Quantum Fusion Intelligence for Integrated Satellite-Ground Remote Sensing

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***Abstract*—Satellite imagery plays a crucial role in integrated satellite-ground remote sensing (SGRS), particularly in applications such as disaster management and military intelligence, where real-time monitoring and forecasting are essential for effective decision-making. However, narrow artificial intelligence (AI) models often face challenges in processing large-scale high-dimensional data efficiently while maintaining the required accuracy and speed, limiting their effectiveness in time-sensitive scenarios. To address these challenges, we explore the integration of satellite remote sensing with large AI, quantum computing, and quantum communication technologies, focusing on enhancing computational efficiency and data security in integrated SGRS systems. Specifically, we put forth an integrated quantum SGRS framework, which combines quantum fusion intelligence (QFI) with quantum anonymous communication (QAC). By integrating quantum and large AI, the QFI models enhance the efficiency, accuracy, and security of satellite imagery analysis while ensuring that the extracted information is transmitted to ground stations in a privacy-preserving manner using QAC. This approach is particularly effective in time- and privacy-sensitive scenarios. To demonstrate the effectiveness of QFI computing, we present case studies in disaster detection and environmental monitoring. This research highlights the transformative potential of quantum-large AI integration in SGRS and its implications for nonterrestrial-terrestrial quantum networks.**

***Index Terms*—Large AI, quantum anonymity, quantum computing, quantum security, satellite-ground remote sensing.**

I. Introduction

REMOTE SENSING with satellite imagery has revolutionized the monitoring and analysis of critical activities in geographically inaccessible locations [1], [2]. Integrated satellite-ground remote sensing (SGRS) systems, in particular, combine satellite-derived data with ground-based observations to offer comprehensive perspectives on a wide range of phenomena, from environmental changes and natural resource management to security threats and climate forecasting [3]. Satellites equipped with advanced processing units can assess remote locations, analyze data in real time, and transmit the results to ground stations for further interpretation [4]. This integration is invaluable for time-sensitive applications such as disaster response and military intelligence, enabling rapid and reliable data-driven decision-making [5]. However, the enormous amount of image data generated by multi-spectral and high-resolution sensors requires advanced processing techniques to efficiently extract semantically meaningful insights in real time [6].

Narrow artificial intelligence (AI) techniques have significantly improved the capabilities of integrated SGRS systems to classify scenarios, detect anomalies, and predict disasters from satellite imagery, enhancing outcomes in disaster management, environmental conservation, and geopolitical monitoring [7]. Despite these advancements, conventional AI models face limitations in computational capacity, latency, and data security [8]. In real-time applications such as war forecasting and rapid-response disaster management, these AI models often face challenges in processing large-scale high-dimensional data efficiently while maintaining the required accuracy and speed, limiting their effectiveness in critical and time-sensitive scenarios [9], [10]. Security concerns are equally important, especially in sensitive or conflict-prone regions, where the secure transmission and processing of classified satellite data are essential [11]. Therefore, ensuring data integrity and preventing unauthorized access are vital to protecting strategic information and preserving operational reliability in such high-risk conditions.

Quantum fusion intelligence (QFI) has emerged as a cutting-edge solution, comprising quantum AI, large AI, and hybrid quantum-large AI, to address the security and computational challenges faced by intelligent integrated SGRS systems [12]. By leveraging quantum principles such as superposition and entanglement, QFI enables faster and more efficient processing of complex satellite imagery. This quantum parallel approach improves the scalability of fusion models, allowing for the real-time integration of diverse data sources, which is crucial for applications such as disaster prediction and security surveillance [13]. In addition to the quantum-enhanced processing power and speed, which help reduce computing latency, quantum systems ensure unconditional security, making them a primary choice for integrated SGRS over its classical counterparts [14]. Moreover, satellite systems transmit application-specific or semantically relevant insights from remote sensing data to ground nodes over integrated satellite-ground quantum networks, ensuring privacy and security throughout the process. In particular, quantum anonymous communication (QAC) protocols leverage the unique properties of multipartite quantum entanglement to ensure participant anonymity by concealing the identities of communicating

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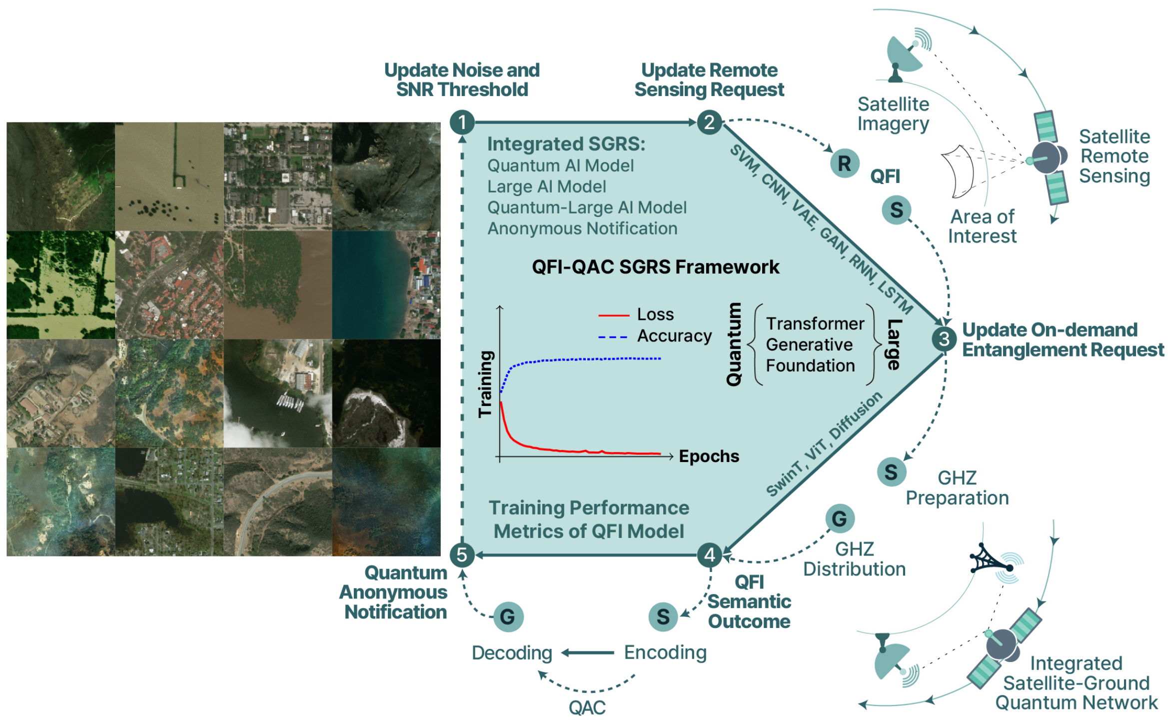

Fig. 1. An integrated SGRS framework combining QFI and QAC. The framework exploits satellite onboard processors (central and quantum processing units) for application-specific satellite imagery analysis in remote sensing. This involves utilizing advanced QFI models to extract semantically rich insights from captured satellite imagery, thereby enhancing tasks such as disaster detection and environmental monitoring. Moreover, satellites generate the entangled photons and distribute them to recipients across the integrated satellite-ground quantum network using optical downlink transmissions. This entanglement network is utilized to anonymously notify the ground station in case of an emergency or actionable situation at remotely sensed inaccessible locations. Herein, S, G, and R denote satellite nodes, ground stations, and remote nodes in areas of interest sensed by the satellites. The model SVM, CNN, VAE, GAN, RNN, LSTM, SwinT, and ViT stand for support vector machine, convolutional neural network, variational autoencoder, generative adversarial network, recurrent neural network, long short-term memory, swin transformer, and vision transformer, respectively.

parties while safeguarding sensitive information by inherently enhancing communication security through quantum principles [15]. This dual functionality addresses critical privacy and security concerns in sensitive communication scenarios by protecting both the identities of the participants and the integrity of the transmitted information.

In this article, we explore the transformative shift from narrow AI to QFI, highlighting quantum potentials in security, privacy, and computation in lieu of the integrated SGRS (see Fig. 1). The main contributions are outlined as follows.

- We present an integrated SGRS framework that combines QFI with QAC. Specifically, we explore the transition from classical narrow AI models to quantum AI, large AI, and hybrid quantum-large AI models for remote sensing with satellite imagery.
- We provide the quantum anonymous notification protocol for privacy-preserving nonterrestrial-terrestrial communication. Two case studies are given to demonstrate various QFI models for remote sensing scenarios involving disaster detection and environmental monitoring.

II. QFI Computing for Integrated SGRS

Narrow AI models have significantly improved the integrated SGRS systems by enabling satellite imagery analysis directly on the satellite's onboard central processing unit (CPU), facilitating tasks such as environmental monitoring and predictive analytics. Table I reviews diverse narrow AI models and their limitations in remote sensing with satellite imagery. In this section, we prototype an integrated SGRS system with QFI computing and QAC, which is designed to support well-informed decision-making in time-sensitive applications. For integrated SGRS tasks, we outline quantum AI, large AI, and hybrid quantum-large AI models for efficiently extracting semantically relevant sensitive information.

A. QFI-QAC SGRS Framework

As depicted in Fig. 1, the proposed framework leverages QFI and QAC to enhance real-time decision-making in time- and privacy-sensitive applications, even under challenging conditions concerning signal-to-noise ratios (SNRs) and quantum noise. Specifically, QFI includes quantum AI, large AI, and hybrid quantum-large AI models to efficiently extract semantically relevant and sensitive information from satellite imagery for disaster management, security, and other critical use cases. For this task, satellites are equipped with onboard processors, including classical CPUs and quantum processing units (QPUs), to perform real-time analysis of application-specific remote sensing image data. The QFI framework employs a hybrid approach, combining classical large AI models, such as transformers, to extract intermediate semantic features from satellite imagery—for example, analyzing pre-disaster and post-disaster images separately for disaster detection tasks

TABLE I
NARROW AI MODELS AND THEIR LIMITATIONS IN REMOTE SENSING WITH SATELLITE IMAGERY

Classification Task	Convolutional Neural Network (CNN)	CNNs classify satellite images by extracting spatial features (edges, textures) using multi-spectral data (RGB, infrared). Techniques like data augmentation, dropout, pooling, and fully connected layers enhance robustness, preventing overfitting and improving land cover classification.
	Support Vector Machine (SVM)	SVMs classify satellite imagery by finding optimal hyperplanes, using texture features or principal component analysis to reduce dimensionality. Kernel functions handle nonlinear separations, improving accuracy. Hybrid SVMs with CNNs enhance performance, especially for large datasets.
Localization Task	Faster Region-Based CNN (R-CNN)	Faster R-CNN is widely used for satellite imagery localization, detecting objects like roads and buildings using region proposal networks to generate bounding boxes. It reduces computational overhead and utilizes anchor boxes of various sizes to handle objects of different scales, improving accuracy.
	You Only Look Once (YOLO)	YOLO excels in real-time object detection for satellite imagery, predicting bounding boxes and classes in a single pass. It divides images into grids, detecting multiple objects efficiently and handling varying object scales using anchor boxes, making it robust for large-scale satellite data.
Semantic Segmentation Task	Mask R-CNN	Mask R-CNN is a CNN-based semantic segmentation model used for pixel-level classification in satellite imagery, detecting and outlining object boundaries. It employs a segmentation branch within Faster R-CNN and uses RoIAlign for spatial accuracy, handling complex cases like overlapping objects.
	U-Net	U-Net is a deep learning architecture for semantic segmentation of satellite data, performing pixel-level classification for land cover types like forests and urban areas. Its encoder-decoder structure with skip connections preserves spatial information, ensuring precise boundary delineation for large and small objects.
Environmental Monitoring Task	Siamese CNN	Siamese CNNs detect changes in satellite imagery by comparing feature representations from two images taken at different times, tracking land cover changes, deforestation, and natural disasters. The model excels in temporal analysis and handles multi-resolution data effectively by leveraging shared weights to ensure consistent feature extraction and precise detection of subtle changes in satellite imagery.
	Recurrent Neural Network (RNN)	RNNs are effective for analyzing time-series satellite data, tracking changes like deforestation and glacier melting. Long short-term memory (LSTM) units capture long-term dependencies, while CNN-RNN hybrids combine spatial and temporal features, enhancing performance. RNNs also handle multi-sensor data, aiding in environmental monitoring, disaster relief, and predicting future trends using historical data.
Semantic Analysis Task	Recursive CNN	Recursive CNNs improve satellite image resolution by iteratively applying convolutional layers, refining details and correcting errors. Combined with residual learning, they enhance high-frequency features and learn hierarchical characteristics, making them effective for large-scale satellite data processing.
	Deep Residual Network (ResNet)	Deep ResNet models handle super-resolution tasks and semantic analysis by using skip connections and residual learning. This allows training deep networks without vanishing gradients, improving image resolution, capturing fine textures, and integrating multi-spectral data for accurate classification.
Anomaly Detection Task	Convolutional Autoencoders	Convolutional autoencoders detect anomalies in satellite imagery by learning typical data patterns and identifying deviations. The model processes multi-spectral data through an encoder-decoder structure, where larger reconstruction errors indicate anomalies like irregular land use or environmental changes. Its ability to reconstruct expected patterns highlights subtle and hard-to-detect anomalies in complex imagery.
	Isolation Forests	The Isolation Forest algorithm is ideal for detecting anomalies in satellite imagery by isolating observations using an ensemble of random trees. It excels in handling high-dimensional data, identifying anomalies based on shorter isolation paths. This method is highly efficient, scalable, and suitable for large-scale, real-time anomaly detection, requiring no prior knowledge of data distribution.
Computational Limitation	Computing Power	Satellite onboard systems often struggle with narrow AI tasks like deep learning, limiting real-time data processing crucial for applications such as disaster monitoring and war predictions.
	Resource Overhead	Narrow AI models like deep neural networks need significant computing power, but satellites' limited resources make real-time image segmentation and anomaly detection challenging to implement efficiently.
	Training Time	Training AI models, especially deep learning, require significant time and resources, posing challenges for satellites. Longer training times delay deploying updated, more accurate models in operational systems.
	Energy Efficiency	Satellite's limited resources restrict continuous AI algorithm use. Real-time processing of high-resolution images consumes significant energy, causing insufficient and inefficient analysis with narrow AI models.
	Computational Latency	Narrow AI systems face delays in processing large, high-dimensional satellite datasets, struggling to balance accuracy and speed for rapid decision-making in emergency situations.
Security Limitation	Model Poisoning	Narrow AI systems risk model poisoning from biased or corrupted data, making them unreliable for critical applications like disaster management and military surveillance.
	Encryption Capacity	Narrow AI models require substantial processing power for encrypting high-resolution satellite images, making real-time data protection challenging in conflict-prone areas, risking eavesdropping and exploitation.
	Insecure Channel	Satellite-to-ground data transmission is vulnerable to security breaches, with narrow AI systems often lacking strong encryption, risking interception of sensitive information with geopolitical consequences.
	Privacy Breach	Narrow AI models struggle with privacy-preserving data analysis in remote sensing, making them vulnerable to breaches, whereas quantum-enhanced models offer superior privacy protection for secure applications.
	Data Corruption	Integrated SGRS systems using narrow AI face tampering and data corruption risks due to continuous transmission, lacking sufficient security measures to ensure data integrity and analytical accuracy.

(see Fig. 2). These intermediate semantic features are then merged and passed through a parametrized quantum circuit (PQC), which utilizes PQC gates to map the combined semantic features into a complex quantum Hilbert space, thereby enhancing pattern recognition. Such PQC-processed features are subsequently fed into a classical classifier, which analyzes them to identify the type of disaster. The outcome of this analysis constitutes the semantic information derived from the satellite imagery in the form of disaster classification. This critical semantic information is then securely transmitted to ground stations using QAC, ensuring participant anonymity and data integrity throughout the transmission process. The QAC framework involves an integrated satellite-ground quantum entanglement network wherein satellites generate and distribute entangled photons to terrestrial nodes by virtue of optical downlinks. The established entanglement enables secure and anonymous communication, ensuring that ground stations receive emergency alerts or actionable insights in a privacy-preserving manner. In essence, satellite nodes sense and process data from remote locations, while ground stations receive quantum-encrypted notifications, facilitating rapid responses to critical events in inaccessible high-risk areas.

B. Quantum AI Models

Quantum AI models represent a significant leap beyond traditional narrow AI by leveraging the principles of quantum computing to overcome limitations in both processing power and data security.

1) Quantum Classification Models: Quantum classification models, including quantum convolutional neural networks (CNNs) and quantum support vector machines (SVMs), harness quantum principles to enhance classification accuracy and efficiency, particularly in the analysis of high-dimensional satellite imagery.

- **Quantum CNNs:** Quantum CNN models are equipped with quanvolutional layers that make them an effective tool for tackling complicated object recognition problems for satellite imagery classification. Specifically, these models process high-dimensional spatial data, allowing for the accurate recognition of buildings, vehicles, and natural landmarks in satellite images. The quanvolutional layers enable quantum CNNs to extract detailed patterns that would be difficult to recognize with classical convolutional layers, providing a considerable advantage in detecting minute variations across vast geographic areas. This extended feature extraction improves accuracy in tasks such as land use mapping, infrastructure monitoring, and environmental change detection.
- **Quantum SVMs:** Quantum SVM models employ quantum computing to augment the classical SVMs, resulting in substantial advances in computational efficiency and scalability for satellite imagery classification. By encoding satellite image data into quantum states and manipulating it using quantum gates, the quantum SVMs utilize the quantum kernel approach to categorize data in high-dimensional feature spaces, efficiently handling the complex patterns observed in satellite images. This quantum kernel technique minimizes computing complexity and the number of required qubits, allowing for faster processing and analysis of massive satellite datasets. The quantum SVMs are particularly useful for discriminating between modest land cover types, detecting changes over time and tracking anomalies such as deforestation or urban growth.

2) Quantum Generative Models: Quantum generative models, including generative adversarial networks (GANs) and variational autoencoders (VAEs), produce high-fidelity samples from complex data distributions to improve data synthesis in satellite imagery.

- **Quantum VAEs:** Quantum VAE models use quantum circuits to improve the learning of latent representations for satellite imagery. These models are especially well-suited to anomaly identification in remote sensing applications, where detecting minuscule and uncommon changes over large geographic areas is critical. Such models efficiently simulate the complex and high-dimensional data distributions apparent in satellite images, leveraging quantum circuits to identify detailed patterns and anomalies that classical VAEs might ignore. The incorporation of quantum Boltzmann machines further enhances their capability to generate synthetic images and identify deviations such as deforestation, urban growth, and infrastructure damage by effectively modeling the inherent data distributions.
- **Quantum GANs:** Quantum GAN models functionally operate similarly to classical GANs, containing a generator and discriminator that adversarially work in tandem, with components implemented as parameterized quantum circuits. The underlying superposition and entangling gates further advance quantum GANs in generating high-resolution satellite images. In this context, these models provide fine-grained details by efficiently acquiring and modeling complex data distributions, thereby delimiting the scope of classical GANs. The quantum advantage invokes faster convergence and more accurate extraction of high-resolution features such as urban structures, disaster patterns, and landform details.

3) Quantum Sequential Models: Quantum sequential models, including quantum recurrent neural networks (RNNs) and quantum long short-term memory (LSTM) networks, leverage quantum computing to improve performance in satellite imagery analysis and time series prediction.

- **Quantum RNNs:** Quantum RNN models, the quantum counterparts of classical RNNs, are specifically designed for sequence modeling and assessing temporal dependencies in satellite imagery. These models can process data over multiple time steps using parametrized quantum circuits. This allows them to effectively handle intricate temporal correlations in instances including variations in climate patterns and land cover over time. Owing to the inherent quantum advantage in processing correlated and high-dimensional time-series data, these models are especially well-suited for time-series analysis in remote sensing applications. Some noteworthy scenarios involve preventing deforestation, tracking urban growth, timely

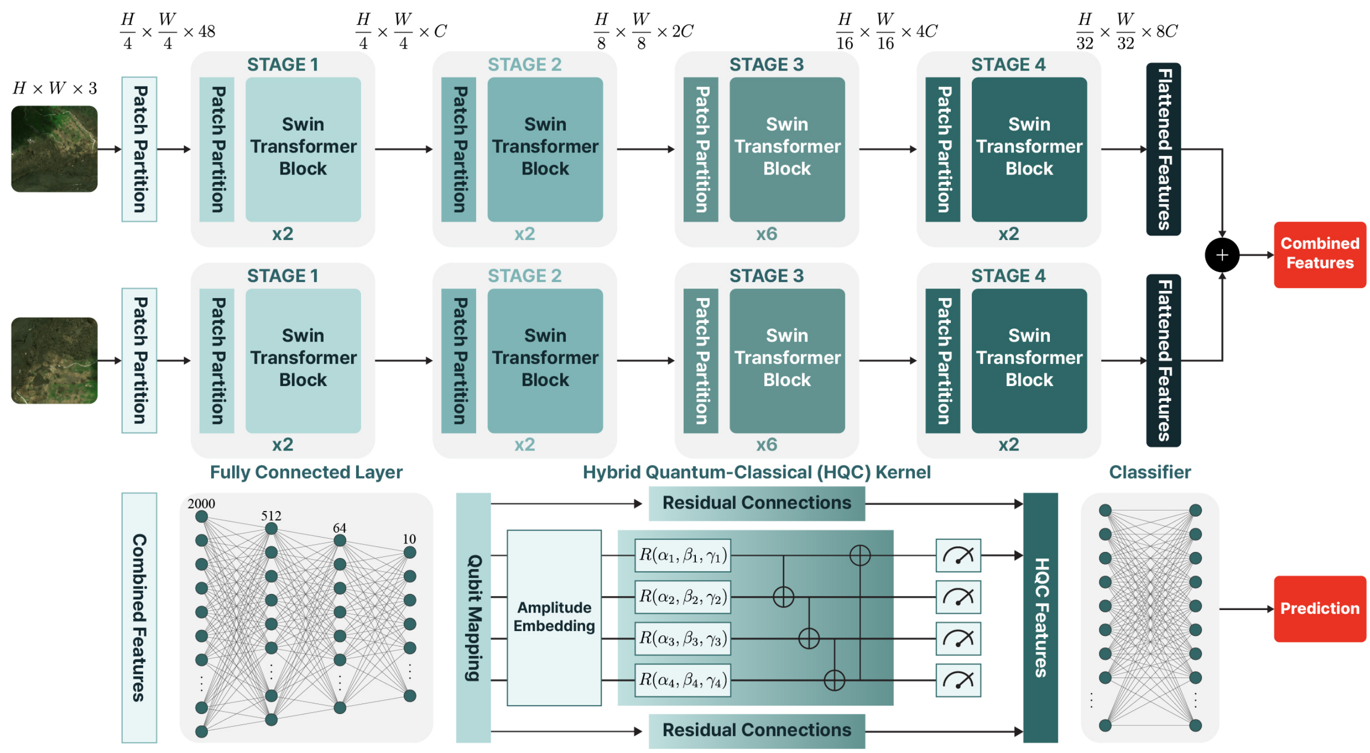

Fig. 2. An exemplary quantum-large AI fusion architecture for disaster image classification. Herein, pre-event and post-event images are processed through an encoder utilizing swin (shifted window) transformer blocks for multi-stage feature extraction, with patch merging to refine spatial and feature resolutions. The outputs from both images are flattened and combined before being passed into a classifier that integrates both quantum and classical computing layers. The classifier uses a hybrid quantum-classical kernel for amplitude embedding, followed by a basic entangling circuit layer and combined with residual connections from previous layers. The final combination is down-sampled to generate the final classification output.

predicting catastrophes, and examining seasonal crop growth patterns.

- **Quantum LSTM Networks:** Quantum LSTM networks are quantum-enhanced versions of classical LSTM networks designed to handle long-term dependencies in satellite imagery time-series data. Herein, the component quantum circuits handle the input, forget, and output gates, efficiently maintaining and updating memory across time steps, thus rendering them appropriate for forecasting tasks in remote sensing. The quantum advantage empowers these models to capture complex temporal patterns, particularly in multi-spectral data and nonlinear interactions, thereby outperforming classical counterparts in predictive applications. The quantum gate-based architecture improves real-time environmental monitoring, disaster risk prediction, and long-term climate forecasting, resulting in higher accuracy and speed for large-scale satellite imagery.

C. Large AI Models

Large AI models leverage vast datasets and advanced deep architectures to efficiently process high-dimensional satellite imagery for environmental monitoring and disaster detection.

1) Transformer Models: Transformer-based models such as swin (shifted window) transformers (SwinTs) and vision transformers (ViTs) employ self-attention mechanisms to enhance the representation of high-dimensional satellite imagery for improved decision-making.

- **SwinTs:** SwinT models are hierarchical ViTs optimized for satellite imagery in remote sensing applications. By partitioning images into non-overlapping local windows and applying self-attention within these windows, SwinTs efficiently capture local contextual information. The shifting window mechanism between layers enables interactions across different regions of the image, allowing the models to integrate both local and global features. This architecture enhances computational efficiency and scalability, making these models particularly suitable for high-resolution satellite imagery analysis. In remote sensing tasks, such as disaster scene classification, SwinTs excel by accurately detecting finer details and broader scene context, ultimately improving classification performance.
- **ViTs:** ViT models adapt the transformer architecture for satellite imagery in remote sensing by treating image patches as sequence tokens. Herein, each image is divided into fixed-size patches, embedded into feature vectors, and processed using self-attention mechanisms to capture global dependencies across the image. In contrast to the conventional convolutional models, ViTs rely entirely on attention mechanisms, allowing for effective feature extraction and modeling of relationships between distant parts of an image. This makes them highly effective for remote sensing tasks such as disaster classification, wherein they can identify widespread patterns, capture long-range dependencies, and enhance scene classification accuracy. Despite performing well on large datasets,

these models require substantial computational resources due to their high capacity, making them best suited for complex satellite imagery analysis.

2) Vision Generative Models: Vision generative models aim to generate realistic images by learning the underlying data distribution for applications involving data augmentation or image synthesis.

- **U-Net Diffusion Models:** U-Net diffusion models are generative frameworks designed to reverse a diffusion process, transforming noise into coherent images. The U-Net architecture captures multi-scale hierarchical features, predicting noise residuals at each timestep to iteratively refine the image. In remote sensing applications involving satellite imagery, these models can generate high-resolution images from noisy inputs, offering detailed reconstructions of geographical features. However, due to their computational intensity and focus on generation rather than classification, diffusion models are less suited for tasks like disaster classification, where discriminative models excel. Their core strength lies in producing high-fidelity images, making them particularly relevant for image reconstruction and enhancement in satellite imagery analysis.
- **ViT-GANs:** ViT-GAN models integrate ViTs into GAN frameworks to improve image generation capabilities for remote sensing. Both the generator and discriminator use transformer architectures during image synthesis and evaluation, leveraging self-attention to capture global relationships and model complex structures and textures. This allows ViT-GANs to effectively generate detailed and high-resolution images by modeling long-range dependencies across image patches. In remote sensing, these models are used for data augmentation by generating synthetic satellite images for various scenarios, such as disaster scenes, enhancing the robustness of classification models. Their ability to produce realistic imagery makes them especially valuable for enriching training datasets when annotated satellite images are limited.

3) Foundation Models: Foundation models are large-scale models trained on extensive datasets, aiming to provide strong general-purpose representations that can be fine-tuned for various downstream tasks.

- **Self-Supervised Learning Models:** Self-supervised learning models are designed to extract robust feature representations from unlabeled satellite imagery by solving pretext tasks. These tasks involve predicting missing or corrupted parts of the data, such as reconstructing masked regions or predicting spatial relationships between image patches. Further advancements incorporating techniques like contrastive learning and masked image modeling enable these models to capture meaningful patterns without manual annotations. Once trained, these representations can be fine-tuned on downstream tasks, such as image classification, requiring fewer labeled instances. In remote sensing with satellite imagery, self-supervised models efficiently leverage vast amounts of unlabeled image data, improving the detection and classification performance by providing rich feature representations, particularly in situations with limited labeled data.

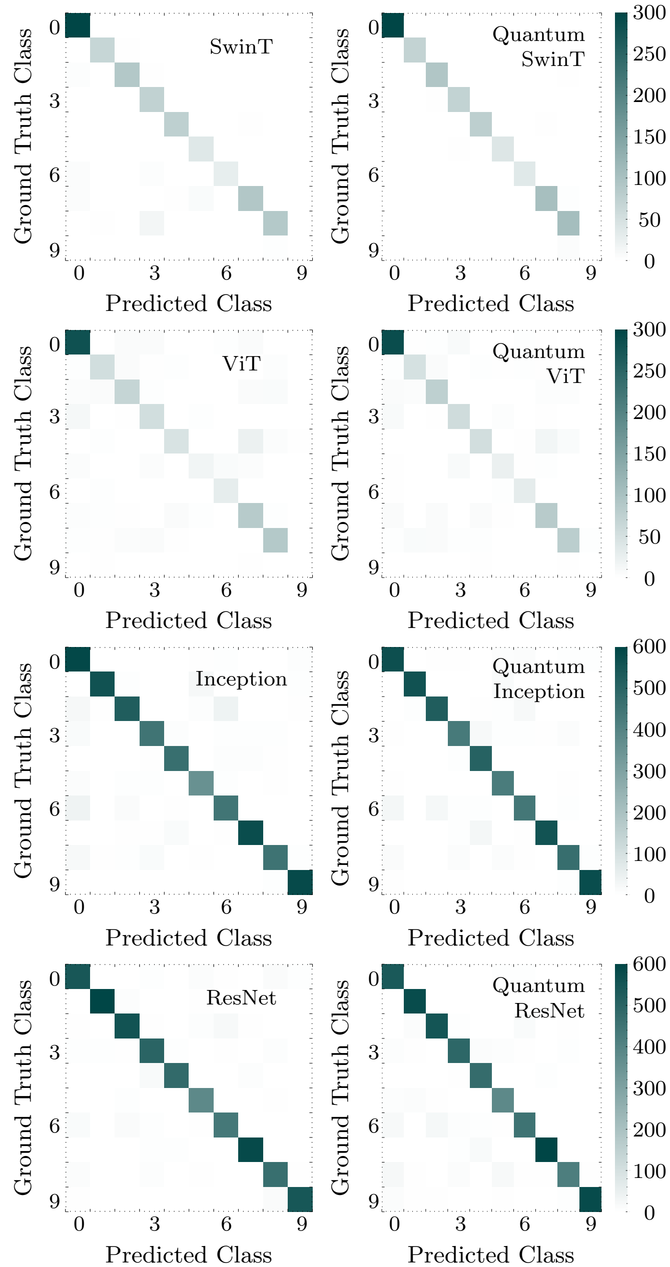

Fig. 3. Confusion matrices for various classical AI (SwinT, ViT, Inception, and ResNet) and their QFI models on the disaster detection (disaster satellite images) dataset (top four) and the environmental monitoring (EuroSAT) dataset (bottom four).

- **Zero-Shot Learning Models:** Zero-shot learning models are designed to recognize unseen classes by leveraging auxiliary information, making them ideal for remote sensing with satellite imagery. Models such as contrastive language-image pre-training, for example, align visual and textual data in a shared embedding space using contrastive learning for image recognition tasks. This allows the models to classify new categories based on semantic similarities to known classes without requiring labeled training data for every class. Moreover, zero-shot learning models can identify emerging and new class types without additional training, enabling rapid recognition and response to new events. This approach is especially applicable when labeled data for all class types is either unavailable or impractical to obtain.

D. Quantum-Large AI Models

Quantum-large AI models remark a convergence of quantum computing and large-scale AI to harness the exponential speed advantages of quantum computing for faster and more efficient processing of vast datasets in advanced AI-driven remote sensing tasks (see Fig. 2 for an exemplary fusion architecture).

1) Quantum Transformer Models: Quantum transformer models extend classical transformer architectures into the quantum domain. These models aim to exploit quantum computing principles to improve the efficiency of self-attention mechanisms and overall model performance.

- **Quantum SwinTs:** Quantum SwinT models integrate quantum computing into the SwinT architecture by utilizing parameterized quantum circuits for shifted window self-attention mechanisms. This approach harnesses quantum parallelism and entanglement, enabling the processing of complex correlations in high-dimensional visual data that may be challenging for classical models. In satellite imagery for disaster classification, these models facilitate faster analysis of high-resolution images, improving both the speed and precision of disaster monitoring and response.
- **Quantum ViTs:** Quantum ViT models enhance the ViT architecture with quantum techniques in self-attention. By employing quantum superposition, these hybrid models process all image patches simultaneously, efficiently capturing global dependencies. This integration offers potential improvements in both computational efficiency and modeling capabilities. In remote sensing applications, quantum ViTs invoke real-time analysis of large datasets, significantly empowering disaster response efforts.

2) Quantum Vision Generative Models: Quantum vision generative models leverage quantum computing to enhance image generation, thereby enabling high-fidelity image synthesis while efficiently capturing complex distributions inherent in satellite imagery.

- **Quantum Transformer GANs:** Quantum transformer GAN models integrate quantum computing into traditional GAN architecture, enhancing their ability to generate complex data efficiently. By incorporating quantum circuits within both the generator and discriminator, these models leverage quantum mechanics—specifically entanglement and superposition—to explore a broader state space, improving the quality and diversity of generated satellite images. In satellite imagery for disaster prediction scenarios, quantum transformer GANs can synthesize high-fidelity images of disaster-affected areas, simulating various scenarios for analysis. Additionally, the quantum advantage allows for more efficient handling of the vast and intricate data typical of remote sensing, accelerating the generation of realistic satellite imagery under different disaster conditions.
- **Quantum Diffusion Models:** Quantum diffusion models leverage quantum computing to enhance the performance of diffusion generative models, improving both sampling efficiency and image quality. By utilizing quantum algorithms, these models simulate the diffusion process to handle complex probability distributions in high-dimensional spaces. The quantum enhancement accelerates the reverse diffusion process, enabling faster generation of high-resolution satellite images with reduced computational demands. In remote sensing tasks, these models excel at reconstructing and denoising satellite imagery affected by noise or incomplete data, providing more precise and usable images. Therefore, this capability comes in handy for accurately identifying disaster-affected areas, improving real-time monitoring and response efforts.

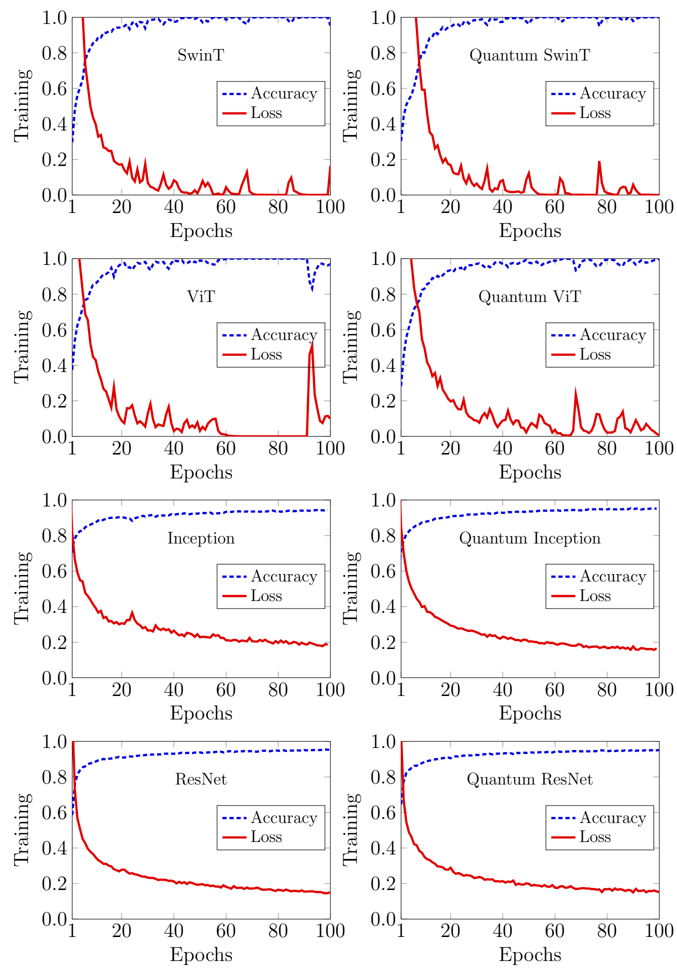

Fig. 4. Training performance of various classical AI (SwinT, ViT, Inception, and ResNet) and their QFI models on the disaster detection (disaster satellite images) dataset (top four) and the environmental monitoring (EuroSAT) dataset (bottom four).

3) Quantum Multimodal Models: Quantum multimodal models integrate visual and textual information, utilizing quantum computing to enhance the understanding and generation of complex multimodal datasets. This approach facilitates

TABLE II
PERFORMANCE OF CLASSICAL AI AND QFI MODELS FOR ENVIRONMENTAL MONITORING (EUROSAT DATASET) AT SNR LEVELS OF 5 dB AND 15 dB

Model	SNR = 5 dB					SNR = 15 dB				
	Accuracy	F1	Precision	Recall	Loss	Accuracy	F1	Precision	Recall	Loss
SwinT	0.8656	0.7744	0.8125	**0.7601**	0.4189	0.8679	0.7802	0.8133	0.7635	0.4000
Quantum SwinT	**0.8772**	**0.7984**	**0.8714**	0.7462	**0.3859**	**0.8834**	**0.8086**	**0.8701**	**0.7641**	**0.3607**
ViT-L/32	**0.7001**	0.1647	0.1400	0.2000	**0.9835**	**0.7001**	0.1647	0.1400	0.2000	**0.9868**
Quantum ViT-L/32	0.6884	**0.1733**	**0.1929**	**0.2041**	1.0190	0.6946	**0.1879**	**0.2789**	**0.2125**	1.0051
Inception-V3	0.8834	0.7895	0.8597	0.7474	0.3457	0.8912	0.8019	0.8562	0.7671	0.3414
Quantum Inception-V3	**0.9215**	**0.8617**	**0.8649**	**0.8592**	**0.2450**	**0.9347**	**0.8881**	**0.8869**	**0.8914**	**0.2281**
ResNet-50	**0.9029**	**0.8466**	**0.8636**	**0.8332**	**0.3128**	**0.9044**	**0.8466**	**0.8699**	**0.8283**	**0.2898**
Quantum ResNet-50	0.8936	0.8181	0.8362	0.8099	0.3358	0.8827	0.7959	0.8311	0.7786	0.3574

extracting insightful and relevant contextual information from satellite imagery.

- **Quantum Vision-Language Models:** Quantum vision-language models integrate quantum computing principles to process both visual and linguistic data simultaneously, enhancing the interpretation of complex multimodal information. Leveraging quantum parallelism, these models capture deep correlations between satellite images and corresponding text, improving their understanding of remote sensing application-specific scenarios. In remote sensing for disaster prediction, such models can analyze satellite imagery and generate detailed textual descriptions, aiding in rapid assessment and reporting. This capability facilitates better communication among decision-makers by automatically highlighting critical disaster impact zones.
- **Quantum Cross-Modal Learning Models:** Quantum cross-modal learning models leverage quantum computing to integrate and interpret relationships across various data modalities, including visual, textual, and sensor data. Using quantum algorithms, these models efficiently process and fuse heterogeneous data sources, providing deeper insights into complex datasets. In the context of satellite imagery for remote sensing, these models link satellite images with inputs like social media updates, ground sensor readings, and textual reports. This integrated approach offers a more comprehensive understanding of critical situations, such as disaster response, security surveillance, and conflict assessments.

E. Case Studies

We present case studies demonstrating the application of QFI models in integrated SGRS for disaster detection and environmental monitoring.

1) Disaster Detection: In this case study, we employ the disaster detection (disaster satellite images) dataset with satellite imagery to detect disasters by comparing pre-disaster and post-disaster images over affected areas. The dataset includes 10 distinct types of disasters. The QFI approach integrates both classical and quantum models for feature extraction and classification, aiming to enhance the accuracy of early warning systems.

We utilize two distinct feature extraction pipelines: one using a ViT and the other using a SwinT. Each classical model is then compared with its quantum-fusion counterpart, namely, the quantum ViT and quantum SwinT. The features from the pre-disaster and post-disaster images are extracted separately using the ViT in the first pipeline and the SwinT in the second. After extracting and flattening the features, we combine them to create a unified feature set. This combined feature set is then passed through the rectified linear unit (ReLU) activation function to introduce nonlinearity and improve the model learning capabilities. Subsequently, we apply amplitude encoding to convert the activated features into a quantum state, enabling processing by a quantum circuit, as shown in Fig. 2. This circuit is designed with parameterized quantum gates and entangling layers to capture complex correlations between the features. At the final stage, the quantum circuit performs measurement operations, and the measurement results are fused with the output from the classical layers via skip connections. This combined information is then passed through a classifier, which determines the type of disaster using the processed data.

The system leverages both classical and quantum learning models to provide a robust mechanism for disaster detection with satellite imagery. Specifically, it enables early warnings by analyzing the changes between pre-disaster and post-disaster images, offering critical information for emergency alerts and warning systems in real time. This innovative integration of quantum-large AI within SGRS marks a significant step forward in enhancing the capacity of disaster management platforms. The confusion matrices and training performance results are depicted for large AI (SwinT and ViT) and their QFI models in Figs. 3 and 4, respectively. We utilize a consistent set of hyperparameters to train both the classical AI and QFI models, ensuring a fair performance comparison. Specifically, we employ the Adam optimizer with a learning rate of 0.0001 and cross-entropy loss as the objective function. The models are trained over 100 epochs to balance convergence and computational efficiency. This uniform configuration allows for a reliable evaluation of the performance enhancements introduced by the QFI models. The training performance results indicate that the QFI models demonstrate faster convergence, lower final training loss, and higher training accuracy compared to their classical counterparts. Similarly, testing performance, evaluated using confusion matrices, further underscores the superiority of QFI models, evidently with sharper diagonal dominance and fewer misclassifications. These improvements highlight the enhanced learning capacity and robustness of QFI models for disaster detection tasks.

2) Environmental Monitoring: In the second case study, we employ the EuroSAT dataset, designed for environmental monitoring through real-time satellite imagery. The dataset consists of $27,000$ labeled and geo-referenced satellite images sourced from Sentinal-2, part of the Copernicus Earth observation program. It includes 10 image classes across 13 different spectral bands. Each image is resized to 64×64 pixels after being extracted from patches standardized to 224×224 pixels.

For model training, we use a $70:30$ training-testing split and train both pretrained classical AI and quantum transformer models. Each model is trained over 100 epochs, employing the Adam optimizer with a learning-rate adjustment strategy that reduces the rate to 0.0001 upon plateauing of validation loss. This refines model parameters optimally over multiple training cycles. The obtained confusion matrices and training performance results are again shown for classical AI (Inception and ResNet) models and their QFI models in Figs. 3 and 4, respectively. Both QFI models demonstrate efficient training, characterized by faster convergence and lower training loss. While the quantum Inception model achieves noticeably higher accuracy, the quantum ResNet performs on par with its classical version. Moreover, the confusion matrices for the testing dataset reveal relatively fewer misclassifications by the QFI models, highlighting their superior capability for accurate environmental monitoring. In addition, Table II compares the environmental monitoring performance for various classical AI (SwinT, ViT, Inception, and ResNet) and their QFI models trained on the EuroSAT dataset under different SNR conditions. In general, although the QFI models exhibit enhanced expressiveness at moderate-to-high SNR levels, they tend to be more sensitive to severe noise, enabling their classical counterparts to remain competitive or even superior at very low SNR levels. Nonetheless, by leveraging optimal network co-design strategies—jointly developing the quantum processing pipeline (PQC architecture), classical large AI architectures, and communication protocols—along with effective error mitigation techniques, quantum-enhanced approaches can still outperform classical methods when the SNR level is sufficiently high. Moreover, current QPUs face hardware limitations such as qubit decoherence, low gate fidelities, and stringent cryogenic operating requirements, thus amounting to additional complexity and cost to onboard satellite deployment. Therefore, addressing these challenges, such as improving environmental resilience and managing high-maintenance conditions, remains crucial for harnessing the full potential of QFI models in practical SGRS applications.

III. QAC for Integrated SGRS

For integrated SGRS tasks, the satellites anonymously and securely communicate with terrestrial network recipients using QAC. Specifically, we outline the quantum anonymous notification protocol for notifying the ground stations of emergency alerts over satellite-ground quantum networks.

A. Satellite-Ground Anonymous Notification

The QPU-equipped satellite notifies the ground stations in case of an emergency using the quantum anonymous protocol. The protocol steps are as follows.

1) Entanglement Preparation: In the first preparation step, satellites prepare multipartite entangled Greenberger–Horne–Zeilinger (GHZ) states.

2) Entanglement Distribution: Each recipient is assigned a set of particles from the entangled states. These particles are indexed, and each recipient receives their particles, which will be used in subsequent operations for encoding and decoding notifications.

3) Phase-Flip Operations: Each network recipient applies the phase-flip (Pauli-Z) operation on their assigned particles based on specific preset rules. The notifier (any satellite) encodes its notification by performing the phase-flip operation on its respective qubit. The intended recipient (any ground station) receives this notification based on the outcomes of these operations. A probability rule governs whether the notification is encoded or not, preventing collisions between multiple notifications. Other parties either leave their qubits unchanged according to the preset protocol rules.

4) Hadamard Operations: All network recipients perform the Hadamard operation on their respective qubits. This operation transforms the current state into a superposition of states, facilitating the propagation of the encoded notification within the system. The Hadamard operations on the shared GHZ state create interference effects, which are essential for decoding the anonymous notification in the final stage.

5) Computational Basis Measurement: After the Hadamard operation, each recipient measures its respective qubit in the standard computational basis. This measurement produces a binary outcome for each qubit, which is then used to decode the notification in classical post-processing.

6) Classical Communication: Once the measurements are completed, each recipient announces its measurement outcome via classical authenticated broadcast channels. This step prevents recipients from directly revealing their own encoded information while providing the necessary data for collective processing by the other involved recipients.

7) Anonymous Notification: Finally, each recipient calculates the binary (modulo 2) sum of the received outcomes. This value determines whether the intended recipient (the ground station) has been notified. If the sum matches the encoded value, the notification has been successfully transmitted to the ground station without disclosing the satellite's identity.

B. Advantages

The key security and privacy benefits of satellite-ground QAC are outlined as follows.

1) Security: Satellite-ground QAC provides robust protection against quantum-capable adversaries, ensuring the integrity of integrated nonterrestrial-terrestrial networks.

- **Traceless Operations:** The satellite-ground anonymous notification protocol ensures that the encoding operations cannot be traced back to the notifying satellite, even if an adversary gains access to all communication data. This prevents any entity from linking actions to a specific network recipient, providing complete untraceability.

- **Adversarial Resilience:** The protocol is designed to be resilient against external adversaries, even those with quantum capabilities and access to all shared network resources. This guarantees secure and tamper-proof notification delivery.
- **Secure Transmission:** The protocol ensures that only the intended ground station receives the notification without revealing any details to other recipients. The mechanism minimizes the risk of interference or manipulation during transmission.
- **Node Integrity Protection:** The protocol is designed to maintain security even if certain network nodes are compromised. This ultimately prevents those nodes from gaining any significant advantage in identifying the notifying satellite or the intended ground station, thereby preserving the overall communication integrity.

2) Privacy: Satellite-ground QAC guarantees complete anonymity for both the sender and receiver, protecting their identities and ensuring that privacy-sensitive communications remain untraceable within the network.

- **Sender Anonymity:** The protocol guarantees anonymity for the notifying satellite, preventing any recipient, including adversaries, from determining its identity. This feature makes it impossible to trace back the notification's origin.
- **Receiver Anonymity:** The protocol also protects the identity of the receiving ground station, ensuring that adversaries cannot determine which ground station is being notified of the emergency alert, even if the adversaries control parts of the network.
- **Hidden Encoding Mechanism:** Encoding operations are performed anonymously within the network, ensuring no recipient can identify which station initiated the notification. This hidden mechanism keeps the notifier's actions private, protecting both their identity and intent.
- **Authenticated Access:** The use of authenticated classical channels for communication prevents eavesdropping and unauthorized access during information exchange. This guarantees that no external entity can intercept or alter the communication, therefore preserving privacy.

IV. Conclusion

We have explored the fusion of large AI, quantum computing, and quantum communication to tackle the computation, security, and privacy challenges in integrated SGRS systems. First, we have discussed the functionality and limitations of narrow AI models in remote sensing tasks. Leveraging quantum advantages, we have put forth an integrated framework that combines QFI computing—to improve scalability, speed, and accuracy of processing high-dimensional satellite imagery data—with QAC—for privacy-preserving and unconditionally secure notification transfer—between satellite and ground systems in time- and privacy-sensitive scenarios. The case studies on disaster detection and environmental monitoring demonstrate the practical benefits of this approach, highlighting performance gains for timely decision-making. This work emphasizes the growing potential of QFI and QAC in advancing integrated SGRS systems.

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