Cropland Quantum Learning: A hybrid Quantum-Classical Neural Network for Cropland Classification

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***Abstract*—Accurate cropland classification is important for sustainable land management and agricultural planning. Remote sensing data, such as Normalized Difference Vegetation Index ($NDVI$) and Enhanced Vegetation Index (EVI), have proven instrumental in vegetation monitoring. Traditional machine learning and deep learning have shown remarkable results in land classification using remote sensing data. However, when facing an immense volume of data or high-dimensional features, deep learning requires large models, extensive parameters, and substantial training resources. To address the above issues, this paper proposes Cropland Quantum Learning (CQL), a quantum-classical hybrid method that utilizes quantum machine learning to extract features from geospatial information, and integrates it with a single-layer fully connected classifier to locate cultivation regions of a given target crop. Experiments show that the proposed CQL can achieve results comparable to traditional deep learning while significantly reducing the number of model parameters.**

We present experimental results demonstrating the effectiveness of our proposed method on $NDVI$ and EVI datasets. The implementation achieved comparable results to traditional deep learning using a network with a lower number of parameters, and in some datasets, even achieved better results in multiple metrics. The CQL network presents an innovative solution for cropland classification, achieving promising results with fewer parameters and reduced resource requirements. As the research continues deeper, the potential of quantum-enhanced approaches in geospatial analysis becomes increasingly evident.

***Index Terms*—Quantum Machine Learning, Remote Sensing Data, Cropland Classification.**

I. Introduction

Recently, machine learning and deep learning has been widely used to analyze remote sensing data and solve cropland classification tasks. In parallel, the quantum algorithm has witnessed remarkable integration with machine learning, leading to the emergence of hybrid models that harness the power of both quantum computing paradigms and machine learning. Hence in this paper, we propose a hybrid neural network architecture which is based on the variational shadow quantum learnig [1] , that utilizes the quantum circuits for feature embedding and neural network as a classifier on cropland classification.

A. Cropland Classification

Introduction to Cropland Classification with Machine Learning and Deep Learning:

Cropland classification, a crucial task in remote sensing and agriculture, involves identifying and categorizing different types of agricultural land based on the crops being cultivated. Accurate cropland classification is essential for various purposes, including land management, resource allocation, yield prediction, and environmental monitoring. In recent years, the integration of machine learning and deep learning techniques has revolutionized the field of cropland classification, enabling more efficient and accurate analysis of agricultural landscapes.

Machine learning, a subset of artificial intelligence, involves the development of algorithms that enable computers to learn from data and make predictions or decisions without being explicitly programmed. Deep learning, a specialized form of machine learning, utilizes neural networks with multiple layers to automatically learn and extract complex patterns from data. Both machine learning and deep learning have been widely adopted to enhance cropland classification methodologies.

Cropland classification with machine learning [2], [3] and deep learning [4]–[9] has demonstrated remarkable accuracy improvements compared to traditional methods. These advanced techniques leverage the ability of models to capture intricate relationships within the data, leading to more detailed and reliable classification outcomes. As technology continues to evolve, the integration of machine learning and deep learning in cropland classification promises to contribute significantly to precision agriculture, sustainable land management, and informed decision-making in the agricultural sector.

B. Quantum Machine Learning

Quantum machine learning (QML) [10], [11] represents a revolutionary paradigm that merges principles from quantum mechanics and machine learning to enable the development of more powerful and efficient computational models. Traditional machine learning techniques have shown remarkable success in various domains, but as the scale and complexity of data continue to grow, the limitations of classical computing become increasingly apparent. Quantum machine learning offers a promising solution to tackle complex computational challenges by harnessing the unique properties of quantum systems.

At its core, quantum machine learning leverages the principles of superposition and entanglement, which are fundamental to quantum mechanics. These principles enable quantum computers to process and manipulate information in ways that are fundamentally different from classical computers. Quantum bits, or qubits, can exist in a superposition of states, allowing them to represent and process multiple possibilities simultaneously. Additionally, qubits can become entangled, leading to correlations between qubits that enable novel methods of information processing.

In the realm of machine learning, quantum computing holds the potential to accelerate tasks such as optimization, matrix inversion, and sampling, which are often time-consuming for classical computers. Quantum algorithms, such as the Quantum Support Vector Machine (QSVM) [12], Quantum Neural Networks (QNN) [13], and Quantum Principal Component Analysis (QPCA) [14], are being explored to enhance the efficiency and capabilities of various machine learning tasks. However, it's important to note that quantum computing and quantum machine information application [15] is still in its early stages, and building practical and scalable quantum computers remains a significant challenge. Quantum bits are delicate and prone to errors due to environmental interactions, requiring sophisticated error correction techniques to ensure the reliability of computations. As a result, quantum machine learning is primarily simulated on classical computers. Platforms such as PennyLane [16], IBM Qiskit [17], and Baidu Paddle Quantum [18] are among the leading tools for implementing hybrid quantum-classical [19] models and quantum machine learning at this stage.

II. Related Work

The study of cropland classification has witnessed significant advancements through the application of machine learning and deep learning techniques. Numerous researchers have explored the integration of these methodologies to accurately discern and classify cropland regions. On the contrary, quantum machine learning and quantum neural networks represent a highly emerging research direction that serves as a crucial bridge between quantum computation and real-world classical problems. They also constitute a significant endeavor to apply quantum algorithms to classical issues. In this chapter, we will delve into the existing deep learning-based approaches for cropland research and explore some of the achievements in the quantum neural networks.

The application of deep learning techniques in remote sensing-based cropland classification has gained significant traction due to its ability to automatically extract complex features from high-dimensional and heterogeneous remote sensing data. Deep learning methods, particularly Convolutional Neural Networks (CNNs) [20] and Recurrent Neural Networks (RNN) [21], have demonstrated remarkable success in various land cover and land use classification tasks. Researchers have increasingly explored the potential of these techniques to accurately classify cropland areas using multispectral imagery, including indices such as the Normalized Difference Vegetation Index ($NDVI$) [22] and Enhanced Vegetation Index (EVI) [23].

CNNs have emerged as a powerful tool for feature extraction from remote sensing images. They excel at capturing spatial patterns and hierarchies of features that are essential for accurate classification. In cropland classification, CNNs have been employed to analyze multispectral imagery, effectively distinguishing different land cover types, including cropland. For instance, Ao et al. [24] utilized CNNs to classify agricultural land use from sentinel-2 images.

Another approach gaining momentum in cropland classification is the utilization of Recurrent Neural Networks to incorporate temporal information. RNNs are well-suited for sequences of data, making them suitable for analyzing the time-series nature of remote sensing data.To illustrate, an LSTM network is employed to learn and classify long-term land cover in China spanning from 1982 to 2015 [25].

Despite the successes of pure deep learning models, challenges persist, including the need for substantial amounts of labeled data and their susceptibility to overfitting. To address these limitations, researchers have explored transfer learning and data augmentation strategies [26]. Transfer learning [27], where pre-trained models are fine-tuned on specific tasks, has been shown to improve the classification accuracy for cropland areas.

While deep learning models have shown significant promise in cropland classification, there is growing interest in leveraging quantum computing to further enhance classification accuracy. Our proposed Quantum-Classical Hybrid Neural Network (QCHNN) builds upon the foundations laid by deep learning methods while exploiting the quantum computing paradigm to accelerate feature extraction and enhance classification performance. By integrating quantum and classical resources, we aim to create a synergistic approach that overcomes the limitations of pure classical methods and advances the state-of-the-art in cropland classification accuracy.

III. Methodology

In this section, we will provide a comprehensive exposition of the methodology employed in this paper. Our elucidation will encompass various facets, including data collection, data encoding, network architecture, and algorithmic specifics. Each of these elements will be thoroughly expounded upon to ensure a comprehensive understanding of our research approach. we will embark on a case analysis centered on Jackson County, situated in the western region of Missouri, within the United States, serving as our designated study area. Elaborate elucidations regarding the data and the devised encoded representations thereof will ensue forthwith. Furthermore, we propose a quantum-classical hybrid model to handle these data effectively, addressing the binary classification task of determining whether corn cultivation is present in the planting regions.

A. Data Collection

In this context, the bands corresponding to corn crops within the CDL dataset were selected for the years 2020, 2021, and 2022 within the specified county. Within each unit area, data pertaining to both EVI and $NDVI$ during the growth stages of corn were extracted. Furthermore, the areas where corn was cultivated were labeled as "1", while regions without corn cultivation were designated as "0." A cumulative total of 9228, 9353, and 9119 data instances were acquired within this region.

$NDVI$: The Normalized Difference Vegetation Index ($NDVI$) dataset is a widely used remote sensing measurement that provides valuable information about the health and vigor of vegetation cover. $NDVI$ is derived from satellite imagery and is commonly used to monitor and assess vegetation growth, land cover changes, and environmental conditions. It is instrumental in agriculture, ecology, and environmental studies. The $NDVI$ is calculated using the following formula:

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

Where

- NIR is the Near-Infrared band reflectance from the satellite image.
- Red is the Red band reflectance from the same image.

EVI: The Enhanced Vegetation Index dataset is another remote sensing measurement used to assess the health and density of vegetation cover, similar to the $NDVI$. The EVI was developed to address some of the limitations of $NDVI$, particularly in areas with dense vegetation or high levels of soil background reflectance. EVI takes into account atmospheric influences and enhances sensitivity to variations in vegetation cover. The EVI is calculated using the following formula:

$$EVI = 2.5 \times \frac{NIR - Red}{NIR + 6 \times Red - 7.5 \times Blue + 1} \tag{2}$$

Where

- NIR is the Near-Infrared band reflectance from the satellite image.
- Red is the Red band reflectance from the same image.
- $Blue$ is the Blue band reflectance from the same image.

Labels: The labels are extracted from the Cropland Data Layer(CDL). The CDL constitutes a yearly generated crop-specific land cover dataset encompassing the entire continental United States. This compilation is crafted utilizing moderate-resolution satellite imagery in conjunction with comprehensive agricultural ground truth information. This dataset furnishes the ground truth essential for our binary cropland classification task, wherein "0" signifies cultivated areas, while "1" corresponds to non-cultivated regions.

Throughout the growth cycle of corn, a total of nine data points, along with a corresponding label, can be extracted for both $NDVI$ and EVI. Summing up, the ultimate raw dataset is composed of individual one-dimensional vectors, each representing a $\{[X_i^j], y_i \in \{0, 1\}\}, j \in 0, 1, ...17$.

B. Data Encoding

Both the original EVI and $NDVI$ data are regarded as foundational datasets, necessitating their conversion into quantum-encoded representations. Quantum encoding methods encompass a spectrum of techniques, encompassing basis encoding, amplitude encoding, and angle encoding, among others. Given the nature of the task, intrinsic data attributes, and the optimization of computational inference, the present study adopts an amplitude encoding approach.

Amplitude encoding encodes a vector $\mathbf{x}$ of length N into amplitudes of an n-qubit quantum state with $n = [\log_2(N)]$:

$$|\mathbf{x}\rangle = \sum_j^N x^j |j\rangle \tag{3}$$

Where $\{|j\rangle\}$ is the computational basis for the Hibert Space. As the amplitudes of a quantum state are constructed from classical information, it is imperative for the input to adhere to the requirement of normalization: $|\mathbf{X}|^2 = 1$.

In our instance, a sampled case X^j could be encoded as:

$$\begin{aligned} |\mathbf{X}\rangle = & x^0 |\mathbf{00000}\rangle + x^1 |\mathbf{00001}\rangle + x^2 |\mathbf{00010}\rangle \\ & + ...x^{16} |\mathbf{10001}\rangle + x^{17} |\mathbf{10010}\rangle \\ & + ...0 |\mathbf{11110}\rangle + 0 |\mathbf{11111}\rangle \end{aligned} \tag{4}$$

In this manner, our feature points have been encoded into quantum states and subsequently subjected to padding. The original $NDVI$ and EVI signals can now be fed into the quantum network component for inference.

C. Model Structure

In this section, we present the underlying architecture of the network, which is composed of three main components. The first component involves a quantum neural network section that takes pre-encoded quantum states as inputs. We draw inspiration from the feature extraction technique employed in VSQL, utilizing a low-parameter variational quantum circuit U for feature extraction. This enables the extraction of all features with minimized parameter degrees. These features are then transmitted as inputs to the second component of the network, which is a concatenation of a fully connected network and a softmax layer. This configuration ultimately generates a probability distribution for classification outcomes. The entire architecture is optimized through a backpropagation process, aiming to minimize binary entropy. The optimization pertains to the parameters θ in the quantum part and parameters ω in the classical part. The holistic framework of the network, illustrated in Figure 1, packages these components in a structure. The feature engineering module $U(\theta)$ of the network consists of a series of variational quantum circuits. Its purpose is to conduct feature extraction and dimensionality reduction on the pre-encoded raw data D to derive the feature set V. The detailed architecture of $U(\theta)$ is depicted in Figure 2.

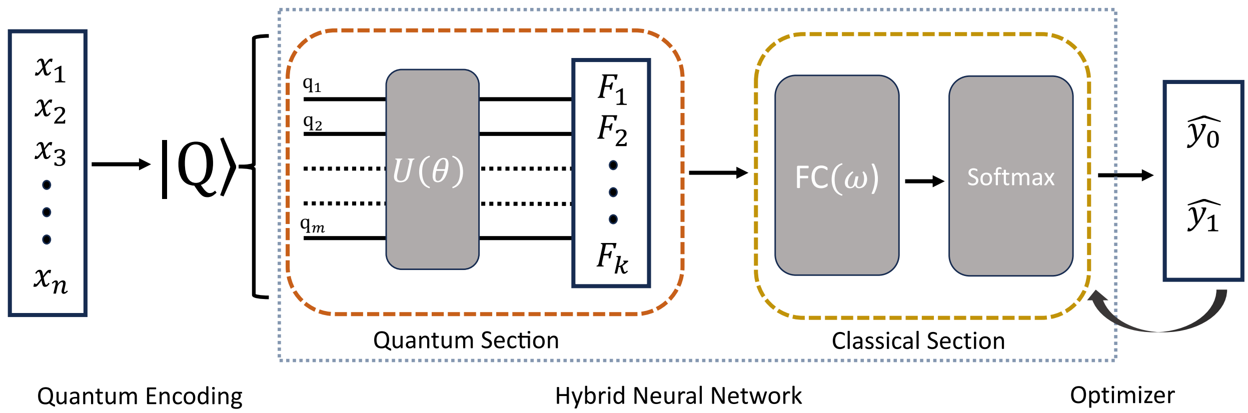

Fig. 1: The overall architecture of the network.

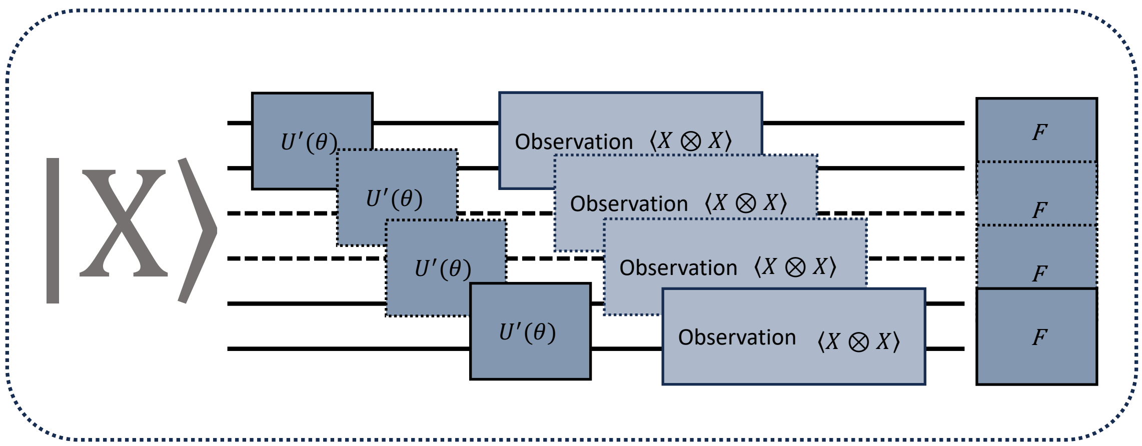

Fig. 2: Details presentation of $U(\theta)$.

The approach employed here involves a $U^{'}(\theta)$ sub-network that operates within the subspace formed by two single qubits. Subsequently, a similar sliding mechanism is applied to the following two signal qubits subspace, and this process iterates progressively until the ith to $i+1$th quantum state's subspace is reached the last two single qubits. Within each subspace, the $U^{'}(\theta)$ quantum circuit is executed, followed by a Pauli-X measurement to observe and compute the corresponding feature v.

Functioning as a sub-quantum circuit, $U^{'}(\theta)$ constitutes an integral component of the core $U(\theta)$. Its specific structure is illustrated in Figure 3. It encompasses a sequence of $Rz-Ry-Rz$ rotations applied successively to the two individual qubit states within the subspace, followed by a controlled-NOT $CNOT$ operation between the two qubit states. In the final step of the $U^{'}(\theta)$ quantum circuit, there is a single qubit gate rotation, specifically a Ry rotation gate. The matrices for the rotations R and the $CNOT$ operation are provided as follows:

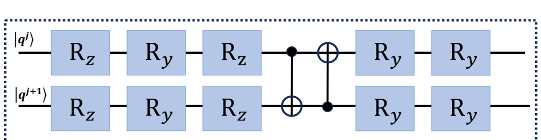

Fig. 3: Details presentation of $U(\theta)$.

$$CNOT = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{5}$$

$$R_y(\theta) = \begin{bmatrix} \cos(\frac{\theta}{2}) & -\sin(\frac{\theta}{2}) \\ \sin(\frac{\theta}{2}) & \cos(\frac{\theta}{2}) \end{bmatrix} \tag{6}$$

$$R_z(\theta) = \begin{bmatrix} e^{-i\frac{\theta}{2}} & 0 \\ 0 & e^{i\frac{\theta}{2}} \end{bmatrix} \tag{7}$$

R_y and R_x are fundamental single-qubit rotation gates in quantum computing used to introduce specific rotation operations on quantum bits (qubits). Meanwhile, $CNOT$ is a type of gate operation in quantum computing that enables controlled flipping between quantum bits. In a $CNOT$ gate operation, one quantum bit serves as the control bit, while another quantum bit serves as the target bit. When the control bit is 1, the target bit undergoes a flip (0 becomes 1 and 1 becomes 0); when the control bit is 0, the target bit remains unchanged.

By utilizing the aforementioned structured quantum circuit block, we are enabled to extract the feature set v during the forward propagation of the network. Subsequently, this feature vector is fed into the subsequent classical network module, which comprises a fully connected network interlinked with a $softmax$ layer. The fully connected layer can capture the complex relationship between the features obtained before, combine these features linearly and input them into the activation function to generate the probability distribution required by the binary classification problem, so as to realize the cropland classification task.

The overall structure of the proposed network is a hybrid model that employs a Quantum encoder to encode the raw data and use it as input. It incorporates a parameterized quantum circuit as the feature engineering module, followed by a classical neural network's fully connected layer and softmax activation function as the prediction module.

D. Algorithm

The training and convergence methods of the entire network are similar to traditional deep learning training methods, as illustrated in Algorithm 1.

Algorithm 1 Hybrid Quantum-Classical Circuit for Cropland Classification: training process

Input: Data set $D := \{[x_i^{0-j}], y_i \in \{0,1\}\}$, $Epoch$
Output: $Loss$, Quantum Circuit Parameters θ, Classical Parameters ω

Initialize the parameters θ of quantum circuit
Initialize the parameters ω of classical block
Quantum Encoding on $[x_i]$, $|X_i\rangle = AmEN([x_i])$ ▷ $AmEN()$ is an Amplitude Encoder.
for $epoch$ = (1,$Epoch$) **do**
    Feed Encoded Data $\psi(i)$ to the varitional quantum circuit.
    Measure the quantum part and receive the quantum part features v_i
    Feed v_i into the classical network and obtain $\hat{y}_i$
    Caculate the the Binary Crossentropy $(\hat{y}_i - y_i)^2$ and update the parameters θ and ω
end for

Firstly, Initialize the parameters θ for the quantum block and ω for the classical block separately. Given the dataset $D := \{[X_i^{0-(N-1)}]\}, y_i \in \{0,1\}$, where i represents the sample index in the dataset and N refers to the feature length of each sample. Apply amplitude quantum encoding $AmEN$ to the data, the feature dimensions are reduced from N to $[\log_2(N)]$.

$$|X_i\rangle = AmEN([x_i]) \tag{8}$$

Then feed the encoded data into the quantum for feature extraction to obtain the feature set v_i. Continuing, the obtained features are input to the classical network for classification. The corresponding loss function is calculated, and the parameters of both modules are updated accordingly.

$$\mathcal{L}_{\text{BCE}}(y, \hat{y}) = -(y \cdot \log(\hat{y}) + (1-y) \cdot \log(1-\hat{y})) \tag{9}$$

where $\hat{y}$ is the predictive classification of the entire network on the training data.

$$\hat{y} = \sigma[F_c(F_q(|X\rangle, \theta), \omega)] \tag{10}$$

For more detail, F_c serves as an abstract representation of the classical network component, which essentially comprises a fully connected layer.

$$F_c = v \cdot \omega + b \tag{11}$$

where v is extracted by F_q which is the denotation of the quantum network section.

$$F_q = {U'}^{\dagger}(\theta) U'(\theta) \tag{12}$$

With this approach, the overarching logical objective of the algorithm is to iteratively update the parameters θ of the quantum circuit and the parameters ω of the classical network. By utilizing the Adam optimizer, the algorithm aims to minimize the value of the loss function, thereby achieving the training of the hybrid network for classification.

IV. Experiments

A. Experimental Setup

1) Datasets: The overview of the datasets split in our experiments is given in the Table I.The data includes preprocessed NDVI and EVI concatenated collection from 2020 to 2022 in County Jackson, USA. The split processing randomly select 80% of the datasets of each year as the training dataset and the rest 20% is reserved for testing the trained models. Within the training set, a further 20% is set aside as a validation set. From the table, the 2022 dataset contains significantly lower number of positive samples (e.g., around 22%). Therefore, after splitting the data for 2022, the Synthetic Minority Oversampling Technique (SMOTE) is applied to oversample the 2022 training set in order to ensure a balanced class distribution. The resultant dataset is denoted as 2022^a in the rest of the paper. On the other hand, both the validation and test sets retain their original, unchanged distribution.

It can be observed from Table I that the datasets from 2020 and 2021 have a fairly even distribution of positive and negative samples, representing a well-balanced data distribution. However,

Data	Train Set	Test Set	Validation Set
2020	5905(47.1%)	1846(46.9%)	1477(45.6%)
2021	5986(43.5%)	1871(45.0%)	1497(45.3%)
2022	5836(22.3%)	1824(22.9%)	1459(22.7%)
2022^a	9038(50%)	1824(22.4%)	1459(22.3%)

TABLE I: Dataset Split Detail (The number of samples in the train, test, and validation sets for each dataset, with the percentage of positive samples in each set given in parentheses.)

2) *Baselines:* To compare with traditional deep learning methods, we employed both LSTM and CNN models. For CNN models, we conducted both 1-Dimensional CNN and 2-Dimensional CNN.

3) *Implementation:* For the proposed Cropland Quantum Learning hybrid network, we devised two distinct network architectures and corresponding experiments. The first approach treats NDVI and EVI data within a single sample, keep them as a unified entity, termed as the One-Head Cropland Quantum Learning(1H CQL). The alternative, the Two-Head Cropland Quantum Learning(2H CQL), treats NDVI and EVI as separate features, encoding them individually and subsequently feeding them into two distinct quantum circuits. To realize the quantum-related feature engineering, our experimental environment primary use Paddle-Quantum(2.4.0). Additionally, the baselines utilize the PaddlePaddle(2.3.0). Both of them are open-source packages from Baidu.

4) *Hyper-Parameters:* To facilitate a more effective analysis of the results, we fix certain hyperparameters across different networks. These include a batch size of 32 and a learning rate of 0.001. For each model on different dataset, we conducted training for 10 epochs. Furthermore, we use Adam as the optimizer. Consequently, the results obtained are more conducive to a controlled variable analysis.

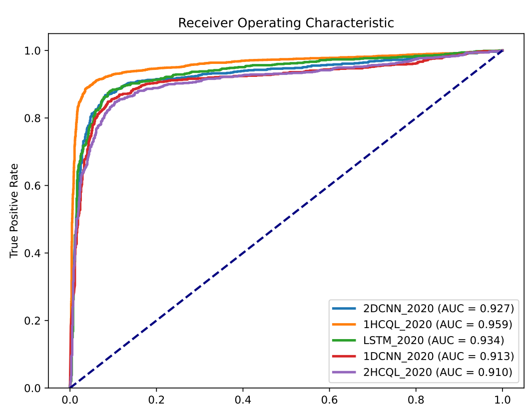

Fig. 4: ROC curves of models on dataset 2020

Methods	Parameters	Layers	FCNN
1D CNN	154	$1\times$ CNN	✓
2D CNN	170	$1\times$CNN	✓
LSTM	138	$1\times$ LSTM	✓
1H CQL	13	$1\times$ CQL	✓
2H CQL	23	$1\times$ CQL	✓

TABLE II: Comparision of Model Complexity

B. Performance and Evaluation

Throughout the experiment, our aim was to compare the performance of different networks across various datasets. By analyzing the experiment results, we gained insights into the strengths and weaknesses of each network for the given task.

1) *Model Complexity:* Before delving into the analysis of the results, we first consider the complexity of the network. To assess model complexity, we utilized the model's training parameters and network depth, with specific network configurations detailed in Table II.

The table illustrates that all models consist of a single layer, excluding pooling layers, activations, and other non-parametric components. Moreover, before get the final outputs, each network terminates with a fully connected layer. Despite their shallow architecture, the Cropland Quantum Learning approach possesses fewer training parameters. what's more, when dealing with more intricate data and transitioning to deeper, more complex networks, the parameter count for quantum networks could exponentially decrease due to their unique encoding mechanism.

2) *Metrics:* In our study, a variety of metrics were employed to evaluate and compare the performance of hybrid networks with that of traditional neural networks. These metrics encompassed the Area Under the Curve (AUC), the F1 Score, and accuracy.

Among them, AUC represents the area under the ROC curve. It primarily quantifies the classifier's ability to rank a randomly chosen positive sample higher than a randomly chosen negative one. The AUC value ranges between 0.5 and 1.0, with values closer to 1.0 indicating superior performance. The F1 score is a crucial performance metric for finding a balance between precision and recall. For a balanced dataset, accuracy serves as an effective performance metric.

3) *Evaluation:* Our experimental results are summarized in Table III. Within the original 2020 dataset, the 1Head CQL model outperformed others in terms of F1 score, AUC, and accuracy, surpassing both CNN and LSTM by two percentage points or more in each metric. We have specifically illustrated the AUC performance, considering its significance in binary classification tasks. As shown in Figure 4, it is evident that the 1Head CQL model exhibited the best performance on the 2020 dataset. Although the CQL model performance on the

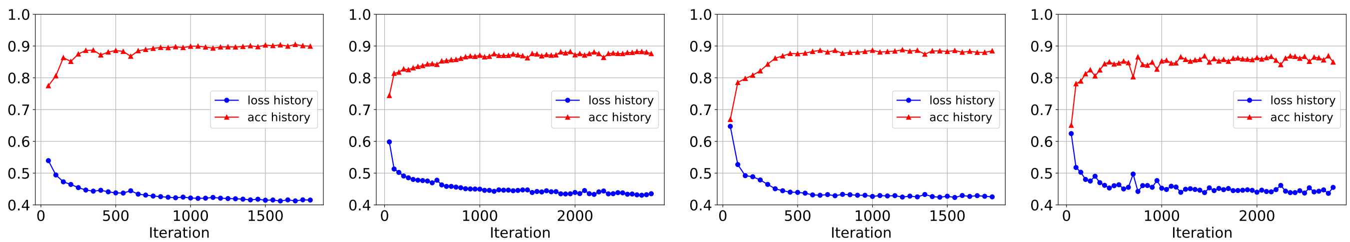

Fig. 5: Validation accuracy and loss history of CQL Hybrid Model on dataset 2020 and 2020^a

2021 dataset dose not achieve the best results, it also shows a results comparabel to traditional CNN and LSTM models.

As observed in the table, traditional networks did not yield results on the original 2022 dataset. In fact, under this experimental setup, traditional models tended to overfit on the relatively imbalanced 2022 data, failing to produce accurate test results. However, the CQL model demonstrated good convergence during the training process, as shown in Figure 5. Furthermore, the 1Head CQL model outperformed the 2Head version. For the oversampled 2022^a data, the 1Head CQL model also achieved the best performance in terms of F1 score and accuracy.

In summary, the hybrid models based on quantum machine learning, when applied to binary classification of agricultural land use, are able to match and often surpass traditional CNN and LSTM networks in most cases. A more significant finding is that, in this task, the CQL model performs better on imbalanced datasets compared to traditional networks. This indicates that quantum-based feature engineering can be more effective than conventional methods in certain specific datasets.

Methods	Test Year	F1 Score	AUC	Acc(%)
1D CNN	2020	0.869	0.913	0.878
	2021	**0.921**	0.969	**0.931**
	2022	–	–	–
	2022^a	0.762	**0.938**	0.878
2D CNN	2020	0.882	0.927	0.889
	2021	0.920	0.965	0.930
	2022	–	–	–
	2022^a	0.756	0.925	0.872
LSTM	2020	0.886	0.934	0.894
	2021	0.917	**0.971**	0.928
	2022	–	–	–
	2022^a	0.740	0.917	0.870
1Head CQL	2020	**0.911**	**0.959**	**0.920**
	2021	0.900	0.948	0.919
	2022	**0.780**	**0.920**	**0.903**
	2022^a	**0.880**	0.935	**0.885**
2Head CQL	2020	0.890	0.910	0.885
	2021	0.915	0.966	0.924
	2022	0.748	0.917	0.890
	2022^a	0.739	0.912	0.868

TABLE III: Corpland Classification on 3 different years(10 epochs training)

V. Discussion

Utilizing a hybrid neural network for cropland classification has proven to be a promising and effective approach. The quantum-classical hybrid neural approach allows us to extract complex features from remote sensing data, capturing patterns and relationships between different features like traditional neural networks. Simultaneously, we conducted training and testing on multiple datasets, and the proposed method yielded consistent performance. On certain datasets, it even exhibited a slightly superior performance compared to results obtained from traditional deep learning feature mappings. However, the feature embedding approach using quantum-inspired techniques capitalizes on the distinctive properties of quantum bits, achieving comparable effectiveness within a network configuration that utilizes fewer parameters. This quantum-inspired approach opens new avenues and solutions for future applications involving larger-scale remote sensing data and more complex tasks. Importantly, while the current implementation involved quantum simulation on conventional hardware, the prospect of utilizing authentic quantum computers offers the potential to leverage quantum algorithms for accelerating classical algorithms when processing traditional data. As we move forward, the incorporation of genuine quantum computation could lead to substantial advancements, ultimately bridging the gap between quantum-inspired methodologies and the untapped power of quantum computing. This promises to provide novel solutions for tackling intricate challenges posed by expansive remote sensing datasets and intricate tasks, transcending the capabilities of conventional deep learning approaches.

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