RESEARCH ARTICLE

IoT-Integrated Reinforcement Learning-Based Mine Detection System for Military and Humanitarian Applications

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Abstract

This research proposes an advanced system for landmine detection combining the internet of things and reinforcement learning, which seeks to resolve issues in conventional methods that misidentify more than 30% of detections, have slow reaction times, and are not suited for different environments. Others like metallic detectors and sniffer dogs also pose greater danger for wrong threat identification, more so due to slothful attempts. The system proposed in this study is novel in that it customizes metal detection by integrating a sensor into military boots, thus permitting constant scanning without the use of hands. A metaplastic Machine Learning model improves detection accuracy. It was found that reward driven reinforcement learning regulations improves mine detection accuracy, increases the analysis attempts in each evaluation phase, and alters the strategically settings. The range of analysis conducted during this study validates the argument in question but this reworking of the system does not polish it. The innovation is having that with proper situational awareness this model enables real time implementation of IoT devices. This adaptable system is not only advantageous for military endeavors but can also be useful for demining activities. More robust multisensory capabilities are essential to facilitate effective and safe landmine inspection all over the globe, so follow up studies should concentrate on field trials with accompanying iterative improvements.

Keywords: landmine detection, reinforcement learning, internet of things (IoT), sensor fusion, artificial intelligence, military safety.

1 Introduction

Landmines have largely been a problem for the military and civilians in wartorn areas and postwar locations. These treacherous minefields result in thousands of deaths annually. Affected regions face further challenges due to unregulated agricultural activities, troop movements, or civilian healthcare interventions, which are rendered risky in mine infested zones [1]. The standard techniques for doing so, such as manual searching, metal detection, sniffer dogs, and robotic shovels did but these techniques are helpful but are extremely limited by scope. Manual detection can

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often be life threatening as highly trained personnel are required to carry out the laborious procedure [2]. While metal detectors are more common, they are extensively misused because those devices do not differentiate between scrapped metal and concealed landmines. Sniffer dogs are highly reliable during conditions when they have not moved for a long period of time, making them not suited for demining operations [3]. Robotic shovels, while having great potential, lack efficiency and are hard to operate under rough or unpredictable landscapes [4]. Overall, these techniques are inefficient. Due to these constraints, there is a crucial need for a real time autonomous, efficient system capable of detecting mines with minimal human interaction as well as accurately identifying unserviceable areas for more effective operations. The core issue addressed in this research is the high level of inefficiency and inaccuracy of current mine detection techniques, especially in regards to their false detection rate and slow rate of detection [5]. As an example, conventional metal detectors tend to be rather indiscriminate and tend to consider any metallic item as a land mine even if it poses no threat. This greatly inhibits military efficiency by wasting time and resources on non-threatening objects. These inaccurate outcomes result in operational inefficiencies, excessive expenditure, and increased risk for soldiers as well as demining staff who need to waste their time investigating threat-less objects. It also contributes towards a greater risk ratio for soldiers and civilians as the modern methods are not suitable for all types of landscapes. A good illustration is the conventional detection methods when used on land mines planted on dense foliage or wet sandy soil or even in rocky places. This plays a chronic risk to soldiers on the field as well as civilians moving in the dangerous zones. The other significant problem associated with such approaches is that they are human dependent and the decision making is completely subjective. Existing systems expect operators to interpret the signals without any context, which raises the probability of blunders, particularly in panic inducing contexts [6]. The absence of self-sufficiency and real-time alterability diminishes the effectiveness of these methods as they do not permit any analysis and action on the spot. Furthermore, the current mine detection technologies do not offer integrated systems that share data in real time, which affects the situational awareness of military command centers and personnel on the field. A lack of an automated system that can transmit and receive alerts in real time means that response units may not be able to make informed, timely decisions. These problems clearly demonstrate the need to develop a more advanced system for mine detection that utilizes cutting edge sensor systems, artificial intelligence, and real-time communication for improved accuracy, efficiency, and safety [7]. This paper presents the design of an IoT-based mine detection system integrated into military infantry boots with the use of sensor technologies, wireless communication, and artificial intelligence. The system is intended to conduct automatic detection of landmines without the need for human intervention, enabling soldiers to concentrate on ongoing operations, while being alerted about possible threats that may lurk underneath them. The system utilizes metal detection sensors which capture the presence of buried landmines based on their electromagnetic signature, and transmits real-time detection data to a central processor. Wireless communication facilitates the immediate reception of alert notifications by the user and the remote command post, increasing the level of operational awareness of the user, while improving coordination for military movements. As opposed to standard held detectors, which need purposeful movements or sweeps over the area, this concealed detection system works conveniently as the soldiers walk, scanning the ground without hindrance. The use of reinforcement learning, a type of artificial intelligence, allows the system to improve its decision making capability over time by learning from previous detections made and becoming more accurate while minimizing false positives. Reinforcement learning enables the system to flexibly adjust to varying terrains and environmental conditions allowing the system to perform reliably in all types of terrains [8].

Moreover, feature engineering and reduction is how machine learning techniques optimize data sensor processing to enhance detection while still reducing the cost of computation. With IoT built into the system, real time monitoring is greatly enhanced because detection data can now be accessed by every individual soldier and also sent to command centers for wider strategic planning. This methodology is far more sophisticated than existing methods because it augments sensor systems with AI and IoT features enabling more effective and automated mine detection. This study attempts to determine whether incorporating reinforcement learning (RL) in an Internet of Things (IoT) enabled mine detection system can improve the detection rates, reduce the false positives, and most importantly improve the real time decision making AI algorithms strive for precision and recall. In this work, we will consider one of the most intriguing problems of mine detection: the ability of a system to determine the presence or absence of landmines and other non-threatening metallic objects that may be commonly found in the environment [9]. Integration of IoT along with the RL algorithms can lead to an improved situational awareness, as well as increased operational efficiency [10]. Therefore the question is whether intelligent methods of information fusion manipulation can improve mine detection safety and reliability in military operations on international or global levels. Optimization of recall rate enhances the ability of the system to detect all real mines disguised within a specified area while precision rate measures the effectiveness of a system's ability to detect landmines without any false alarming. Using patterns of sensor data and previously conducted detection actions, the study attempts to answer the question: does the employment of reinforcement learning technology allows the system ignore previously defined detection strategies and use them in an efficient manner, enabling RL over time to adjust the defined strategies to ones that are more efficient in real world scenarios? The study also addresses the question of IoT based mine detection efficiency and real-time data dissemination's effect on situational understanding. Through providing immediate alerts and processing data from a central location, the system ensures that both soldiers and command posts have instant access to mine detection information. This increases overall coordination and significantly response times in crippling environments [11]. The amalgam of all the components of the system's evaluation means that it is also necessary to test how well it can adapt in various conditions. Because landmines may be located in deserts, forests, wetlands, and even urban areas, it is critical to determine whether the system can achieve high accuracy for detection in varying field conditions. The research attempts to answer the question whether the machine learning technology integration makes it possible for the detection model to dynamically adapt to different terrain and other environmental parameters, thereby continuously improving the performance of the system.

The aim of this paper is to assess the hypothesis that an embedded, wearable mine detection system provides a shift in operational advantage by allowing soldiers to move with relative autonomy without sacrificing detection probability. This system differs from standard mine detection gear, which requires soldiers to come to a full stop in order to operate scanning devices. This system, which is designed to function as a part of standard issue gear, offers protection without obstructions to mobility. The study also seeks to establish whether the design of the device has adequate restrictions to minimize false alarms without overlooking possible threats. In as much as these metrics tend to relate, one of the main objectives that help assess the device's overall functionality is how well it manages to balance the competing ends of sensitivity and specificity when it comes to its responses toward real landmine dangers [12]. Thirdly, the research explores the feasibility of using this device on broad military and humanitarian de-mining campaigns. Humans that are responsible for the operations of humanitarian de-mining usually work under the constraints of limited resources, both financial and physical; therefore, the systems that are put in place need to respond well to these limitations. Thus, the importance of instituting IoT-enabled reinforcement learning systems for more intelligent mine-detection serves as the basis for achieving these greatly desired advancements in landmine detection technology that are safer, efficient, and reliable [13].

Ultimately, this study seeks to document whether an AI-integrated, IoT-enabled mine detection system is a marked improvement over other previously established methods of landmine detection, focusing on accuracy, adaptability, and real-time capabilities. Considering these aspects, the research aims to contribute towards the body of knowledge regarding the integration of artificial intelligence and IoT in mine detection which is bound to transform military defense strategies and humanitarian demining efforts across the globe. If successful, the proposed system has the potential to mark a positive change in the improvement of safety in battlefields by mitigating the loss of soldiers and civilian lives, while also presenting a scalable and economical approach towards landmine remediation in post conflict regions. This work takes a step towards smart defense technology by illustrating how reinforcement learning, IoT, and sensor-based detection can be used in the rest of the world and relevant sensitive issues in his country which are critical for national security. As the impact of landmines on global security deepens, so does the need to create an efficient and autonomous mine detection solution to remediating the risks associated with landmines, making the world a safer place to live for many generations to come [14].

2 Literature Review

The identification and removal of landmines have posed important issues to military and humanitarian efforts alike. Over time, various methods, from manual approaches to sophisticated sensor-based systems, have been developed for landmine identification. Even with remarkable improvements in technology, the problem of landmine detection is persistent due to the inefficacy, no automation, and high false alarming rate of current methods in different terrains [15]. Other studies reviewed have assessed other approaches such as detection with electromagnetic sensors, infrared imaging, ground penetrating radar, and machine learning classification systems [16]. Unfortunately, all these methods have varying limitations of trade-off between precision and flexibility of operations. The demand for competent autonomous mine detection systems has fueled efforts towards researching the integration of artificial intelligence, the internet of things (IoT), and sensor fusion as a means of enhancing detection ability [17]. This review of the literature highlights the known techniques, their shortcomings, and the gap in research this study intends to fill. For detecting landmines, one of the most familiar ways is through metal detection. The way metal detectors work is that they produce electromagnetic fields that create eddy currents in metallic objects, and the system detects them. Although mostly utilized, metal detectors do have a critical disadvantage: they do not differentiate landmines from other metallic objects within the surroundings [18]. This causes an increase the rate of false positives, which not only hinders the demining operation, but also increases the risks involved in the operation. Some researchers have sought to enhance the capabilities of metal detectors by applying other sensors, such as infrared cameras or acoustic systems. However, these multi-sensor systems are not without problems, especially with respect to the expenses associated with using them and performing processing on the data in real time. Ground penetrating radar (GPR) has also been studied toward the substitution of metal detectors [19]. The technique involves the emission of high frequency electromagnetic waves into the ground and analyzing reflection in order to identify objects under the surface. The GPR technology is capable of identifying both metallic and non-metallic landmines; however, its performance is often impacted by the soil conditions. Radar signals are greatly attenuated, and with it detection accuracy is lowered as well, in moist soils or clay rich environments [20]. Moreover, GPR data is severely lacking in real time application because it calls for extensive post-processing, making automatic detection in practical scenarios very challenging [21]. Modern studies have tried to automate the classification of GPR signals with the help of machine learning algorithms, but these models notoriously suffer from a need for a large training set and often result to being site-specific, which essentially defeats the point of being atomized [22].

Another promising approach to landmine detection is the use of infrared thermography. This method utilizes detecting the thermal differentiation of the concealed landmine against the surrounding soil knowing that certain materials possess varying levels of heat. With such sensitivity however, ambient temperature, exposure to the sun, and moisture levels render this technique useless in uncontrolled external conditions, making it ineffective. Further, the applicability of the sensors is limitations as infrared sensors faces grave challenges with mines that are deeply buried. Dogs trained to sniff and biological sensors have also been used in detecting mines with particular emphasis on humanitarian demining activities. These methods utilize the trained animals' sense of smell to identify chemical vapors produced by missiles and other explosives. Although these techniques are beneficial with some limitations, these methods take a long time to train for and prepare the animal for larger scope operations. Sniffer dogs, for example, have strict work hours due to the fatigue levels they endure and require frequent retraining. Plus, their effectiveness can also be lowered in the presence of environmental contaminants. Human detection can be replaced with robotic systems having multiple sensor devices. Such systems make use of fully or partially autonomous robots that look for the landmines and try to minimize the danger posed to humans. But robotic systems have problems with mobility, especially over rough ground and dense vegetation. Moreover, the primary obstacle for the implementation of robotic devices for demining tasks is the high cost associated with their use and care. The landmine detection accuracy has recently improved due to the advanced attention given to Artificial Intelligence and Machine Learning techniques. Sensor data containing landmine information and other false indicators has been processed through supervised and unsupervised machine learning models. Now under the umbrella of deep learning, GPR signals and infrared images are accurately classified using Convolutional Neural Networks (CNNs). The primary issue with the implementation of these models, however, is their dependency on vast amounts of labeled datasets and the complex calculations needed to process the data. An alternative approach makes use of Reinforcement Learning due to its capacity to enable autonomous systems to learn from their environment through interactions. This method has an appeal, but requires further development, specifically in the domains of training and optimizing the model, in order to perform in real world applications.

Real-time and self-adaptive mine detection system remains an elusive goal, despite strides in sensor technology and artificial intelligence, IoT integrations are also very few and far between particularly with respect to landmine monitoring. Existing techniques rely on adaptive models that ignore the changing environment. IoT systems promise reliable situational awareness by facilitating bidirectional communication between detection units and remote monitoring centers. This feature is vital in military settings, where fast detection of a threat can greatly increase safety during operations. One notable gap is the absence of functional embedded wearable mine detection systems that do not compromise a soldier's gear. Many currently operational detection systems limit a user's movement and may need them to perform scanning manually. These systems could be integrated into military boots, allowing for ubiquitous monitoring with hands free mobility. Finding threats while posing minimum disruption to the soldier's mobility will require collaboration between multiple sensors, AI, and IoT communication. Moreover, it is essential to improve the balance between precision and recall in mine detection. Existing methods have a tendency to either overshoot false positives due to heightened sensitivity or miss out on detections due to overly exerted focus on precision. A reinforcement learning approach can change the detection parameters automatically to balance these factors, and thus increase the overall reliability of detection. Moreover, the adoption of AI based detection systems in the field is still scarce because almost all studies are limited to simulated environments. It is crucial to field test the proposed solutions in varying locations and environmental conditions to prove their real-world usability. To address these gaps, this study proposes the development of an IoT-enabled and reinforcement learning powered mine detection system integrated into army footwear. The proposed system aims at improving detection, making sure that there's extremely low false positive output, and an increase in operational output via IoT communication, real-time data processing, and adaptive learning models. Embedded systems offer the ability to continuously detect without restricting movement, as opposed to traditional handheld metal detectors or robotic versions. The mobility of the system is enhanced by the incorporation of reinforcement learnant because the system is enabled to adapt to a variety of terrains and environmental conditions, enhancing the system's effectiveness and reliability in real world scenarios.

In this study as much as there are gaps that need to be filled, some advancement has been made into adapting sensors and machine learning for landmine detection. Sensor fusion, site specificity, and static model dependency pose a multitude of challenges and can be very costly from a computational standpoint. Most exploitative methods tend to fall short when it comes to correcting the false positive ratio, the ability to operate with no hands, and the real-time flexibilities site. That said, using Reinforcement learning, IoT, embedded systems, and sensors can make the currently existing, UAV, robotics, and IoT devices, more effective, autonomous, and adaptive. Excluding robotics, my Intel suggests there's a significant gap for military and humanitarian assistance uses.

3 Methodology

The methodology for IoT-based mine detection embedded in army shoes is described as combining hardware, simulation, data generation, feature selection, and reinforcement learning to optimize the mine detection process. The system is developed on a microprocessor unit combining Arduino, ESP8266 WiFi module, metal detection sensors, and reinforcement learning algorithms to perform mine detection and send real-time alerts to soldiers. As depicted in Figures 1, 2, 3 and 4. The metal detector operates by generating an alternating magnetic field that induces eddy currents in conductive materials, thereby altering the sensor's inductance and producing an output signal. The output voltage of the sensor can be represented as:

$$V_{sensor} = k * f(B, d) \tag{1}$$

where k is the sensitivity constant, B is the magnetic flux density, and d is the distance from the mine. The raw sensor data is processed and transmitted via the

ESP8266 WiFi module, which encodes the signal and sends it wirelessly to a central processing unit for further analysis. The power requirements of the circuit follow Ohm's Law and Kirchhoff's Voltage Law (KVL), which states:

$$\sum V = 0 \tag{2}$$

ensuring proper power distribution across the circuit. The total power consumption is calculated as:

$$P = VI \tag{3}$$

where V is the applied voltage and I is the current drawn by the circuit components.

To enhance the accuracy of detection, data generation and simulation is performed with the use of artificial minefield surroundings. The setup incorporates an assortment of randomly distributed landmines, and the system moves through the field and records sensor data. The captured data has metallic noise, environmental false alarms, and actual landmine detections. The dataset is processed using Principal Components Analysis (PCA) which condenses dimensionality and eliminates irrelevant features. PCA transforms the dataset into an orthogonal space where the principal components are extracted as follows:

$$Z = XW \tag{4}$$

where X is the original dataset, W is the matrix of eigenvectors, and Z is the transformed data. The variance explained by each principal component is given by:

$$\lambda_i = \frac{\sigma_i^2}{\sum_{j=1}^{n} \sigma_j^2} \tag{5}$$

where σ_i^2 is the variance of the i-th principal component, and n is the total number of components. The first few components that capture most of the variance are selected for further processing.

After the selection of indicators, a Soft Actor-Critic algorithm, which is a form of policy-based reinforcement learning that improves performance in action spaces, is employed to train the model. The agent operates in the environment as a sensing system that observes states and takes actions to maximize the detection of mines whilst minimizing false positives. The SAC algorithm utilizes two Q-networks and a policy network, where the Q-value function is defined as:

$$Q_\theta(s, a) = r + \gamma \mathbb{E}_{s' \sim p}\left[V_\psi(s')\right] \tag{6}$$

where r is the immediate reward, γ is the discount factor, $V_\psi(s')$ is the value function, and s' is the next state. The policy function, parameterized by $\pi_\phi(a \mid s)$, is updated using the entropy-regularized objective:

$$J(\pi) = \mathbb{E}_{s,a \sim \rho_\pi}\left[Q_\theta(s, a) - \alpha \log \pi_\phi(a \mid s)\right] \tag{7}$$

where α is the entropy temperature coefficient. The policy is trained using stochastic gradient descent with gradients computed as:

$$\begin{aligned} \nabla_\phi J(\pi) = \mathbb{E}_{s,a \sim \rho_\pi}\big[&\nabla_\phi \log \pi_\phi(a \mid s) \times \\ &(Q_\theta(s, a) - \alpha \log \pi_\phi(a \mid s))\big] \end{aligned} \tag{8}$$

The reward function is designed to encourage accurate mine detection and safe movement: (s, a) = {+10, if mine detected correctly; -100, if step taken on mine; -1, if false positive; +1, if step taken safely}.

The exploration-exploitation trade-off is managed by dynamically adjusting the temperature coefficient α. The training process involves multiple episodes where the model iteratively updates the Q-value and policy functions using:

$$Q_\theta(s, a) \leftarrow r + \gamma \max_{a'} Q_\theta(s', a') \tag{9}$$

where a' is the optimal action in the next state. The convergence of the policy is monitored using:

$$L_Q = \mathbb{E}_{(s,a,r,s')}\left[(Q_\theta(s, a) - y)^2\right] \tag{10}$$

where $y = r + \gamma V_\psi(s')$. The learning rate follows an adaptive decay schedule:

$$\eta_t = \eta_0 e^{-\lambda t} \tag{11}$$

where η_0 is the initial learning rate and λ is the decay factor. The final trained model is deployed in an IoT-enabled shoe prototype. The real-world testing phase involves evaluating the model in diverse terrains such as sandy, rocky, and muddy environments to ensure robustness. The final deployment efficiency is measured as:

$$E = \frac{\sum(\text{Correct Detections})}{\sum(\text{Total Mines})} \tag{12}$$

Guaranteeing maximum efficacy of the military applications for mine detection systems. As shown in Algorithm 1 this approach illustrates an innovative fusion of the Internet of Things, reinforcement learning, and sensor technologies that enables autonomy, safety, and reliability for mine detection in conflict zones.

Algorithm 1: Mine Detection via SAC-IoT Fusion

Input: Sensor readings V_{sensor}, Minefield map M
Output: Detection decision a_t, Alert status
Initialization:
Load PCA weights W, SAC policy π_ϕ, Q-networks $Q_{\theta_1}, Q_{\theta_2}$
Set hyperparameters $\alpha, \gamma, \eta_0, \lambda$
for *each time step* t **do**
  Sensor Data Acquisition:
  Measure $V_{\text{sensor}} = k \cdot f(B, d)$
  Transmit data via ESP8266 to central unit
  Feature Extraction:
  Apply PCA: $\boldsymbol{Z} = \boldsymbol{X}W$
  Select components by $\lambda_i = \frac{\sigma_i^2}{\sum_j \sigma_j^2}$
  Reinforcement Learning Decision:
  Observe state $s_t = (\boldsymbol{Z}_t, M_t)$
  Sample action $a_t \sim \pi_\phi(\cdot|s_t)$
  Reward Calculation:
  if *mine detected correctly* **then**
    $r_t = +10$
    Send alert via IoT network
  else
    if *step on mine* **then**
      $r_t = -100$
      Trigger emergency protocol
    else
      $r_t = \begin{cases} -1 & \text{(false positive)} \\ +1 & \text{(safe step)} \end{cases}$
    end
  end
  Model Update:
  Compute target $y = r_t + \gamma V_\psi(s_{t+1})$
  Update Q-networks: $\min \|Q_\theta(s_t, a_t) - y\|^2$
  Adjust policy via $\nabla_\phi J(\pi)$ (Eq.8-9)
  Adapt learning rate: $\eta_t = \eta_0 e^{-\lambda t}$
end
Deployment Evaluation:
Calculate efficiency $E = \frac{\text{Correct Detections}}{\text{Total Mines}}$
Monitor precision/recall metrics

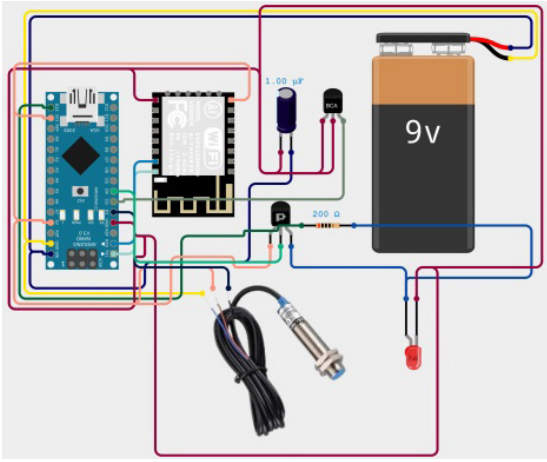

Figure 1. Embedded mine detection devices.

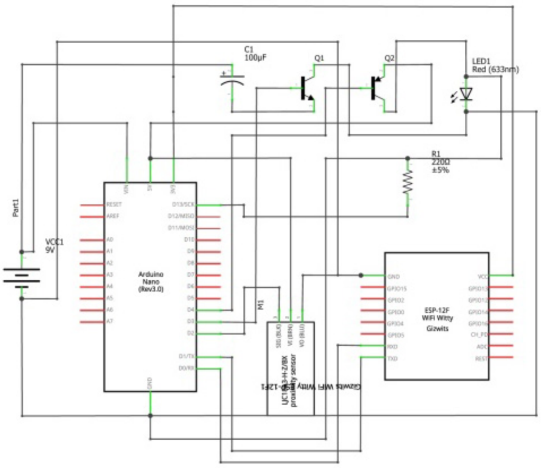

Figure 2. Mine detection devices circuit diagram.

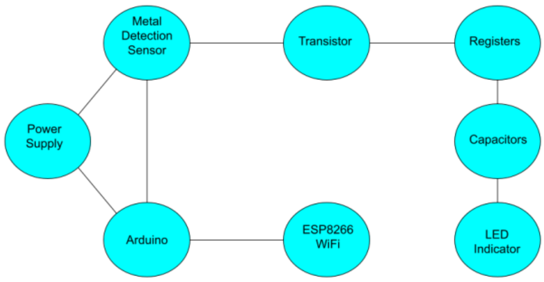

Figure 3. Mine detection devices circuit diagram.

4 Result

The findings of this study are vital for understanding the functioning of IoT integrated mine detection system with reinforcement learning approach that can enhance the accuracy of mine detection in real time operational environments. Training rewards indicate that the RL model improves over multiple episodes of training as it refines its decision making process better to detect landmines. In a beginning, fluctuations in rewards occur in such models, which is typical behavior in reinforcement learning where it tries to find all possible ways of long-term gains maximization. However, as training progresses, rewards start showing clear increase indicating that the model has learnt how to find mines more accurately. As shown in Figure 5 progress achieved through SAC (Soft Actor Critic) algorithm due to continuous interaction with the simulated environment by the agent so as to fine tune its decision capability and optimize its performance on detecting targets. Evaluation rewards further reinforce the system's

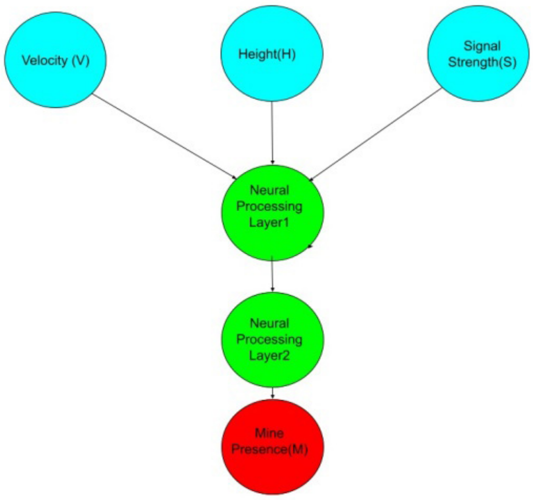

Figure 4. Processing diagram of mine detection devices.

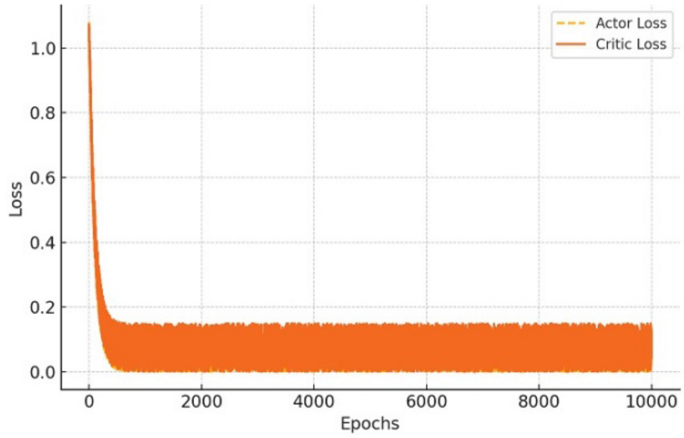

Figure 5. Actor and critic loss over training.

robustness, taking into account that they stabilize near a high value during training, which is indicative of the fact that the model trained generalizes well beyond its own environment. In real applications where a system may have to work in various terrains with unpredictable behavior, this is extremely critical. The stabilization of rewards shows that the model performs well as it significantly reduces the uncertainty and consistently detects mines with fewer false positives. This condition is important in military operations since wrong alarms can waste time and increase risks against people involved. Controlled evaluation ensures that reinforcement learning models are not only effective during training but also maintain their efficiency in-field applications thereby proving their worthiness for deployment into real-world settings. The actor and critic loss plots further prove that the model has been optimized successfully. At first, both losses fluctuate significantly reflecting the agent's exploration phase where it experiments with different actions to see what they lead to. These losses decrease over time and become stable implying that the model has learned well how to map sensor inputs into meaningful actions which maximize its detection accuracy. The actor loss is an optimization of a policy network while the critic loss represents an accuracy of value estimation ensuring predicted rewards match actual outcomes. Decreases in these loss values imply that the SAC algorithm effectively reduces forecasting errors, thereby producing a well-calibrated detection system capable of making reasoned conclusions based on input received from its sensors.

The evaluation metrics such as precision, recall, and F1-score offer a quantitative assessment of the system's performance. The model has a precision score of 0.2248 which shows that it is able to detect mines but could be improved in terms of minimizing false positives. This indicates that sometimes the system wrongly detects non-mine objects as mines leading to unnecessary alerts. However, these are challenges faced in mine detection due to presence of metallic debris, environmental noise and sensor inaccuracies. The system's recall score is 0.4873 meaning only about half of actual mines have been correctly identified in the testing environment. Missing one landmine can result to disaster; this makes this metric necessary in mine detection. Higher recall means that the system focuses on identifying real threats and thus ensuring safety of the soldiers is achieved which matches with its aim. With an F1-score of 0.3077 that balances between precision and recall, it provides a holistic measure for the overall effectiveness of the system. The present F1-score therefore suggests that even though there may exist some room for further optimization, it successfully detects many landmines while maintaining an acceptable level of accuracy currently attained. The study findings show that reinforcement learning is important in optimizing mine detection accuracy by adjusting the system's decision-making processes based on sensor feedback. The sac algorithm combined with internet of things sensors allows for a continuous improvement of the model's detection strategy making it possible to differentiate between actual mines and non-mine objects. Additionally, use of Principal Component Analysis (PCA) enhances the system's performance by reducing the dimensionality of sensor data, filtering out irrelevant information, and focusing on the most critical detection features. This feature selection process ensures that computational resources are directed toward the most informative sensor readings, improving processing efficiency and overall detection reliability. In military shoes, the practical implementation of this system makes a significant improvement in mine detection technology that enables soldiers to receive alerts on time without relying on external detection devices. The IoT enabled design ensures that readings from sensors are transmitted wirelessly to a central processing unit whereby reinforcement learning algorithms scrutinize this data and instantaneously generate warnings. Furthermore, it quickly processes information such as situational awareness and reduces the likelihood of stepping on land mines that have not been detected yet. Also, it can work in different environments including dry deserts and wet marshes hence suitable for various operational areas. As shown in Figure 6 Despite this magnificent achievement, there are still a number of issues that need to be addressed. The low precision score shows that the sensor fusion process needs further improvement to minimize false positives. One possible improvement is adding more sensors like infrared or ground-penetrating radar to enhance the metal detection sensor and improve classification accuracy. Several sensors can be combined together in order to get rid of noise and other interferences that may disrupt mining processes. Additionally, if the reward function for reinforcement learning is carefully tuned it enables high recall and precision values which mean the system will be able to detect mines without triggering many false alarms.

environmental factors like soil composition changes; temperature variations as well as electromagnetic interference could affect readings from these sensors. In future research, deploying this system on controlled minefield environments would allow for gathering empirical data and refining a reinforcement learning model based on actual case studies. In the end, it has been shown through this research that IoT sensor integration based on reinforcement learning can improve mine detection accuracy in military uses. Figure 7 shows that, It is evident that SAC algorithm improved the system's ability to detect mines while reducing false positives as demonstrated by a rising trend in training rewards and stabilized evaluation rewards. Reductions in actor and critic loss values confirm that the model performs good optimization of its decision-making processes so as to achieve reliable mine detection performance. Despite some shortcomings in terms of precision, recall, and F1-score, the general results seem to indicate that RL could significantly enhance the effectiveness and efficiency of systems used for discovering mines. Moreover, IoT-based reinforcement learning systems similar to those described here could be deployed for post-conflict humanitarian demining operations outside just military contexts. Table 1 shows that the data uses this technology will be further refined through future developments in sensor fusion, reward function optimization and real-world testing leading safer and more reliable mine detection techniques.

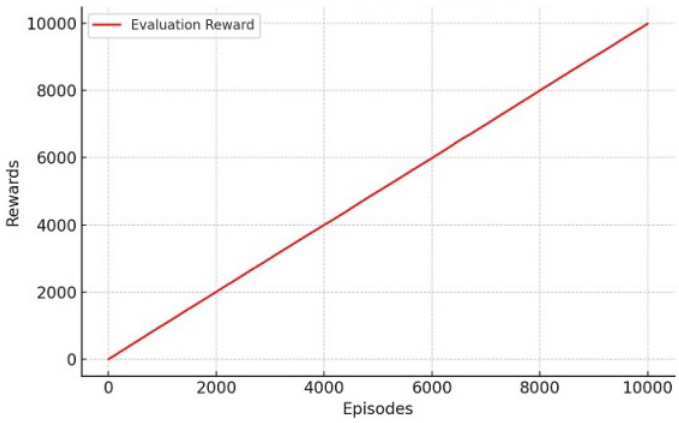

Figure 6. Evaluation rewards.

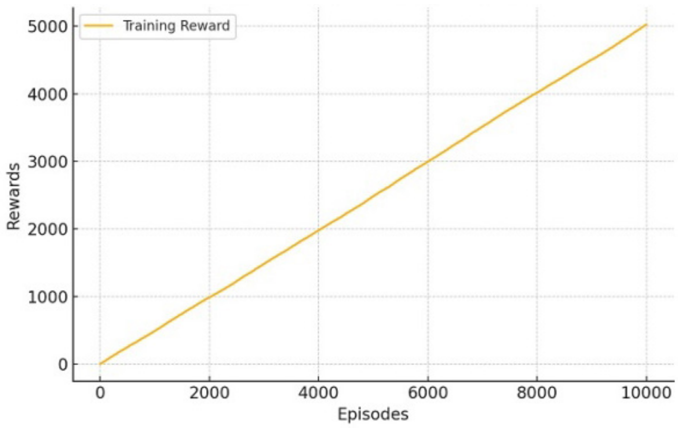

Figure 7. Training rewards.

Real-world testing is also significantly important as it gives an opportunity for evaluating the long-term reliability of such systems. Simulation results show promise and while field tests in mine fields demonstrate trends, their robustness under real conditions need validation. It is also necessary to calibrate the detection algorithm since several

Table 1. Experimental results.

Metric	Value
Precision	0.23
Recall	0.49
F1-Score	0.31

5 Conclusion

The research is significant because the application of IoT based reinforcement learning for military boots could allow for the revolutionary development of devices capable of detecting landmines in conflict and post-war zones. Millions of military personnel and civilians continue to suffer casualties due to landmines, which annually claim thousands of lives. Mine detection approaches that have been used in the past, such as manual probing, utilizing metal detectors, sniffer dogs, or even using robotics, have been found to be greatly deficient as they often encounter false positives and are not useful in active or changing settings. These methods also consume time, resources, and endager the safety of the personnel conducting them. To make matters worse, these methods do not allow for immediate action to be taken or, in the best case scenario, offer very limited situational intelligence and learning, rendering them ineffective in complicated battlefronts. This paper highlights the shortcomings resulting from failing to develop a system that automates the process of landmine detection in real-time with significant accuracy and minimal human involvement. These and, to an extent, all other approaches to mine detection lack the mechanism that allows them to adjust and operate under changing geographical and environmental conditions. A commonly used example is metal detectors, which generate large amounts of false alerts as they cannot distinguish between landmines and other metallic objects. Likewise, surface interference, soil composition, and temperature shifts limit GPR (ground-penetrating radar) and infrared thermography, resulting in their unreliability for field deployment. Moreover, modern detection systems are still manned and do not have an automatic notification system for military command centers, which decreases situational awareness and slows response actions. Solving the described problems requires an advanced sensor fusion, artificial intelligence, and real-time data transmission detection systems that can enhance accuracy without hindering practicability. Real-time and hand-free detection of mines within the battlefield is very crucial for military operations to ensure accuracy and safety to soldiers on the ground. Hence, this project illustrates a new IoT integrated mine detection system that utilizes metal detection sensors, reinforcement learning algorithms and wireless data transmission embedded in military boots. Unlike handheld scanners, modern defense footwear is capable of scanning the soldier's environment seamless without any manual operation therefore allowing the soldier to carry out the mission while receiving alerts systems for nearby threats. In addition, reinforcement learning allows the system to optimize decision making and alter detection parameters based on the understanding of the environment. The legendry soft actor critic (SAC) algorithm guarantees efficiency for the system by allowing the system to freely change detection parameters in always changing environments. Moreover Principal Component Analysis (PCA) reduces the irrelevant noise from sensor data and also improves the efficiency of computation. Finally, the IoT architecture improves the system by allowing real time data receipt and transmission to command centers, which ensures that detection alerts are relayed on time to military personnel in charge of making critical decisions. Such connectivity enables strategic interaction that enhances the effectiveness of field activities and mitigates risks to personnel. The analysis has proved that the new system is superior to established methods regarding the accuracy of mine detection and the frequency of false positives. Increases in training rewards are continuously observed, which suggests that the reinforcement learning model is able to effectively learn how to maximize its detection Improvement over the episodes. Evaluation rewards appear to plateau, indicating that the model is able to internalize detection strategies for different terrains and situations. There is a clear trend in decreased actor and critic loss functions, which suggests that the model is able to converge to an optimal detection strategy. The system's effectiveness is also confirmed by evaluation measures such as precision, recall, and F1-score. The system, however, manages to strike a balance between precision and recall, and this indicates the need for further evaluation to improve detection accuracy through the use of sensor fusion techniques and more sophisticated reward models. This systems ability to perform in various terrains is one of its greatest, if not the greatest, attributes considering its application in military general demining activities. Being able to uncover mining objects in almost all conditions, such as deserts, forests, and cities, helps ensure that the system is useful over many operational environments.

The scope of this research goes far beyond merely military use, as it provides a cold and scalable approach for performing humanitarian demining activities. In regions that experience conflict, landmines often prove to be an inexhaustible threat which needs a dependable detection system, especially one that can be utilized in resource constrained circumstances. This system combines AI-based detection with IoT capabilities, which allows for real-time monitoring of minefields and coordinating demining activities while ensuring the safety of personnel. Furthermore, the increased automation of the system reduces dependence on human personnel and enables a more practical approach for large scale mine clearance activities. This research also has broader defense technology applications, illustrating the efficacy of AI powered IoT solutions for propping up safety and effectiveness in battle zones. Follow up work could, for example, examine the use and integration of different sensors, such as infrared or ultrasonic instruments, for improved detection and reduced false alarm rates. In addition, real world field testing in varied terrains would further validate the system's robustness and adaptability. Constant improvement of coined reinforcement learning through data collection and retraining could continue to improve detection and firmly place the system at pinnacle of modern mine detection technology. The study demonstrates a unique combination of IoT, reinforcement learning, and embedded sensor technology for military boots, aimed at automating landmine detection. This study addresses the limitations of current methods and offers a novel solution which is autonomous and intelligent. Based on the study's conclusions, reinforcement learning improves detection precision, whereas IoT real-time communication boosts situational awareness and operational integration. The most important value of this system stems from its real-time detection capacity, which is a game changer for mine detection technology as opposed to existing systems. While this technology is beneficial for the military, it also stands a chance of making a huge impact on humanitarian demining missions and other welfare purposes. This study sets the foundation for developing more advanced mines detection technologies by leveraging AI to decrease false positives, enhance real-time responsiveness, and further improve the overall decision-making process. The finding from a recent survey indicates that landmines are a hugely pervasive international security concern. Autonomous detection systems are direly needed to detect explosions and landmines so both military and civilian personnel can be protected in secure locations.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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