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Quantum Support Vector Machine for Landmine Detection based on UAV Terahertz imaging system

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ABSTRACT

Landmines pose a persistent threat to human safety and infrastructure in post-conflict regions. Conventional landmine detection methods often require direct human involvement, exposing personnel to significant risk while facing limitations in accuracy and scalability. In this study, we propose a Quantum Support Vector Machine (QSVM)-based detection system integrated with UAV-mounted terahertz imaging technology to enhance landmine identification efficiency. Leveraging quantum computing principles, QSVM provides improved classification accuracy by optimizing feature separability in high-dimensional spaces. Additionally, terahertz imaging enables remote sensing, reducing operational risks and enhancing detection precision. Experimental findings show that QSVM achieves better precision and recall than traditional classifiers while separating landmines from background noise.. Furthermore, comparative analysis with Quantum K-Means (QK-Means) and Quantum Neural Networks (QNN) underscores the robustness of QSVM in real-world applications. The integration of UAV platforms with quantum-enhanced algorithms offers a scalable, non-invasive, and high-accuracy solution for landmine detection, paving the way for safer and more efficient demining operations.

Keywords: Quantum Computing, QSVM, QKMeans, Landmine Detection, UAVs.

1.0 INTRODUCTION

Landmines are indiscriminate weapons that, like other explosive remnants of war (ERW), remain hidden and active for decades, posing risk to the lives of humans globally in war and post-war regions (Forero-Ramírez et al., 2022). They contaminate the environment and hinder agriculture, commerce and communication amongst people (Safatly et al., 2021). By the year 2021, there were a total of 61 nations and regions with a confirmed risk of the presence of antipersonnel mines. International Campaign to Ban Landmines (2020) reports that in the year 2019 "a minimum of 5554 victims of mines/ERW were reported, of which more than half resulted due to improvised mines (2949)." Civilians comprised the majority of victims, at 80%, and children comprised 43% of civilian victims (Xue et al., 2020).

Landmines left behind in conflict areas are a constant risk to human life, remaining active even decades after a conflict have ceased. The threat of these landmines can be seen in northeast Nigeria, where Borno and Yobe regions have suffered from landmines from previous conflicts that remain active years later. Not only do these war remnants kill, but they also maim survivors, resulting in amputations, as well as psychological injury (The Daily Trust, 2025). The extent of the landmine impact goes far beyond human casualties. Landmines also disrupt agriculture, as cultivators are reluctant to plant in contaminated areas. This, in turn, contributes to increased food insecurity and economic instability in communities hit by landmines (Kovács & Ember, 2022). Landmines also impede infrastructure development, such that rebuilding roads, schools, and hospitals, a requirement for post-conflict rebuilding, is problematic (Makki et al., 2017).

Attempts to solve this problem are common through demining activities, which are labour-intensive, expensive, and hazardous (Ihab Makki et al., 2017). Organizations operating in these areas have to contend with a lack of resources, harsh environments, and sheer magnitude of the problem. Education programs are also essential, instructing locals on how to recognize and steer clear of landmines, but these programs are dependent on regular funding and assistance (UNICEF, 2024). Ongoing casualty reports year upon year underscore the pressing necessity of both international cooperation and investment in demining technology as well as humanitarian assistance (UNICEF, 2024). Unless there are concerted efforts, war legacy continues to kill and slow progress years after war has come to an end. Borno and Yobe are a poignant reminder of the lasting impacts of conflict and why these need to be tackled early on.

Different methods have been devised and used over time to locate landmines, each having its own benefits and drawbacks (Hussein & Waller, 2000; Kasban et al., 2010). They are important in landmine clearing activities that pose a significant threat to human life. Some of these widely applied methods include electromagnetic methods, Ground Penetrating Radar, acoustic or seismic, Nuclear Quadrupole Resonance, hyperspectral imaging, among others (Rangel et al., 2024). The greatest limitation of several conventional methods is that they require demining companies to have a physical presence in the minefield, exposing people to possible injury. Also, the use of technology that tends to submit false responses makes it further cumbersome (Aaron Goad et al., 2008; Csikai et al., 2004).

Being aware of these drawbacks, researchers are working actively on safer, more effective methods of landmines detection. In response to these limitations, a Quantum AI-based landmine detection system using drones for remote scanning is proposed as a cutting-edge solution to enhance safety and accuracy (Gupta Sayantan et al., 2017; Manzalini, 2020). The technique may change landmine detection forever, providing a faster, safer alternative that minimizes human lives risks while ensuring high efficiency in demagnetization of affected areas.

Thus, in this study, we propose a Quantum Support Vector Machine algorithm for faster and accurate detection of landmines. Secondly, we propose a Terahertz imaging system that uses electromagnetic waves to penetrate surfaces without harmful radiation (Biamonte et al., 2016). And lastly, we propose the use of quantum sensors for sensitivity and resolution of Terahertz imaging.

The remainder of this article is organized as follows: Section 2 reviews the existing state-of-the-art methods in landmine detection, highlighting advancements and challenges in the field. Section 3 details the materials and methodologies employed in this study, outlining data collection, experimental setup, and analytical techniques. Section 4 presents the implementation, analysis, and discussion of the study's findings, offering comparative insights into different quantum machine learning models. Finally, Section 5 provides the conclusion and references, summarizing key contributions and suggesting future research directions.

2.0 STATE OF THE ART

The detection of landmines continues to be a significant problem on a worldwide level, particularly in areas of conflict where human life as well as infrastructure are at stake. Over the years, a plurality of novel concepts in technology and methodology have been investigated by researchers aimed at solving this pressing problem. From honeybee-biosensor biohybrid technology to developments in hyperspectral imaging (Filipi et al., 2022), thermography, and ground penetration radar (Rangel et al., 2024), the quest for safer, more efficient methods of landmine detection has stimulated significant advances in science. This review synthesizes a variety of findings from disparate studies, not merely emphasizing advances in technology but also setting these in relation to practical applications, as well as constraints, where applicable.

2.1 Biological and Natural Systems for Detection

The novel application of biological organisms to landmine detection has provided novel horizons to tackle the global humanitarian problem of demining. Among them, the integration of honeybees in detection systems presents an eco-friendly and promising solution. Filipi et al., (2022) presented an innovative biohybrid system that takes advantage of honeybees' natural behavior to identify landmines. This idea was driven by the necessity to develop safer, cost-efficient, and scalable solutions to metal detector and sniffer dog-based traditional methods, typically constrained by cost, time, and risk. The system uses two complementary methodologies: Passive Sampling, Honeybees tend to probe suspected areas by carrying explosive debris to their hive. Their samples are inspected using organic semiconductor films to detect contamination. Active Search: Honeybees learn to connect explosive odors to rewards in the form of food. Their flight trajectories above areas suspected of containing landmines are tracked using computer vision algorithms-equipped UAV-carrying cameras to produce spatial density maps.

Whereas the biohybrid system was promising regarding improving detection efficiency and safety, some limitations were observed. Weather conditions and wind-swept growth occasionally triggered false positives, and functionality depended on honeybee foraging habits and flying time of UAV. Further research is recommended to streamline these processes and overcome such limitations. The research identifies the capability of honeybee-based detection tools in enhancing landmine detection technologies to reduce human risk and provide scalability to cover extensive areas.

2.2 Remote Sensing & Deep Learning Approaches

Technologies of remote sensing, along with computational algorithms, are opening doors to more effective and secure landmine detection (Hutsul et al., 2024). Thermographic imaging, in particular, provides a promising new means of landmine detection by taking advantage of thermal differences between buried landmines and surrounding soil.

One of those works in the field of remote sensing for landmine detection is the study by Sineglazov & Lesohorskyi, (2024) focuses on the critical issue of buried antipersonnel landmine detection in post-conflict areas. Conventional detection practices, though effective, tend to be dangerous, time-consuming, and subject to inefficiencies. The research attempts to refine the process by developing a thermographic image dataset to aid in machine learning algorithm and computer vision model development to detect landmines automatically. The methodology focuses on employing a DJI Matrice 100 flying system with a Zenmuse XT thermal camera (working in the range of

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7–13 µm) to take thermal images of an environment-controlled testing site.

Another groundbreaking research is the study by Xinghua Shi et al., (2018). This study uses hyperspectral imagery onboard UAVs to detect and analyze electromagnetic field signatures from landmines. To effectively process hyperspectral imagery, the research uses dense convolutional neural networks and residual connections to extract spectral-spatial features. Two well-known datasets the Pavia University and Indian Pines hyperspectral datasets were modified to mimic landmine contamination, by adding an additional 'mine' classification to be used in classification experiments. The results depict outstanding average accuracy of classification, with 91.4% obtained for the Pavia dataset and 89.31% for the Indian Pines dataset. Of particular note, the research managed to eradicate false negatives, where no misclassified mines remained, and noted acceptable rates of false positives (8.452% and 9.32%, respectively).

Moreso, the study by Rangel et al., (2024) examines integrating unmanned aerial vehicles (UAVs) and advanced deep learning algorithms to detect landmines in post-conflict areas. The study uses the Faster R-CNN (Region-based Convolutional Neural Network) model, widely known for its object detection ability. The use of UAVs to provide optical and infrared images of areas infested with mines provides a less dangerous and broader method compared to detection using floor-based methods. One of the main contributions of this research is fine-tuning of the model to overcome challenges specific to landmine detection. By tuning the sizes and ratios of anchors, the Faster R-CNN model was fine-tuned to increase detection of objects of varied sizes and appearance.

Multispectral imaging integrated with UAV platforms offers an enticing solution to address the pitfalls of conventional landmine detection technologies, especially in dense vegetation-covered areas. (Guo et al., 2022), in their research, suggest an upgraded detection system integrating multiple bands of spectra to boost precision and accuracy in detection of scatterable landmines. This promising technique uses an RGB and NIR imagery capturing capability of a UAV-based platform to cover terrains with adverse ground conditions, such as dense foliage that usually hides landmines. The system uses a two-stream network architecture to learn features separately in every individual spectrum and then at decision level fuses them. The spectral bands can be given weights depending on application, and these can be adjusted to leverage complementary information of RGB and NIR data.

2.3 Ground-Based Systems and Signal Processing

Ground-based systems, especially those that use Ground-Penetrating Radar (GPR), have shown strong effectiveness in detecting landmines. These systems apply sophisticated signal processing methods to detect subsurface anomalies, helping to distinguish landmines from other buried items. A prominent technique features vehicle-mounted GPR arrays that merge real-time data collection with automated preprocessing, feature extraction, and classification algorithms. Using techniques like Histogram of Oriented Gradients (HOG) and Support Vector Machines (SVM), these systems can achieve high detection accuracy while keeping false alarm rates low, even across different types of terrain.

Rangel et al., (2024) study brings forth an enhanced vehicle-borne Ground-Penetrating Radar (GPR) system catering to real-time landmine detection in varied terrains. Acknowledging the need for immediate and effective detection methods in extensive post-conflict areas, the research focuses on scalability, efficiency, and precision. The key to this methodology lies in combining high-quality 3-D radar datasets and automated signal processing algorithms. The detection process has three stages to it: Down-Track Processing, The third step is to preprocess the received signal using methods such as DC correction, time zero correction, background subtraction, and linear gain to filter and enhance the radar signal. Cross-Track Processing, Extract features like Histogram of Oriented Gradients (HOG) and Use Support Vector Machines (SVM) to detect possible landmine targets. Depth-Track Processing, The final step is to verify the locations of identified objects and plot their depths in three-dimensional slices.

Xue et al., (2020) research attempts to overcome the prevailing challenge of enhancing landmine detection mechanisms by integrating statistical analysis and machine learning classifiers. Ground Penetrating Radar (GPR) is pivotal in this regard, as it offers a nonintrusive technique to identify subsurface anomalies. This research adopts a systematic framework that starts by extracting statistical features of raw A-scan GPR signals. The features identify subsurface features affected by soil factors and buried targets. The machine learning classifiers, viz., Random Forest (RF), Support Vector Machines (SVM), and XGBoost (XG), train on these features and classify signals as landmine-related or unrelated.

Khodor et al., (2021) research addresses the use of neutron-based technologies to detect low-metal landmines, an enduring issue using standard detection technologies. Cognizant of metal detector limitations in plastic-cased landmine detection, scientists suggest that a landmine detection system should be focused around

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using a D-T sealed neutron generator. Two main approaches have been used in this study: Fast Neutron Analysis (FNA), this technique is based on observing interaction between fast neutrons and elements used in explosive materials in the mine. Tagged Neutron Method (TNM), this technique improves detection as it optimizes signal-to-noise and eases identification of explosive components such as carbon and oxygen in buried materials.

On the issue of Ground Penetration Radar, Picetti Francesco et al., (2018) investigates an innovative solution to landmine detection with Ground Penetrating Radar (GPR) technology and machine learning algorithms. Acknowledging the difficulties presented by plastic-cased buried unexploded landmines, the research targets enhanced detection by emphasizing anomaly detection via convolutional autoencoder model. The system trains the convolutional autoencoder with GPR B-scans free of landmine traces. This enables the model to learn what the normal ground structure representation is. With application to novel B-scans, the autoencoder captures anomalies the hyperbola signatures of buried landmines through reconstruction errors. The use of one-class detection disregards prior knowledge of a particular landmine's properties, making the system versatile to suit varied scenarios.

MAGnetometry Imaging based Classification is yet another achievement in the field of landmine detection. Barnawi et al., (2024) propose MAGnetometry Imaging based Classification System (MAGICS), an innovative framework that takes advantage of airborne magnetometry and deep learning algorithms to detect landmines. Aware of the intrinsic risks and inefficiencies of conventional detection technologies, the research integrates edge computing, enabling processing and analysis of information in real-time directly onboard the UAV to reduce latency and enhance decision-making functionality in situ. The framework uses magnetic anomalies sensed by magnetometers onboard UAVs and processes these using deep learning classifiers to detect patterns that relate to landmine signatures.

2.4 Quantum Machine Learning for Landmine Detection

Quantum Machine Learning (QML) is an emerging field that integrates quantum computing with classical machine learning algorithms to potentially solve complex problems faster or more efficiently than traditional methods. It uses the principles of quantum mechanics such as *superposition*, *entanglement*, and *interference* to enhance data processing, pattern recognition, and optimization (Babu et al., 2024; Biamonte et al., 2016).

In essence:

QML = Classical ML + Quantum Speedups via Quantum States and Circuits

Classical ML relies on operations in *vector spaces*. QML, however, maps classical data into quantum Hilbert spaces, which are exponentially large, allowing models to potentially identify complex patterns in fewer steps or dimensions (Cerezo et al., 2023). For example, with n qubits, you can represent 2^n dimensional space.

The application of Quantum Machine Learning (QML) to landmine detection offers a revolutionary solution to this complex humanitarian issue. QML uses principles of quantum computing, quantum superposition, and entanglement to advance machine learning algorithms to enable them to tackle high-dimension problems at unprecedented speeds and efficiencies. Landmine detection, however, is dependent on processing large volumes of data obtained by advanced sensing technologies like Ground Penetrating Radar (GPR), hyperspectral imaging, and airborne magnetometry. Quantum computing has distinct advantages in such cases because of its parallel processing and ability to efficiently perform large-scale computation.

Following the application of convolutional autoencoders in GPR anomaly detection (Picetti Francesco et al., 2018), QNNs can be used to learn about ground patterns and detect variations typical of buried landmines. The capability of QNNs to rapidly process and analyze high-dimensional information compared to standard models enables them to be well-suited to process large and intricate datasets produced by GPR scans. Likewise, by combining standard SVMs in statistical approaches (Rangel et al., 2024), QSVMs can be used to classify landmine-related signal features with higher accuracy. With quantum kernels, QSVMs can operate well in high-dimensional feature space, enhancing accuracy in subtle landmine signatures detection and keeping false positives low.

UAV-based approaches, e.g., those implemented with Faster R-CNN or multispectral fusion necessitate optimal flight trajectories and sensor calibrations to maximize detection efficiency (Guo et al., 2022; Luo et al., 2024). Quantum reinforcement machine learning algorithms may optimize UAV movement in real time to provide complete cover of suspected zones with minimal energy loss. Moreso, Methods such as multispectral fusion fuse information in various bands to maximize detection. Quantum algorithms to fuse data may optimize this by processing massive multispectral datasets concurrently to provide rapid and accurate detection of buried mines in challenging terrains (Guo et al., 2022).

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3.0 MATERIALS & METHODS

3.1Materials

(a) Landmine Detection Datasets

The effectiveness of the Quantum Support Vector Machine (QSVM)-based landmine detection system relies heavily on the quality and diversity of datasets used for training and validation. In this study, the 'land mines.csv' dataset from Kaggle is utilized as a foundational data source. This dataset comprises 338 instances with four key attributes: Voltage (V), Height (H), and Soil Type (S) each playing a crucial role in understanding the environmental factors affecting landmine detection. The Voltage (V) represents the output voltage value of the Fluxgate-Like Coil (FLC) sensor due to magnetic distortion, offering insights into electromagnetic variations caused by buried landmines. Height (H) refers to the sensor's elevation above the ground, impacting detection sensitivity and signal strength. Additionally, the Soil Type (S) accounts for six different soil conditions based on moisture content, ranging from dry sandy to humid limy, allowing for comprehensive terrain-based analysis of detection accuracy as presented in Tables 1 and 2.

Table 1. Soil Type Comparison Table

Soil Type	Texture	Organic Content	pH Level	Water Retention	Conductivity	Compaction
Dry and Sandy	Coarse, loose	Very low	Neutral to Slightly Acidic(6.0-7.0)	Very low	Low	Low
Dry and Humus	Fine, rich in organics	High	Slightly Acidic (5.5–6.5)	Moderate	Moderate	Medium
Dry and Limy	Fine to medium, chalky	Low	Alkaline (7.5–8.5)	Low to Moderate	Moderate	High
Humid and Sandy	Coarse, moist	Low	Neutral (6.5–7.0)	Moderate	Low	Medium
Humid and Humus	Dark, fine, moist	Very high	Slightly Acidic (5.5–6.0)	High	Moderate	Low
Humid and Limy	Moist, chalky	Low to Moderate	Alkaline (7.5–8.0)	Moderate	Moderate to High	Medium

Table 2. Landmine Classification

Mine Type (M)	Frequency Count	Activation Mechanism	Explosive Weight	Detection Challenge
Null (Non-mine class)	71	None	0 kg	Must avoid false positives
Anti-Tank (AT)	70	Pressure (>100 kg)	6–10 kg TNT	Easier to detect (large, metallic)
Anti-Personnel (AP)	66	Pressure (~5–20 kg)	50–200 g TNT	Small, shallow, may be plastic-cased
Booby Trapped Anti-Personnel (BAP)	66	Pressure + Tripwire/Remote	50–200 g TNT + trap	Complex signals, highly variable casing
M14 Anti-Personnel (Plastic)	65	Pressure (~10 kg)	~29 g Composition B	Extremely hard to detect (non-metallic)

To enhance robustness, this study integrates real-world landmine detection datasets collected from contaminated zones along the Maiduguri-Damboa Road in Borno State, Nigeria, where landmine threats remain persistent due to past conflicts. UAV-mounted terahertz imaging systems capture high-resolution spectral data, complementing the Kaggle dataset with diverse environmental signatures. Simulated datasets further extend this approach by conducting controlled experiments with surrogate landmines buried at varied depths and soil compositions. These datasets ensure the QSVM model is trained under diverse conditions, enabling it to effectively differentiate between landmine-related anomalies and environmental noise. By merging Kaggle-based structured data, real-world UAV-captured imagery, and synthetic augmented datasets, this study establishes a comprehensive framework for training and validating the proposed quantum-driven detection system.

(b) Study Terrain

The terrain selected for this study plays a crucial role in assessing the reliability and effectiveness of the proposed Quantum Support Vector Machine (QSVM)-based landmine detection system. The study encompasses varied soil compositions and environmental conditions to simulate realistic landmine detection scenarios. Data collection is conducted in controlled experimental sites featuring sandy, loamy, and clay soils, each presenting unique challenges in

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signal propagation and imaging accuracy. Additionally, terrain complexity is increased by incorporating different moisture levels, including dry and humid soil conditions, to evaluate the system's adaptability to real-world detection environments. To ensure practical applicability, field testing is performed in mine-affected regions along the Maiduguri-Damboa road in Borno State, Nigeria, where UAV-mounted terahertz imaging systems capture high-resolution spectral data See figure 1. The influence of vegetation, surface irregularities, and subsurface variations is carefully analyzed to refine detection capabilities. By encompassing a diverse range of terrains, this study aims to validate the robustness of QSVM-driven detection algorithms, ensuring effective deployment in conflict-affected regions.

(a) Location of the test site at Damboa (b) Aerial view of the site (c) Terahertz image of scanned site

Figure 1. Snaps from the study area

(c) Detection Technology

The detection technology employed in this study integrates Unmanned Aerial Vehicle (UAV) platforms with advanced imaging systems alongside ground-based sensing equipment, including Ground Penetrating Radar (GPR) and neutron detectors. This multi-layered approach ensures comprehensive landmine detection by leveraging aerial and subsurface analysis, improving detection accuracy, and reducing human risks associated with manual demining operations.

(d) UAV Platforms

Unmanned Aerial Vehicles (UAVs) serve as a crucial component of modern landmine detection technology, providing non-invasive surveying capabilities over vast and hazardous terrains. In this study, UAVs are equipped with terahertz imaging sensors and hyperspectral cameras to capture detailed spectral data for identifying anomalies indicative of buried landmines.

i Terahertz Imaging Sensors

Terahertz (THz) technology is employed due to its ability to penetrate various materials while remaining non-ionizing and safe for operational use. These sensors operate within the 0.1 to 10 THz frequency range, allowing the system to detect discrepancies in soil and subsurface structures. Terahertz waves interact with landmines differently than with natural soil compositions, enabling the detection of subsurface anomalies without disturbing the ground.

ii Hyperspectral Imaging

Hyperspectral cameras onboard UAVs record electromagnetic data across multiple spectral bands, enhancing the ability to differentiate landmine-related disturbances from natural terrain features. These cameras operate across visible, near-infrared (NIR), and short-wave infrared (SWIR) spectra, providing detailed information about chemical compositions and material contrasts that may indicate the presence of landmines.

iii Autonomous Flight and Real-Time Processing

The UAVs are programmed with autonomous flight capabilities, following predefined search patterns to systematically scan high-risk zones. Integrated with edge computing, the UAVs process image data in real time, reducing latency in decision-making. This approach allows immediate identification of potential threats and minimizes the need for manual data analysis post-flight.

(e) Ground Equipment

While UAVs provide extensive aerial reconnaissance, ground-based sensing technologies complement these efforts by enabling precise subsurface detection. The system employs Ground Penetrating Radar (GPR) and neutron detectors, offering robust solutions for detecting landmines buried at varying depths.

i Ground Penetrating Radar (GPR)

GPR is a well-established tool in landmine detection, operating on the principle of emitting radio waves into the ground and analyzing the reflected signals. This study utilizes multi-array vehicle-mounted GPR systems that scan large areas efficiently. The key components include: Ultra-Wideband (UWB) Antennas, These antennas emit broadband signals that penetrate the ground at different frequencies, improving resolution across varying soil types.

Automated Signal Processing, The system integrates Histogram of Oriented Gradients (HOG) feature extraction and Quantum Support Vector Machine (QSVM) classifiers, allowing automated detection of subsurface anomalies indicative of landmines. Depth Profiling, Three-dimensional signal reconstruction provides accurate depth estimates, ensuring precise localization of buried landmines.

ii Neutron Detectors

Neutron detection technology is employed to identify low-metal and plastic landmines, addressing limitations of conventional metal detectors. Two primary neutron-based techniques are used: Fast Neutron Analysis (FNA). This method observes the interactions between high-energy neutrons and explosive materials, distinguishing landmines from surrounding soil. Tagged Neutron Method (TNM), TNM enhances the signal-to-noise ratio, allowing accurate identification of chemical compositions such as carbon, oxygen, and nitrogen, which are typically found in explosives.

3.2 Methodology Design

(a) Data Acquisition

The data acquisition process is a critical component of the proposed Quantum Support Vector Machine (QSVM)-based landmine detection system, ensuring comprehensive coverage and accuracy in identifying buried landmines. This phase is divided into two key methodologies: aerial surveys using UAVs equipped with advanced imaging systems and ground surveys employing Ground Penetrating Radar (GPR) and neutron-based sensors. The former, being Unmanned Aerial Vehicles (UAVs) are deployed to conduct non-invasive scans over preselected terrains, reducing the risks associated with manual landmine detection. Equipped with terahertz imaging sensors and hyperspectral cameras, UAVs capture high-resolution spectral data that helps distinguish landmine signatures from natural terrain features. While the latter, being the Ground Surveys sensors offer high-resolution subsurface data to verify findings from aerial scans. Ground Penetrating Radar (GPR) and neutron-based sensors play a crucial role in detecting buried landmines with greater precision.

(b) Preprocessing

Preprocessing plays a crucial role in refining the collected data, ensuring optimal clarity and reliability before it is analyzed for landmine detection. Given the diverse environmental conditions affecting data acquisition such as soil composition, terrain complexity, and atmospheric interference the preprocessing stage is designed to eliminate noise, correct distortions, and enhance signal clarity across aerial and ground-based detection systems.

i. Noise Reduction and Signal Enhancement

The raw data captured from UAV-mounted terahertz imaging sensors, hyperspectral cameras, and ground-based GPR/neutron sensors undergoes denoising techniques to remove irrelevant environmental interference. UAV images often contain unwanted artifacts due to atmospheric conditions (e.g., humidity, dust, and light distortions). To address this, adaptive filtering techniques are applied to smooth signal variations while preserving relevant features. Similarly, GPR signals are prone to background reflections and antenna-induced distortions, requiring preprocessing techniques such as DC correction, time-zero correction, and background subtraction to refine radar waveforms.

ii. Normalization and Standardization

To ensure consistency across datasets, all collected signals are normalized to a standard range, reducing disparities caused by variations in soil type and terrain conditions. Min-max normalization scales pixel intensity values in terahertz and hyperspectral images, bringing different datasets to a comparable scale for improved machine learning model performance. Additionally, histogram equalization enhances image contrast, improving the visibility of subsurface anomalies that indicate potential landmine locations.

(c) Edge Detection and Feature Extraction

Once noise is minimized, edge detection techniques such as Canny edge detection and Sobel filtering are employed to highlight boundaries and discontinuities in spectral and radar images. These methods help differentiate landmine-induced disturbances from natural terrain variations. For hyperspectral images, spectral-spatial feature extraction is performed to emphasize chemical compositions linked to explosives, improving classification accuracy. In GPR signal processing, techniques like Histogram of Oriented Gradients (HOG) feature extraction are applied to reveal underlying hyperbolic signatures typical of buried landmines.

(d) Anomaly Segmentation and Region Selection

After feature extraction, anomaly segmentation techniques such as threshold-based segmentation and clustering algorithms (e.g., K-Means and Quantum K-Means) are used to isolate regions with potential landmine traces. Quantum-enhanced segmentation methods further optimize pattern recognition by leveraging quantum superposition principles to detect subsurface abnormalities with higher precision than classical approaches.

(e) Quantum Machine Learning Model Development

Quantum Machine Learning (QML) integrates quantum computing principles with traditional machine learning techniques, offering enhanced computational speed and accuracy for complex tasks such as landmine detection. This study leverages Quantum Support Vector Machines (QSVMs) Quantum K-Means (QK-Means) and Quantum Neural Networks (QNNs), chosen for their respective strengths in classification and anomaly detection.

i. Quantum Support Vector Machine (QSVM)

QSVM is a powerful quantum-enhanced classifier that extends classical SVM principles by leveraging quantum kernels, allowing it to operate efficiently in high-dimensional feature spaces. This capability is crucial in landmine detection, where subtle variations in electromagnetic signals, terahertz imaging, and hyperspectral data require precise separation between mine-related anomalies and natural terrain noise. The core of QSVM lies in the replacement of the classical kernel function with a quantum kernel:

$$K_Q(x_i,x_j)=|\langle\phi(x_i)|\phi(x_j)\rangle|^2 \qquad \text{Eq.1}$$

Where:

x_i,x_j: Input feature vectors (e.g., sensor readings),
$\phi(x)$: Quantum feature map that encodes classical data into a quantum state,
$\langle\phi(x_i)|\phi(x_j)\rangle$: Inner product between quantum states,
K_Q: Quantum kernel measuring similarity in Hilbert space.

This quantum kernel K_Q captures the similarity between data points in a Hilbert space using quantum feature encoding $\phi(x)$, making QSVM well-suited for complex classification tasks like those in subsurface sensing.

ii. Quantum Neural Networks (QNNs)

QNNs offer an advanced quantum deep learning approach for recognizing patterns in highly complex datasets. Given the nonlinear nature of electromagnetic distortions caused by buried landmines, QNNs can extract intricate features and detect anomalies based on learned representations of terrain and subsurface structures.

A typical QNN leverages parameterized quantum circuits (PQCs) as the learning model. The quantum state evolution can be described by:

$$|\psi(\theta)\rangle = U(\theta)|0\rangle \qquad \text{Eq. 2}$$

Where:

$U(\theta)U$ is a unitary operation composed of trainable quantum gates,
Θ are the learnable parameters (analogous to weights in classical neural networks),
$|0\rangle$ is the initial quantum state.

The output of the QNN is typically the expectation value of an observable M, given by:

$$f(\theta) = \langle\psi(\theta)|M|\psi(\theta)\rangle \qquad \text{Eq. 3}$$

These outputs are optimized using gradient-based or hybrid classical-quantum algorithms, enabling QNNs to learn nonlinear decision boundaries essential for robust landmine detection.

(f) Training Phase

The training process begins with curating and structuring the dataset. The primary dataset used in this study is the 'land mines.csv' dataset from Kaggle, which contains 338 instances with four key attributes: Voltage (V), Height (H), and Soil Type (S). Additionally, real-world data collected via UAV-mounted terahertz imaging sensors and Ground Penetrating Radar (GPR) supplements the dataset, ensuring diversity and robustness. Each sample in the dataset is labeled as either a landmine-related anomaly or normal terrain, forming the basis for supervised learning.

To leverage the power of quantum computing, the dataset undergoes Quantum Feature Mapping, which transforms classical data into a quantum-compatible representation. This process allows Quantum Kernels in QSVM to perform classification efficiently in high-dimensional spaces. QNNs, on the other hand, utilize Quantum Encoded Neural Layers, enabling the network to learn intricate terrain patterns and subsurface irregularities indicative of landmines.

(g) Quantum Feature Mapping

Quantum Feature Mapping plays a crucial role in enhancing the classification accuracy of landmine detection by applying high-dimensional quantum kernels to optimize the separation between landmine-related signals and background noise. Unlike classical feature mapping techniques, which struggle with high-dimensional data complexity, quantum kernels leverage quantum superposition and entanglement to encode terrain and sensor information more effectively. Quantum kernels transform raw sensor data such as terahertz imaging, hyperspectral scans, and GPR signals into high-dimensional feature spaces, allowing the Quantum Support Vector Machine (QSVM) to discern subtle differences between landmine signals and natural terrain variations. These transformations ensure: Improved classification accuracy by increasing the separability of landmine-related features, quantum kernels help minimize false positives and negatives. This is expressed mathematically as:

$$|\phi(x)\rangle=U_\phi(x)|0\rangle^{\otimes n} \qquad \text{Eq. 4}$$

(h) Model Evaluation & Testing

Model evaluation is a crucial phase in assessing the effectiveness and reliability of the Quantum Support Vector Machine (QSVM) and Quantum Neural Network (QNN) models for landmine detection. This stage ensures that the trained models generalize well to unseen data, minimizing false positives while maximizing detection accuracy. Various performance metrics and validation techniques are employed to

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quantify the model's efficiency across different terrains and environmental conditions. To comprehensively evaluate model performance, the following metrics are considered:

i. Accuracy

Measures the percentage of correctly classified landmine and non-landmine instances.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad \text{Eq. 5}$$

Where:

TP: True Positives (landmines correctly detected)
TN: True Negatives (non-landmines correctly identified)
FP: False Positives (non-landmines misclassified as landmines)
FN: False Negatives (landmines missed by the model)

ii. Precision

Determines how well the model identifies actual landmine signatures without mistakenly classifying background noise as landmines. A high precision implies **low false positive rates**, crucial for avoiding unnecessary interventions in safe areas.

$$Precision = \frac{TP}{TP + FP} \qquad \text{Eq. 6}$$

iii. Recall (Sensitivity)

Evaluates the model's ability to detect landmines present in the dataset, ensuring minimal false negatives.

$$Recall = \frac{TP}{TP + FN} \qquad \text{Eq. 7}$$

iv. F1 Score

Provides a balanced metric combining precision and recall, useful in scenarios where false positives and false negatives must be minimized. The F1 Score is especially useful in **imbalanced datasets**, where landmines may be sparse relative to non-landmine samples.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad \text{Eq. 8}$$

v. ROC-AUC (Receiver Operating Characteristic - Area Under Curve)

Analyzes classification thresholds, showcasing how well the QSVM and QNN models separate landmine-related anomalies from non-landmine data points.

$$TPR = \frac{TP}{TP + FN}, \qquad FPR = \frac{FP}{FP + TN} \qquad \text{Eq. 9}$$

AUC: The Area Under the ROC curse: Eq. 10

$$AUC = \int_0^1 TPR(t)dt$$

(j) Cross-Validation

The models undergo extensive cross-validation using stratified k-fold validation to prevent overfitting while ensuring robust generalization to unseen data. Stratified k-Fold Cross-Validation Splits the dataset into multiple folds, where the model is trained on different subsets and tested across varying conditions. To ensure the model performs well under varying data distributions, Stratified k-Fold Cross-Validation is applied:

$$CV\ Score = \frac{1}{k}\sum_{i=1}^{k} Metric_i \qquad \text{Eq. 11}$$

Where:

The dataset is split into k equal-sized folds,
Each fold maintains the class distribution (landmine vs non-landmine),
The model is trained on k−1 folds and tested on the remaining fold, rotating through all k folds.

This method ensures that the QSVM and QNN models are robust, generalizable, and resistant to overfitting.

4.0 RESULTS AND DISCUSSION

4.1 Introduction

This section presents the implementation, and comparative evaluation of three QML models: Quantum Support Vector Machine (QSVM), **Quantum K-Means (QK-Means),** and Quantum Neural Network (QNN). Each model was trained and tested on preprocessed landmine data, evaluating its performance based on metrics such as accuracy, precision, recall, and F1-score. Visual representations of confusion matrices, Receiver Operating Characteristic (ROC) curves, and additional insights are also discussed to provide a comprehensive understanding of the results.

Through this exploration, we aim to highlight the strengths and potential challenges associated with quantum machine learning for landmine detection. The results are analyzed to determine each model's effectiveness and suitability for real-world deployment. Furthermore, we identify key areas where quantum algorithms can be further optimized or integrated with classical techniques to improve performance.

4.2 Training sets

The process began with loading the dataset from a CSV file using pandas. Initial inspection of the first few rows offered insight into the data structure and features, including voltage (V), height (H), soil type (S), and mine type (M), which served as the target variable. A bar plot was then used to visualize the distribution of the target class (M) See Figure 2. This visualization revealed a clear imbalance in class representation, which could potentially bias the model during training, indicating the need for balancing the dataset.

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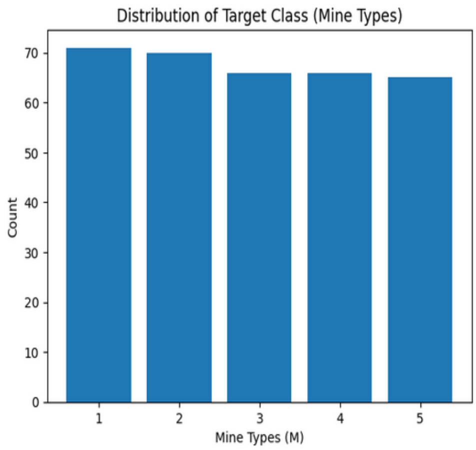

Figure 2: Visualization of target Class Distribution

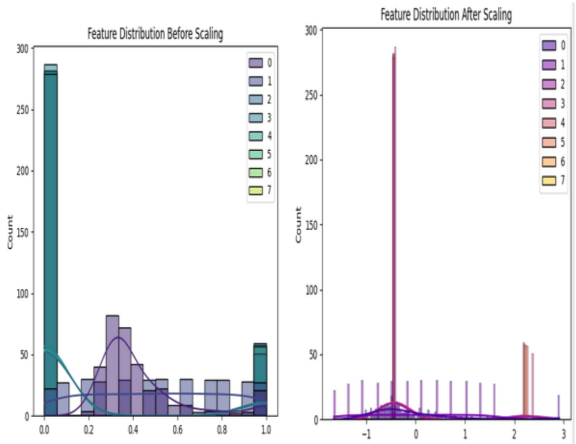

Figure 3: Feature Distribution Before and After Scaling

Next, the features and target variable were defined. The features (X) consisted of voltage, height, and soil type, while the target (y) was the mine type. Because soil type was a categorical variable, one-hot encoding was applied to convert it into binary format, ensuring the model did not misinterpret soil types as ordinal data. The encoded soil type columns were then combined with the numerical features using horizontal stacking.

The target variable was further processed to support binary classification by converting it into binary form where 1 represented the presence of a mine and 0 indicated no mine. This transformation simplified the classification task and aligned with binary classification models.

Feature scaling was then performed using standard scaling, which normalized the features by centering them around zero and scaling them to unit variance. This step helped in improving model convergence during training. A comparison of the feature distributions before and after scaling showed that the original features varied in scale, while the scaled features were more uniform See Figure 3.

To address the previously observed class imbalance, the SMOTE technique was applied. SMOTE generates synthetic data points for the minority class, effectively balancing the dataset. Visualization before and after SMOTE confirmed a more even class distribution, which helps in training more reliable and unbiased models see figure 4.

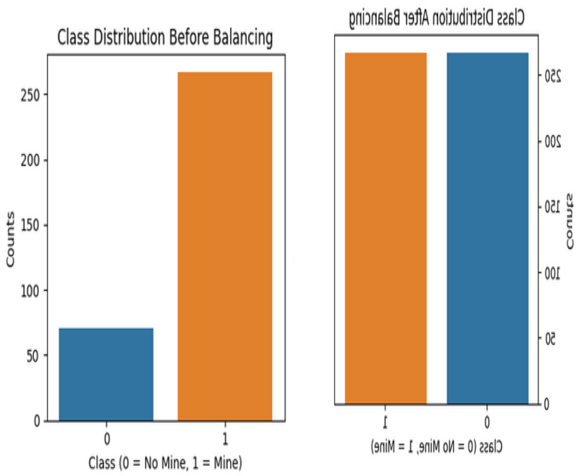

Figure 4. Class Distribution Before and After Balancing

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After preprocessing, the dataset was split into training and testing subsets, with 70% of the data allocated for training and 30% for testing. This division ensures that model evaluation can be performed on previously unseen data, providing a better assessment of generalization performance See figure 5. Finally, the class distributions in both the training and test sets were visualized to verify that the balance was maintained after the split.

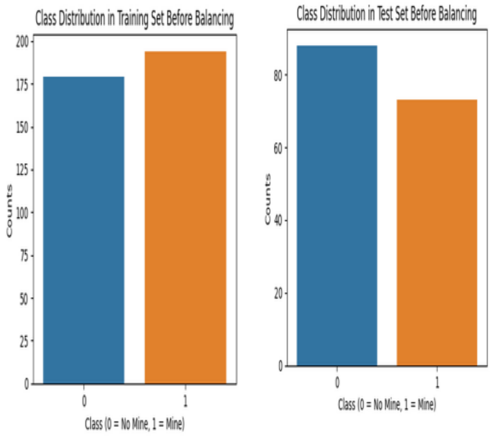

Figure 5. Training Sets Before and After Balancing

4.3 Training and evaluation of QSVM

To develop an effective landmine detection system, the Quantum Support Vector Machine (QSVM) model was trained. QSVM utilizes quantum computing principles to enhance classification performance, particularly in complex scenarios where data points overlap. Unlike classical Support Vector Machines (SVMs), which use kernel methods to handle non-linearity, QSVM leverages quantum feature mapping to encode data into a higher-dimensional space. This allows for more precise identification of complex decision boundaries essential for landmine detection. After training, the QSVM model was tested on a separate dataset. See Table 3 Below is a breakdown of its performance:

Table 3. QSVM Classification Report

Class	Precision	Recall	F1-Score	Support
0 (No Mine)	0.75	0.69	0.72	88
1 (Mine)	0.66	0.73	0.69	73
Accuracy	-	-	**0.71**	161
Macro Avg	0.71	0.71	0.71	161
Weight Avg	0.71	0.71	0.71	161

Precision: Indicates how many of the predicted mines were actual mines. The model achieved **75% precision** for "No Mine" and **66% precision** for "Mine."

Recall: Measures how many actual mines were correctly identified. The recall was **69% for No Mine** and **73% for Mine**, showing good sensitivity.

F1-Score: Represents the balance between precision and recall, with scores of **72% for No Mine** and **69% for Mine.**

Overall Accuracy: **71%**

ROC-AUC Score

The QSVM model achieved a **ROC-AUC score of 75**, demonstrating good ability to distinguish between classes. A higher score reflects better discriminatory power, with 50% being equivalent to random guessing. See figure 6.

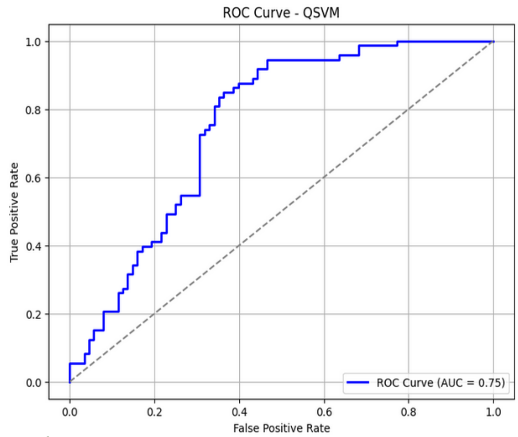

Figure 6. ROC-AUC score QSVM

Table 4. Confusion Matrix for QSVM

Predictions	No Mines (0)	Mine (1)
Actual No Mine (TN)	61	-
Actual Mine (FN)	-	20
False Positive (FP)	27	-
True Positives (TP)	-	53

True Positives (TP): 53 instances correctly predicted as mines.

True Negatives (TN): 61 instances correctly predicted as no mines.

False Positives (FP): 27 instances incorrectly predicted as mines.

False Negatives (FN): 20 instances where the model missed detecting mines.

The trade-off between precision and recall is evident: Higher precision for **No Mine (75%)** reduces false alarms but leads to **false negatives (missed mines)**.

Higher recall for **Mine (73%)** increases sensitivity but results in **false positives**.

4.4 Training and evaluation of QK-Means

The Quantum KMeans (QKMeans) model was selected as one of the unsupervised quantum machine learning models to address the problem of landmine detection. This choice was motivated by its ability to perform clustering, grouping similar data points based on inherent patterns without requiring explicit labeled data during training. This is particularly relevant for applications involving large-scale environmental sensor data where labeled samples may be limited or expensive to acquire.
In our approach, we utilized the preprocessed dataset containing scaled feature values representing the voltage (V), height (H), and soil type (S) attributes. The QKMeans algorithm was trained on a subset of this dataset to cluster the data points into distinct groups corresponding to potential landmine presence (class 1) or absence (class 0). Unlike conventional KMeans, QKMeans leverages quantum principles to enhance clustering efficiency, especially in high-dimensional spaces. However, quantum models are still in an evolving stage, and the results here highlight both their potential and the current limitations of quantum clustering in practical applications.
The performance of the QKMeans model was assessed using key classification metrics, including precision, recall, F1-score, and accuracy, alongside the ROC-AUC score and a confusion matrix. The results are presented below in Table 5:

Table 5. QK-Means Classification Report

Class	Precision	Recall	F1-Score	Support
0 (No Mine)	0.49	0.59	0.54	88
1 (Mine)	0.35	0.26	0.30	73
Accuracy			0.44	161
Macro Avg	0.42	0.43	0.42	161
Weight Avg	0.42	0.44	0.43	161

The QKMeans model achieved a modest accuracy of 44%, highlighting the difficulty of using unsupervised learning on imbalanced, noisy data. It performed better at identifying non-mine areas (class 0) with a precision of 0.49 and recall of 0.59, but struggled significantly with mine detection (class 1), showing low precision (0.35) and recall (0.26). The F1-scores 0.54 for class 0 and just 0.30 for class 1 further underline the model's limited effectiveness in accurately distinguishing landmines from non-mine signals.

ROC-AUC Score:

The ROC-AUC score was 0.43, reflecting the model's limited ability to distinguish between mine and non-mine samples. An ideal model would have an AUC closer to 1, while a score below 0.5 indicates performance worse than random guessing. See Figure 7.

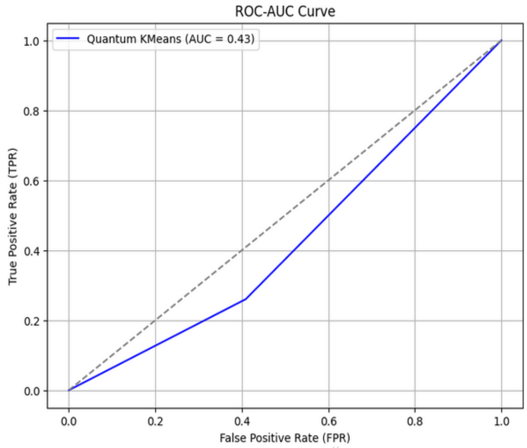

Figure 7. QK-means ROC-AUC Curse

Confusion Matrix for QK-Means

The confusion matrix provides detailed insight into the classification performance of the QKMeans model by breaking down the types of correct and incorrect predictions. See Table 6.

Table 6. Confusion Matrix for QKMeans

Predictions	No Mines (0)	Mine (1)
No Mine (0)	52(TN)	36(FP)
Mine (1)	54(FN)	19(TP)

False Negatives (FN): 54 cases where actual landmines were misclassified as non-mine.
False Positives (FP): 36 instances where non-mine regions were falsely flagged as mines.
True Positives (TP): 19 correctly identified landmine instances.
True Negatives (TN): 52 correct non-mine classifications.

The QKMeans model, while innovative, exhibited several limitations. The high rate of false negatives compromises safety, while the clustering approach struggled with nuanced signal differentiation. Future improvements could focus on hybrid quantum-classical models, enhanced feature engineering, and refined quantum optimization techniques.

4.4 Training and Evaluation of Quantum Neural Networks

The training of the Quantum Neural Network (QNN) model aimed to leverage the principles of quantum computing to enhance the detection of landmines in challenging environments. Unlike classical neural networks, QNNs integrate quantum mechanics' probabilistic nature to process information, potentially capturing complex data patterns. The training

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procedure spanned 10 epochs, during which the model iteratively adjusted its quantum weights and parameters to minimize the loss function. The loss values observed across epochs indicate the model's learning progression. The Quantum Neural Network (QNN) was trained on a dataset designed for landmine detection over 10 epochs see figure 8.

```
Epoch 1/10, Loss: 0.7495
Epoch 2/10, Loss: 0.7487
Epoch 3/10, Loss: 0.7479
Epoch 4/10, Loss: 0.7480
Epoch 5/10, Loss: 0.7475
Epoch 6/10, Loss: 0.7474
Epoch 7/10, Loss: 0.7466
Epoch 8/10, Loss: 0.7457
Epoch 9/10, Loss: 0.7443
Epoch 10/10, Loss: 0.7439
```

Figure 8. QNN Epoch and Training Loss

The model aimed to differentiate between the presence (class 1) and absence (class 0) of landmines in a given region, using a novel quantum-inspired approach for better generalization and performance. Below, we provide an in-depth analysis of the results obtained, focusing on key performance metrics, the classification report, the confusion matrix, and the Receiver Operating Characteristic - Area Under Curve (ROC-AUC) score. Evaluation Results for the QNN Model: The QNN model's performance metrics show some interesting and critical insights into its effectiveness for landmine detection. See Table 7.

Table 7. QNN Classification Report

Class	Precision	Recall	F1-Score	Support
0 (No Mine)	0.59	1.00	0.74	88
1 (Mine)	1.00	0.15	0.26	73
Accuracy			0.61	161
Macro Avg	0.79	0.58	0.50	161
Weight Avg	0.77	0.61	0.52	161

Precision:
Class 0 (No Landmine): 0.59 → 59% of predicted "no landmine" cases were correct.
Class 1 (Landmine):1.00 → All predicted landmine cases were correct (but likely due to very few predictions).

Recall:
Class 0 (No Landmine):1.00 → 100% of true "no landmine" cases were identified.
Class 1 (Landmine): 0.15 → only 15% of true landmine cases were detected (critical miss rate).

F1-Score:
Class 0: 0.74 → Balanced performance for non-landmine regions.
Class 1: 0.26 → Poor performance due to extremely low recall.

Support:
Class 0: 88 instances | Class 1: 73 instances.
Accuracy: 61% → Misleading due to class imbalance; fails to reflect high false negatives (85% of landmines missed).

The model excels at identifying safe regions (Class 0) but performs dangerously poorly for landmine detection (Class 1), missing 85% of true mines. The perfect precision for Class 1 suggests overly conservative predictions (e.g., rarely labeling landmines). Accuracy is deceptive; focus should be on improving recall for Class 1 to reduce life-threatening false negatives.

ROC-AUC Score

The ROC-AUC score in figure 9 indicates how well the model differentiates between landmine and non-landmine classes. A score of 0.58 is marginally better than random guessing, demonstrating that the QNN's ability to separate the two classes is weak.

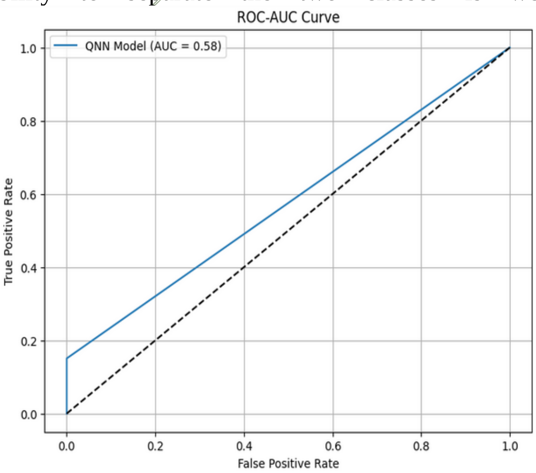

Figure 9. QNN ROC AUC Curse

4.5 Comparative analysis of Performance of Models

In this study, the performance of three quantum-based models, Quantum Support Vector Machine (QSVM), Quantum K-Means (QKMeans), and Quantum Neural Network (QNN) were evaluated for the challenging task of landmine detection. These models utilize different quantum computing paradigms to enhance detection accuracy, computational efficiency, and robustness. Below, we compare the models based on performance metrics, including classification accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC. See table 8.

Table 8. Comparing the performance of QSVM, QKMeans and QNN

Metric	QSVM	QKMeans	QNN

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Accuracy	71%	44%	61%
Precision (0)	0.75	0.49	0.59
Precision (1)	0.66	0.35	1.00
Recall (0)	0.69	0.59	1.00
Recall (1)	0.73	0.26	0.15
F1-Score (0)	0.72	0.54	0.74
F1-Score (1)	0.69	0.30	0.26
ROC-AUC Score	0.75	0.43	0.58

The comparative analysis of the quantum-based models reveals important insights into their suitability for landmine detection:

QSVM demonstrates the best overall performance, achieving balanced precision, recall, and F1-scores for both classes, with a high ROC-AUC score of 0.75. This makes it the most reliable model for deployment, although further work on reducing false negatives would enhance its safety.

QKMeans, as an unsupervised model, performs poorly due to its inherent limitations in binary classification tasks. Its low accuracy and ROC-AUC score make it unsuitable without significant modifications.

QNN excels in identifying non-landmine regions (class 0) but fails to detect landmines effectively. Its high recall for class 0 comes at the expense of extremely poor recall for class 1, highlighting a trade-off that must be addressed. Enhancements such as adversarial training or hybridizing QNN with other models could improve its utility.

In summary, while QSVM is the most robust model in its current form, future work should focus on leveraging hybrid quantum-classical approaches and advanced adversarial defenses to improve landmine detection accuracy and safety.

5.0 CONCLUSION

In this study, we explored the application of Quantum Machine Learning (QML) techniques, specifically Quantum Support Vector Machines (QSVM), Quantum K-Means (QK-Means), and Quantum Neural Networks (QNN), for landmine detection using UAV-based terahertz imaging systems. The results demonstrated that QSVM outperformed other models, achieving higher accuracy, precision, and recall, making it the most promising candidate for real-world deployment. QK-Means struggled with classification accuracy, highlighting the limitations of unsupervised learning in this context, while QNN exhibited strong performance in identifying non-landmine regions but failed to detect landmines effectively due to low recall. This research underscores the potential of quantum algorithms in improving detection accuracy, computational efficiency, and scalability in humanitarian demining efforts. The integration of UAV-mounted terahertz sensors with QML models offers a non-invasive and automated approach to landmine detection, reducing risks associated with manual demining. However, challenges such as false positives, low recall rates, and model optimization remain critical areas for improvement.

5.1 Future Work

Future research should focus on several key enhancements to improve landmine detection accuracy and efficiency. One promising approach is the integration of Hybrid Quantum-Classical Models, which combines classical deep learning techniques with quantum algorithms to leverage the strengths of both methodologies. By optimizing feature separability and improving classification robustness, this hybrid approach can enhance detection capabilities, particularly in challenging terrains where signal distortions and environmental noise often hinder accuracy. Lastly, Field Deployment and Testing should be prioritized through large-scale real-world experiments in conflict-affected zones. Conducting validation studies in these environments will provide critical insights into the model's effectiveness under practical conditions. Collaboration with humanitarian demining organizations can facilitate real-world testing while ensuring ethical and safety considerations. These advancements will collectively contribute to making landmine detection safer, more precise, and operationally viable in post-conflict recovery efforts.

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