TinyML technology is found to be highly potential for use in IoT applications. The recent studies have shown that the TinyML technology is capable of effectively implementing lightweight machine learning algorithms, such as decision trees, logistic regression, and neural networks, on the ESP32 microcontroller [6], [20].

Apart from the application of edge intelligence, advanced data analysis techniques are also being adopted to analyze the data and identify abnormal patterns in the sensor networks [18]. Isolation Forest is an algorithm that is being successfully implemented to detect abnormal patterns in IoT networks. Isolation Forest is an unsupervised machine learning algorithm that helps detect abnormal patterns by identifying the data that is significantly different from the normal patterns. If the data is related to maritime monitoring, the abnormal patterns might indicate suspicious patterns in the movement of vessels, abnormal signal strength, etc. Although significant technological advancements have been made, most maritime monitoring systems are still using traditional data processing techniques [2], [12].

III. EXISTING SYSTEM

The existing maritime monitoring systems and fishing vessel tracking systems have been based on satellite navigation systems and centralized monitoring systems. In general, satellite navigation systems have been based on various technologies, such as the Global Positioning System (GPS), for tracking the real-time location of fishing boats [16], [17]. The position information collected using GPS technology is transmitted to the centralized monitoring stations through communication networks. In general, geo-fencing techniques have been utilized for maritime boundary definition. If a fishing boat crosses the boundary, an alert signal is generated at the monitoring center.

Many of the existing monitoring systems have been based on communication systems, such as LoRa (Long Range Communication) technology, for transmitting information collected from fishing boats [3], [14], [15]. In general, this system includes GPS receivers installed at fishing boats and a centralized server for monitoring all vessel information. The information collected using GPS technology includes coordinates, timestamp information, and communication parameters. Another important parameter utilized for wireless communication analysis is the "Received Signal Strength Indicator" (RSSI). In some monitoring systems, RSSI is utilized for estimating communication quality between transmitting devices and receiving stations. In addition, the values of RSSI can be used to calculate the distance between the nodes, as well as to determine whether the vessel is moving further away from the shore monitoring station. Nevertheless, the accuracy of the distance calculation using RSSI is usually very low due to signal attenuation, multipath propagation, and other interferences [14], [15].

In traditional maritime monitoring systems, the architecture is usually centralized, meaning that all the processing and decision-making are done at the monitoring stations, while the vessels are not involved in the process [2],[12]. As a consequence, the vessels are completely dependent on the external infrastructure in receiving warnings from the shore stations. In situations where the network is not very strong or is disconnected, the vessels may not receive timely warnings concerning violations of boundaries or other hazardous conditions while in operation. This increases the network bandwidth requirements, while the decision-making process will be delayed. In addition, the traditional architecture may experience scalability challenges when handling a large number of vessels at the same time.

To put it simply, existing maritime monitoring systems offer basic vessel tracking and boundary detection functions but have some drawbacks, such as high communication dependency, delayed alerting, no predictive intelligence, and low signal variation analysis, such as RSSI changes. These drawbacks indicate the requirement for a more intelligent and distributed monitoring system, enabling real-time analysis directly on devices and supporting centralized analysis for large-scale monitoring systems [2], [12].

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IV. PROPOSED SYSTEM

To overcome the limitations associated with the traditional maritime monitoring system, this paper proposes an intelligent distributed monitoring system that incorporates the concept of edge computing, long-range wireless communication, and machine learning techniques [2], [3], [5]. The proposed system is intended to track the movement of fishing boats in real-time and detect potential maritime boundary violations. The system architecture is composed of two main components, namely the transmitter unit, which is fixed on the fishing boat, and the receiver unit, which is fixed on the monitoring station.

The transmitter unit is developed using the ESP32 microcontroller, which is considered the central processing unit of the system. The ESP32 is connected to the Global Positioning System (GPS) module, which is used to track the latitude and longitude coordinates of the fishing vessel in real-time [16], [17]. The coordinates of latitude and longitude will continually monitor aspect of the fishing vessel to determine its location in relation to the sea boundaries. An ESP32 will be the best platform to use because it has large amounts of processing capability, has Wi-Fi and Bluetooth capabilities, and will use very little power.

In addition to the GPS technology, the transmitter part of the system uses Long Range Communication technology, which facilitates wireless communication over a large distance between the fishing boat and the coastal monitoring station [3], [14], [15]. The communication occurs in the Low Power Wide Area Network spectrum, which enables the transmission of data over a distance of several kilometers while consuming very low power. The transmitter uses LoRa technology to send data periodically to the receiver part of the system, which is located in the coastal area.

Another parameter, which is used in the proposed system, is the Received Signal Strength Indicator (RSSI). The RSSI values indicate the signal strength received through the wireless communication network using LoRa technology. The variations in the RSSI values are used to determine the relative distance between the fishing boat and the coastal monitoring station, as well as to detect anomalies in the signal strength received in the system. In addition, the RSSI values are used as an additional feature in the machine learning algorithm to improve the accuracy of the results obtained from the system [18].

In contrast to conventional systems that depend on centralized processing, the newly proposed architecture includes edge computing on the boat unit [2], [12]. Lightweight machine learning models are used on the ESP32 based on Tiny Machine Learning [5], [20]. These machine learning models are used to perform preliminary analysis on the transmitter. For instance, trajectory prediction models are used to predict the future location of the vessel based on past movement patterns. This allows for early warnings to be sent even before the violation occurs.

V. METHODOLOGY

The proposed system utilizes a hybrid Edge–Centralized Artificial Intelligence for monitoring fishing boats and preventing maritime boundary violations [2], [12], [20]. The system design includes a boat unit, a land unit, and a monitoring system integrated with a web dashboard.

An ESP32 microcontroller receives input from both a GPS module and a LoRa communication module in the boat unit. The GPS module continuously provides information about the boat's location via latitude and longitude [16][17]. The ESP32 processes this information to establish the distance from the boat to a defined maritime boundary. Furthermore, the system uses the RSSI value reported by the LoRa module to evaluate the quality of communication between the boat and shore unit [14][15].

Lightweight machine learning models will also be deployed at edge devices via TinyML for this purpose [5],[20]. A zone classification model will classify the zone of the boats current location as being a safe zone, warning zone or danger zone based on how close they are to the internal maritime boundary. A trajectory prediction model is used to predict where the next position of the boat will be based on previous historical GPS data. If the boat is approaching a restricted zone, these models will allow for the early alert capability for that boat. To assist with this, a technique called RSSI filtering will be applied to stabilize environmental factors that can cause measurement errors in the signal [18].

Once the data has been processed by the above described model, the relevant data will consist of GPS, RSSI and zone status will then be sent back to shore-based monitoring using the LoRa [3], [14],[15] communication protocol. As the shore monitoring receives that information through another ESP32, it will then forward that data to a computer system for analysis.

Once received by the shore computer system, additional machine-learning algorithms will analyze that information to detect irregular movement patterns and predict the likelihood (probability) of crossing the internal boundary [18],[20]. Finally, that information is displayed on a web-based dashboard for real-time tracking of boats. Hence, this method allows for near real-time monitoring, predictive capabilities and efficient long-distance communication making it highly suitable as a method of intelligent monitoring of maritime boundaries.

Therefore, an edge computing approach has been introduced to improve the scalability and reliability of the system [2], [12]. With this approach, an edge device is placed on the boat, so that real-time analysis of the location of the boat is done, as well as a prediction of where the boat will be located next and how it will move in relation to where it has already been.

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VI. BLOCK DIAGRAM

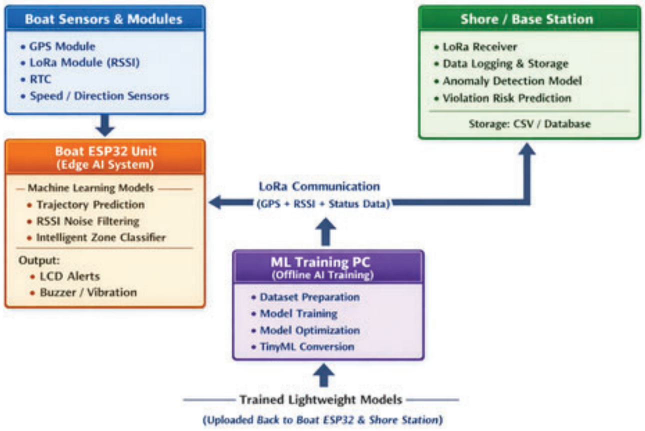

Figure 1 : Block Diagram of AI-Based Boat Alert Monitoring System

The proposed system is intended to be a distributed maritime monitoring system that uses the concepts of the Internet of Things (IoT), long-range wireless communication, and Artificial Intelligence to monitor and prevent fishing vessels from crossing international maritime boundaries [1], [3], [20]. The system architecture of the proposed system includes three major components: the Boat Unit (Transmitter Node), the Shore Unit (Receiver Node), and the Central Monitoring System with a Web Dashboard. This system uses a hybrid approach of edge and centralized intelligence, where the decision-making process happens at the edge device and the complex analysis and storage of the data happen at the monitoring station [2], [12].

The Boat Unit of the proposed system uses an ESP32 microcontroller as the edge AI device and integrates various sensors and modules with the microcontroller. Some of the integrated modules are a GPS module to obtain the real-time latitude and longitude values of the vessel [16], [17], a LoRa module to communicate with the shore station and obtain the signal strength of the transmitted signal using the received signal strength indicator (RSSI) value [14], [15], a real-time clock (RTC) to timestamp the received signals, and speed and direction sensors to obtain the dynamics of the vessel's movement.

At the edge level of the system, machine learning is implemented using the TinyML approach [5]. This approach uses a machine learning model to perform various functions such as trajectory prediction, RSSI noise filtering, and intelligent zone classification [18], [20]. Using the machine learning model implemented at the edge level of the system, the system can predict the trajectory of the vessel and classify the zone of the vessel into safe, warning, and restricted areas. Depending on the results obtained after processing the signals received at the vessel, the system can display a real-time alert using an LCD display and a buzzer or vibration mechanism.

The Shore/Base Station of the system uses a LoRa receiver and performs the functions of receiving the signals transmitted by the vessel and the intelligent analysis of the signals received at the vessel [3], [14], [15].

Advanced machine learning techniques are utilized at this level for anomaly detection and risk prediction of boundary violations [18], [20]. The module for anomaly detection helps identify unusual patterns like sudden changes in trajectory, while the risk prediction module helps estimate the probability of boundary violations or risky navigation. Additionally, an offline machine learning training module is included in this system. Typically, this module is part of a central processing computer. The machine learning module is utilized for preparing data, training models, and optimizing them based on historical data collected from the system [9], [10]. Various machine learning techniques can be utilized for optimizing prediction accuracy. These optimized models can be converted to a lightweight form using TinyML frameworks for deployment on edge devices [5].

The optimized machine learning models can be deployed back to the ESP32 edge device and the shore station. In this way, the system can be continuously improved through periodic updates. The proposed hybrid system effectively utilizes edge computing and centralized intelligence for efficient decision-making on the boat and analysis at the shore [2], [12]. It can thus be concluded that this system can be an efficient and reliable solution for real-time maritime monitoring and safety enforcement.

VII.MATHEMATICAL MODELING

The boat position at time t is represented as $P(t) = [\phi(t), \lambda(t)]$, where ϕ and λ denote latitude and longitude. The displacement between two positions is computed using the Haversine formula:

$$d = 2R \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\Delta\lambda}{2}\right)}\right)$$

The velocity is defined as $v(t) = \frac{d}{\Delta t}$, and trajectory prediction is modeled as:

$$P(t+1) = P(t) + v(t)\Delta t$$

RSSI-based distance estimation follows the log-distance path loss model:

$$RSSI = RSSI_0 - 10n\log_{10}(d)$$

which gives:

$$d = 10^{\frac{RSSI_0 - RSSI}{10n}}$$

Noise in RSSI measurements is reduced using filtering techniques such as the Kalman filter. The zone classification is defined as:

$$Z = g(P(t)) \in \{0, 1, 2\}$$

representing safe, warning, and restricted zones. Boundary detection is performed using distance thresholding:

$$\text{Alert} = \begin{cases} 1, & d_{boundary} < d_{th} \\ 0, & \text{otherwise} \end{cases}$$

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Anomaly detection is modeled using an anomaly score $S(x)$, where values above a threshold indicate abnormal behavior. The overall risk is estimated as:

$$R = w_1 \frac{1}{d_{boundary}} + w_2 v + w_3 \Delta\theta$$

Thus, the system integrates position tracking, signal modeling, and machine learning for real-time maritime monitoring.

VIII. EDGE AI IMPLEMENTATION

The importance of edge artificial intelligence (AI) in our proposed system for monitoring navigation in water bodies, allowing decisions to be made in real-time on board the vessel, rather than relying entirely on cloud-based technology [2], [12]. Data processing for our implementation is performed locally on an ESP32 microcontroller aboard the vessel, thereby minimizing both the amount of time it takes to provide a response and the level of dependency on constant network connectivity for processing.

Location data is collected in real-time from the GPS module by the ESP32 and is used to calculate the distance to the boundary, thus indicating how far the vessel is from the boundary [16], [17]. Processing of raw GPS data on board rather than transmitting it to a shore-based facility will greatly reduce communication loads. This processing requires very lightweight TinyML models that are capable of running on microcontrollers [5],[20].

At the edge, the overall system performs zone classification, trajectory forecasting, and signal quality assessment. The first function of the system is to measure the distance from the vessel to the boundary using the Haversine formula. The second function classifies the current position of the vessel into one of three zones, called safe, warning, and restrictive, based on the calculated distance to the boundary. During the trials, we found that local alerts could be generated virtually instantaneously based on the vessel's proximity to restrictive boundaries.

The second task is to predict where a boat will be in the future based on its GPS coordinates over time [9], [20]. By continuously predicting the future location of a boat, you can provide early alerts to prevent your boat from violating the boundary before it actually happens. Therefore, the ability to generate advanced warning of a possible boundary violation is another key benefit of this system.

Finally, all the RSSI values from the VoRa module are evaluated as well. Because the RSSI value may vary based on the environment due to different factors such as wind and waves, machine learning-based filtering will be used to smooth out the RSSI data [14], [15], [18]. In general, computing at the edge will assist in reducing latency and improving system reliability in remote marine areas where internet connectivity is a concern [2], [12]. The collected data, including classification results, predicted path, and RSSI, is then sent to the shore monitoring station for additional analysis and visualization.

IX.SHORE-LEVEL ANALYTICS

Although the edge device is used to immediately process the information and generate alerts, the shore monitoring station is used to perform more detailed analysis in order to advance the overall intelligence of the system [2], [12]. The shore unit receives information sent from the boat via LoRa and further processes that data [3], [14], [15].

The information received includes GPS coordinates; the zone classifications that were generated; the predicted trajectory; and communication parameters such as RSSI [16], [17]. The data will then be transferred from the shore system to a monitoring computer via an ESP32 interface and stored in a central database for future analysis [8].

At the shore, there are also more advanced ML techniques to be able to identify abnormal movement patterns and assess the risk of boundary violations [18], [20]. The models will analyze data including speed, direction, and historical movements. For our approach, we will use a Logistic Regression model to predict the probability of boundary violations based on distance to the boundary and reliability of the received signal [9], [10]. Another benefit of the shore system is that it enables continuous improvement of the models. Historical data collected from multiple boats can be used to retrain and optimize machine learning algorithms on the monitoring computer, where ample computational resources are available [5].

The system contains an optional web-based dashboard providing real-time boat location data, communication status, and alerts on multiple boat connections. This is an important feature to enable ways for agencies to have visibility of numerous vessels and quickly respond to any issues that may arise based on their operational activity. The use of both edge processing units on the boat and shore-based analytics provides greater efficiencies in the use of available resources while maintaining higher accuracy in predicting vessel behavior and increasing maritime safety. The shore system serves as a central intelligence layer for the long-term monitoring of vessel activity and for making strategic decisions regarding these activities [2], [12].

The shore-based monitoring system also accounts for the need to manage simultaneous data from many vessels. During our testing, we considered possible scenarios where data from different vessels arrived at the same time at the monitoring site. The system assigns each vessel a unique identifier to avoid the overlapping of data or confusion by having more than one vessel with the same data. As a result, it is easier to track individual vessels and determine how the vessels are moving. This will also assist authorities in identifying potential abnormal behaviors, such as sudden changes in direction or strange movement patterns, by comparing vessel characteristics between two or more data sets from different vessels [18], [20].

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An additional important characteristic of the shore system is the capability to analyze large amounts of data for storage and processing. The information that is collected, such as GPS data, RSSI measurements, and alert status, gets stored within a centralized database. When we performed testing on the system, we discovered that being able to view historical data made tracking movement patterns and identifying high-risk areas much easier, thus providing better monitoring capabilities as well as making it possible for better decision-making [8]. In our observations, being able to access historical data also improved prediction accuracy and reduced the number of false alerts produced. The system can be updated periodically from real-life data, thereby increasing its reliability and ability to be scaled in the future for long-term maritime monitoring capabilities [5], [20].

X.COMMUNICATION PROTOCOL

A successful communication system between the boat unit and the shore monitoring station will be key to providing an efficient maritime monitoring system, as the system will provide long-range wireless communications to enable data to be transmitted efficiently between the boat, and the shore monitoring station, via communication systems operating over long ranges (in many cases thousands of kilometres) in the ocean, areas where there are no other sources of communications. The system uses LoRa communication modules and an ESP32 microcontroller for the efficient transmission of data [3], [14], [15]. The boat will receive periodical updates of GPS coordinates and system parameters such as the status of zone classifications and signal strengths [16], [17]. The boat unit will send these data via a LoRa transmitter module. The data packet sent from the boat to the shore monitoring station is critical as it contains the following key parameters; latitude and longitude of the boat, RSSI, status of the zone in which the boat is currently located, and time stamp of when the data was sent out. The shore monitoring station will be able to successfully monitor the boat by using the data that has been received adequately.

The shore monitoring station will receive data from the boat unit via the LoRa receiver module [3], [14]. The shore monitoring station will pass the received data to the monitoring computer via the ESP32 interface. Error checking will be incorporated within the system to improve the overall response time of the information being sent from the boat to the shore monitoring station and therefore reduce the impact of errors caused by communications interference on the data received.

To enhance the reliability of communications, the communication system utilizes a method of periodic transmission. This means that each boat unit transmits data packets to the shore monitoring stations at certain fixed intervals. Due to the fact that packet transmissions are made at periodic intervals, the system is able to continually monitor the vessel's movements without placing more than necessary burden on the communication network [15]. Another component of the communication system includes the ability to adjust the frequency of transmissions based on how close the vessel is to shore. When the vessel is inside a restricted area, the communication system can increase the frequency of transmissions from the vessel to the monitoring stations.

In addition, another important function of the communication system is the ability to monitor the communication link between the vessel and shore monitoring stations using RSSI (received signal strength indication). The communication system uses the RSSI value to determine how well the wireless communication link between the vessel and the shore monitoring station is working [14], [15]. The communication system can use the RSSI measurement to identify when environmental conditions such as sea surface reflections, and atmospheric disturbances affect the quality of the wireless communication link.

Researchers also investigate how this data can be used to improve communication through time by analyzing RSSI data collected at monitoring stations [14], [15], [18]. Another important feature of this protocol is that it is designed to be scalable and compatible with future maritime monitoring technologies that may emerge [8]. This allows for each boat unit to communicate with the same shore station using uniquely identifiable elements in every data packet, allowing multiple vessels to be monitored at once without having any communication conflict between them. Cloud-based services and/or satellite-based communication network connections are also able to be integrated into the monitoring capability [1], [2].

XI.EXPERIMENTAL EVALUATION

Different tests were carried out to evaluate if the suggested Maritime Boundary Monitoring System was effective. The purpose of the evaluation was to see how well the suggested system communicated reliably, predicted results reliably, and alerted in real-time. For each of the tests, 2 nodes were created with ESP32 microcontrollers (1 for transmitting and 1 for receiving). The node located on the boat transmitted information obtained from the GPS (i.e., coordinates) and long-range communication using the LoRa module. The location of the receiving node was connected to computer systems located at the shore station, where the receiving node could view the transmitted information.

While testing, the boat transmitted data packets that included, but were not limited to: GPS coordinates, received signal strength indicator (RSSI) values, and zone classifications. Data packets were transmitted back and forth while performing the absolute time duration based on the distance from the boat and the shore monitoring station (TESTS were conducted over various distances). The information received by the shore monitoring station could be used to analyze the proposed system performance.

In essence, the experiment's findings demonstrated that the maritime boundary monitoring system worked as anticipated; namely, it allows for reliable communications across long distances while performing real-time vessel tracking [3], [14]. Additionally, the predictive model that was created on board could predict multiple different types of vessel activity, and provide alerts before they entered restricted areas [2], [12]. The predictive model created on board also allows for alerts before an area is restricted [9], [20].

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The centralised analytics conducted on the centralised computer allowed for efficient processing of data received from the vessel-based system, and allowed for real-time display of that data on a web interface [8]. In addition, the system also saved data from the movement of the vessel that could be used in the future for training machine learning models to assess maritime activity [5], [18].

The experimental evaluation of the proposed maritime boundary monitoring system has confirmed the effectiveness of the proposed architecture, which provides efficient communication, accurate location information, and reliable early warning systems for intelligent maritime boundary surveillance [3], [14], [16], [17].

In addition to communication performance, the system was evaluated for its capability to operate under continuous monitoring conditions. The system was subjected to multiple test runs to evaluate the consistency of data transmission as well as location tracking. Results of the test demonstrate that the system maintained stability in terms of both communication and locations throughout long-term continuous operation. Additionally, using edge processing capabilities available within the ESP32 module resulted in the ability to generate alert messages at very low delays, and the centralized system accomplished efficient processing of data streams from all incoming sources with minimal latency.

XII.COMPARATIVE ANALYSIS

A comparison was made between how efficient the new way of doing maritime monitoring compared to how traditional ways of monitoring maritime operations work. Traditional maritime monitoring systems use Global Positioning System (GPS) technology for tracking the movement of vessels on the water, including sending their GPS location data to a remote central monitoring station [16], [17]. Although traditional vessel tracking provides basic ability to track vessels, it has limitations such as slow communications time (latency), inability to foresee next moves (predictive capabilities to a limit), and continuous communications (need for constant communication back to remote central monitoring station) [2], [12].

The proposed system has been shown to be more efficient than conventional systems because of the use of edge (ESP32) as an intelligent edge device which allows each marine vessel to classify areas and predict which direction they will travel [5], [20]. By using edge systems, communications time (latency) is greatly reduced with this proposed system compared with traditional systems.

The system being discussed has better performance compared to previous methods because it includes long-range wireless technology such as LoRa (Low Power Wide Area Network). Previous methods had to rely on cellular networks in order to communicate with their unit.

As such, there were many issues with communicating in the ocean/on the sea versus using LPWAN technology which solves those problems and allows for reliable communication in areas that would normally have poor service. In addition to better communications due to the use of long-range wireless technology, there is also significant improvement in how well this new system predicts the future through the use of machine learning algorithms. Conversely, the past has only been able to provide real-time information on the location of units for monitoring and very little predictive ability.

Also, predicting past trajectory data allows for evaluating potential violations which also will help improve the predictive capability of the overall monitoring system. All things considered, the comparative examination reveals that the new system provides the best in all areas when compared to prior systems/approaches in terms of performance (accuracy), communications (low latency), predictive capabilities, and scalability. There are other advantages as well, such as edge computing that reduces the processing requirements placed on the centralized server or using predictive analysis to improve overall outcome decision-making processes compared to more traditional systems. Overall, the information presented above supports the use of the proposed new system for the development of intelligent adaptive maritime monitoring systems.

XIII. RESULT & CONCL

This paper has proposed an intelligent maritime boundary monitoring system based on IoT technology and machine learning algorithms [1], [20]. The proposed system improves the safety and efficiency of fishing operations in coastal areas. The architecture comprises a boat unit, a shore monitoring unit, and a centralized analytics unit, all interconnected through long-range wireless communication [3], [14], [15]. The boat unit is based on the ESP32 platform and is used to collect GPS information for real-time location tracking [16], [17]. This information is utilized to determine the proximity of fishing vessels to maritime boundaries. Lightweight machine learning algorithms are employed to classify operational zones and predict vessel trajectories, enabling early warning generation when boats approach restricted areas [5], [20].

The intelligent maritime boundary monitoring system is developed using IoT technology and machine learning algorithms [1], [20] to enhance the safety and efficiency of fishing operations within coastal waters. It consists of a boat unit, a shore monitoring unit, and a centralized analytics unit that communicate with one another using long-range wireless communication [3], [14], [15]. The boat's unit is based on the ESP32 platform and will collect GPS data. This data will provide real-time positioning for the boat's location [16], [17]. This will provide the necessary information used to determine how far fishing boats are from maritime boundaries. With the use of lightweight machine learning algorithms, the system will identify operational zones and predict the movement of vessels, giving an early warning when vessels get too close to restricted areas [5], [20].

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The results of this study give evidence that the system proposed allows for long-distance communications to take place in an efficient manner using LoRa technology [3],[14]. Additionally, it is a low-cost option to provide improved security to coasts as well as improve the monitoring of the maritime environment while maintaining reliable operation.

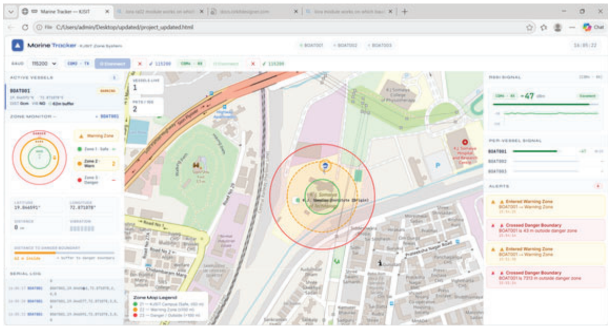

Figure 2 : Dashboard showing Vessel tracking with geo-fencing and RSSI.

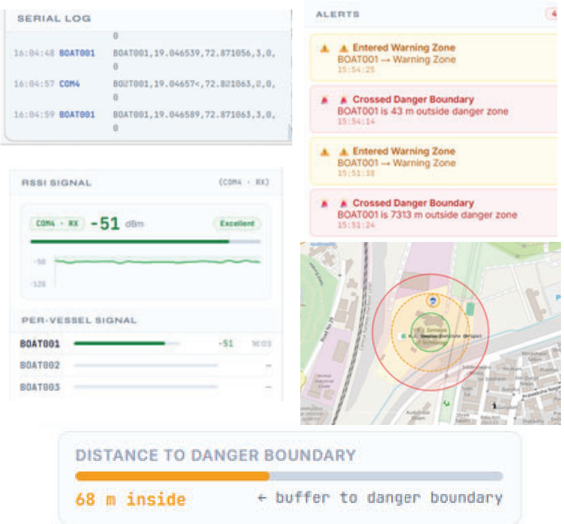

Figure 3 : Alerts and RSSI signal analysis.

Parameter	Value	Description
Latitude	19.046455°	Real-time GPS location of boat
Longitude	72.871040°	Accurate position tracking
RSSI Signal Strength	-47 dBm	Strong LoRa communication
Zone Status	Warning / Danger	Based on boundary proximity
Distance To Boundary	~77 m(Can Vary)	Indicates closeness to danger zone
Alerts Generated	Yes	Real-time warning notifications
Communication Type	Lora	Long-range, low-power transmission

Table 1 : System Observations from Real-Time Dashboard

Table 1 summarizes the key parameters observed from the real-time monitoring dashboard during system operation. The results show that the system is able to accurately track the boat's location using GPS coordinates, while maintaining stable communication through LoRa, as indicated by the strong RSSI value. The zone status and distance to the boundary clearly reflect the boat's position relative to predefined limits, allowing the system to identify whether it is in a safe, warning, or danger zone. Additionally, the system successfully generates real-time alerts whenever the boat approaches or crosses restricted boundaries. Overall, the observations confirm that the proposed system performs reliable tracking, communication, and alert generation in real-time conditions.

XIV. FUTURE SCOPE

The results obtained from this system appear to be quite promising; however, there are many different ways the system could be expanded and further developed in the future. There is an opportunity for the use of deep learning techniques to perform trajectory prediction, which would improve the overall accuracy of the predictions for the system. Additionally, it could be possible to implement either satellite communication or hybrid communication methods in order to provide coverage to a greater geographic area. More sensors in the form of weather data, collision detection and vessel identification could also be integrated into this system in order to provide additional useful data for decision making. Future opportunities could include the establishment of cloud-based data analytics platforms as a means of processing large amounts of data and monitoring large geographic areas.

XV. CONCLUSION

In this paper, an AI-Based Boat Alert Monitoring System using RSSI technology has been proposed and implemented to address the limitations of traditional maritime monitoring methods. The system combines GPS-based tracking, LoRa communication, and edge intelligence using TinyML to provide real-time monitoring and early detection of boundary violations. By processing data directly on the ESP32, the system reduces dependency on centralized systems and enables faster decision-making.

The results obtained from the web-based dashboard demonstrate that the system is capable of accurately tracking boat location, maintaining reliable long-range communication, and generating timely alerts when the vessel enters warning or danger zones. The use of RSSI further enhances the system by providing additional insight into signal strength and proximity, improving overall monitoring reliability.

Overall, the proposed system offers a practical, low-power, and scalable solution for maritime boundary enforcement. It can be effectively used for applications such as fishing vessel monitoring and coastal security. In the future, the system can be improved by integrating more advanced machine learning models, expanding coverage for multiple vessels, and enhancing user interfaces for better visualization and control

XVI. ACKNOWLEDGMENT

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XVII. REFERENCES

[1] L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," Computer Networks, vol. 54, no. 15, pp. 2787–2805, 2010.

[2] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," IEEE Internet of Things Journal, vol. 3, no. 5, pp. 637–646, 2016.

[3] S. Raza, P. Misra, Z. He, and T. Voigt, "Building the Internet of Things with low power wide area networks," IEEE Communications Magazine, vol. 55, no. 5, pp. 84–89, 2017.

[4] M. Centenaro, L. Vangelista, A. Zanella, and M. Zorzi, "Long-range communications in unlicensed bands: The rising stars in the IoT and smart city scenarios," IEEE Wireless Communications, vol. 23, no. 5, pp. 60–67, 2016.n Computer Systems, vol. 29, no. 7, pp. 1645–1660, 2013.

[5] P. Warden and D. Situnayake, TinyML: Machine Learning with TensorFlow Lite on Arduino and Ultra-Low-Power Microcontrollers, O'Reilly Media, 2019.

[6] S. Haykin, Neural Networks and Learning Machines, 3rd ed., Pearson Education, 2009.

[7] A. Zanella et al., "Internet of Things for smart cities," IEEE Internet of Things Journal, vol. 1, no. 1, pp. 22–32, 2014.

[8] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," Future Generation Computer Systems, vol. 29, no. 7, pp. 1645–1660, 2013.

[9] T. Mitchell, Machine Learning, McGraw-Hill, 1997.

[10] C. Bishop, Pattern Recognition and Machine Learning, Springer, 2006.

[11] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, pp. 436–444, 2015.

[12] M. Chiang and T. Zhang, "Fog and IoT: An overview of research opportunities," IEEE Internet of Things Journal, vol. 3, no. 6, pp. 854–864, 2016.

[13] H. Gupta, A. Vahid Dastjerdi, S. K. Ghosh, and R. Buyya, "iFogSim: A toolkit for modeling IoT applications," Software: Practice and Experience, 2017.

[14] F. Adelantado et al., "Understanding the limits of LoRaWAN," IEEE Communications Magazine, vol. 55, no. 9, pp. 34–40, 2017.

[15] U. Raza, P. Kulkarni, and M. Sooriyabandara, "Low power wide area networks: An overview," IEEE Communications Surveys & Tutorials, 2017.

[16] E. Kaplan and C. Hegarty, Understanding GPS: Principles and Applications, Artech House, 2005.

[17] B. Hofmann-Wellenhof, H. Lichtenegger, and J. Collins, GPS Theory and Practice, Springer, 2001.

[18] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection: A survey," ACM Computing Surveys, vol. 41, no. 3, 2009.

[19] J. Brownlee, Machine Learning Algorithms From Scratch, 2016.

[20] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning, MIT Press, 2016.