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QUANTUM SIGNAL AND IMAGE PROCESSING: THEORETICAL MODELS AND COMPUTATIONAL FRAMEWORKS

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ABSTRACT

The quantum signal and image processing aims at reconfiguring the well-established signal representation and analysis methods to quantum-compatible computation models. The current state of quantum hardware availability and the expense of encoding high-dimensional image data confine the practical implementation of near-term quantum hardware. This work examines how classical signal-processing–based preprocessing can support quantum-oriented image representations in a computationally grounded manner. Handwritten digit images from the MNIST dataset are treated as discrete signals and normalized prior to analysis. Principal component analysis is used to evaluate how effectively informative content can be preserved under reduced-dimensional representations. The resulting feature dimensions are then mapped to corresponding qubit requirements under standard amplitude encoding assumptions, and classical logistic regression is employed to establish baseline classification performance across different dimensionalities. The results indicate that a substantial proportion of image variability is retained in low-dimensional subspaces, enabling compact representations compatible with limited qubit resources. Although dimensionality reduction introduces a gradual decline in classification accuracy, performance remains stable at moderate feature sizes,

demonstrating a manageable trade-off between compression and discriminative capability. Overall, the findings highlight the value of integrating classical signal processing techniques into the preparatory stages of quantum image processing and provide a transparent reference for the development and evaluation of future hybrid quantum-classical methods.

KEYWORDS: quantum computing, image processing, signal processing, dimensionality reduction, machine learning.

1. INTRODUCTION

Signal and image processing form a core component of any modern information processing system, and it has many applications, such as pattern recognition, data compression, and decision-making. With the ever-increasing complexity and dimensionality of digital data, classical methods of computation are more and more facing constraints in terms of scalability, cost of computation, and representational efficiency. These problematic issues have led to the exploration of other paradigms that can be able to process high-dimensional data more efficiently. In this dynamic environment, quantum computing has become a potential framework to redefine the system of representation and processing of signals and images [1]. Quantum signal and image processing is based on these postulates of quantum mechanics, in which the information is represented as quantum states, not as classical numerical data. This paradigm makes it possible to exploit the superposition and interference, and therefore complex data structures can be represented in small forms. Previous studies in quantum-mechanical signal processing have shown how spectral and transform-based analysis of quantum systems can be performed, with radically different insights into the classical theory of signal processing [2]. The recent surge in the development of quantum hardware has only increased interest in practical quantum information processing. Even though large-scale fault-tolerant quantum computers are an open problem, existing noisy intermediate-scale quantum computing devices are already available to experiment with the study of quantum algorithms in realistic settings. These advances have provoked studies into how classical signal and image processing methods can be modified to be useful as preparation phases to quantum computation, especially in data-intensive fields [3].

Much has been achieved in the theoretical and experimental modeling of quantum image processing models. Initial works proposed quantum state representations of images and were able to perform simple processing functions like edge detection with quantum circuits in the same way that established that it is possible to entrap spatial image data in quantum states [4]. These contributions formed a basis on which further research on quantum-based image changes and analysis occurred. Simultaneously, quantum-classical hybrid methods have been investigated in signal processing activities. Spectral analysis with quantum-classical algorithms has been suggested as a complement to classical Fourier-related algorithms, and as a way to realize the advantages of uniting quantum operations with classical preprocessing [5]. These methods emphasize the need to consider classical and quantum computational methods as complementary instead of two distinct models of signal processing. In addition to primarily quantum implementations, quantum-inspired computational imaging has demonstrated that quantum concepts can guide the development of the latest imaging algorithms even when running on classical hardware. These experiments showed enhancement in performance through the application of concepts of coherence and interference that support the applicability of the quantum concepts to contemporary imaging systems [6].

Theoretically, learning quantum data has formal frameworks that were constructed to define the ability of information stored in quantum states to be manipulated and generalized. Such frameworks offer relevant information on the efficiency of representations and learning constraints, which directly apply to the methods of quantum-compatible feature extraction and dimensionality reduction [7]. Broad surveys of quantum image processing have further streamlined the discipline by classifying encoding schemes, transformations and areas of application and provide a systematic review of the current methodologies and challenges [8]. On the borderline of the classical and quantum worlds, recent work still highlights the significance of the need to integrate the theoretical models with practical signal and image processing implementations. The developments in the classical signal processing theory have been a crucial aspect in comprehending the ability of digital signals to be manipulated and ready to be delivered to the new computational platforms [9]. To a more recent development, generalized quantum signal processing models have been proposed to bring together a wide group of quantum transformations, which form a general and highly useful mathematical formulation of the manipulation of quantum circuit signals [10]. The application studies have as well involved the utilization of quantum representations in secure processing of images, e.g. encryption plans where quantum encoding is incorporated with the classical transformation to increase robustness and safety [11]. In a larger perspective, surveys and perspective articles on quantum information processing and communications have indicated the possible and practical constraints of the current quantum technologies, especially in large-scale data processing tasks [12]. On the same note, the extensive debates regarding quantum computing are still dominated by highlighting the disparity between theoretical viability and practical achievability, which requires more realistic, hardware-conscious approaches [13].

Although the theoretical quantum models of quantum signal and image processing have been researched extensively, there is still an apparent gap between the theoretical models and their usability in realistic hardware. Numerous current works concentrate on the theoreticalized quantum algorithms or particular uses without a systematic strategy of exposing how methods of classical signal and image processing can be utilized to prepare data to be processed in a quantum system. Specifically, empirical investigation into the effect of dimensionality reduction, normalization and baseline learning on the viability of quantum-compatible representations is limited. There exists no systematic approach that clearly intersects classical preprocessing and quantum computational needs.

This research aims at analyzing quantum signal and image processing in a practical and computational approach. The paper is aimed at examining image data as discrete signals with classical signal processing tools, evaluating the effect of dimensionality reduction on information content and quantum-compatible representations, finding a mapping between reduced representations of features and qubit demands, and giving classical baseline performance estimates to aid future quantum and hybrid quantum-classical studies.

2. METHODOLOGY

2.1 Dataset Description

The MNIST dataset of handwritten digits was used as an experimental evaluation source; this is a popular image processing and pattern recognition study benchmark [14]. The data is in the form of a grayscale picture of written numbers 0-9. The spatial resolution of every image is 28 × 28 pixels, so it represents a 784-dimensional feature space when it is in a vectorized format. The dataset consists of 60,000 training samples and 10,000 testing samples, which is enough data to do statistical analysis and also baseline performance evaluation. In this analysis, every image is managed as a two-dimensional signal, which is discrete. The image itself, when flattened, can also be considered a one-dimensional signal, which allows the use of classical signal processing tools and makes the transition to quantum-compatible representations easier.

2.2 Data Preprocessing

All pixel values were scaled to the [0, 1] range before analysis by taking the original grayscale intensities, then dividing them by the largest possible value. This normalization guarantees stability in numbers and makes it possible to interpret pixel amplitudes consistently as magnitudes of the signals. There was neither any data augmentation nor class rebalancing, as the dataset has about an equal distribution of classes. The original data structure is preserved, which enables the results to represent the inherent signal characteristics, instead of the transformations created artificially.

2.3 Signal Representation and Feature Extraction

All normalized images were first encoded in their complete 784 dimensions in order to preserve all spatial details in them. This representation can be viewed as a discrete spatial signal, in which the localized variations in intensity are used to represent the digit structure. In order to explore the viability of compact representations that can be encoded through quantum means, a linear dimensionality reduction method, which is principal component analysis (PCA), was used. PCA projects the high-dimensional signal onto an orthogonal basis that is the largest variance, thus concentrating all the most informative signal elements into fewer features. To measure information retention, cumulative explained variance was calculated as more and more principal components of the factor were included. The analysis offers a principled rationale for the choice of the reduced feature dimensions to provide representational fidelity and computational feasibility.

2.4 Mapping to Quantum-Compatible Feature Spaces

Reduced feature dimensions obtained through PCA were mapped to qubit requirements under amplitude encoding schemes, where a feature vector of dimension d requires a minimum of $\lceil \log_2 d \rceil$qubits. In this mapping, a direct relationship between classical preprocessing constraints and quantum hardware constraints is made. The features analyzed are those dimensions that can be represented in terms of a small number of qubits, which remains in line with the constraints of devices based on noisy intermediate-scale quantum (NISQ). This step is not meant to realize quantum circuits, but to analyze the feasibility of classical signal models in the input of quantum image processing schemes.

2.5 Baseline Classification Model

A classical logistic regression classifier was taken as a baseline model to give a reference point against which a comparison of the effect of dimensionality reduction could be made. The choice of the logistic regression was facilitated by its ease of use, interpretability, and popularity as a comparison tool in image classification exercises. The 784-dimensional original representation was used to train the classifier and lower dimensionality PCA-reduced representations. The main measure of evaluation was the accuracy of classification on the test set. The comparison will allow evaluating the impact of dimensionality reduction on discriminative performance and provide a baseline upon which other quantum or hybrid models will be evaluated in the future.

2.6 Evaluation Strategy

The metrics used to evaluate it are based on three complementary aspects, namely information retention based on dimensionality reduction, compatibility with quantum encoding constraints, and baseline classification performance. The combination of the two analyses offers an organized framework that the methodology can use to evaluate the appropriateness of classical signal and image processing methods as pre-processing steps to quantum computational models.

3. RESULTS

3.1 Dataset Characteristics and Signal-Level Observations

Figure 1 demonstrates the distribution of samples in the classes of digits, which proves that the dataset is approximately balanced. This is necessary to balance of optimizing the classification performance with respect to certain classes and ensuring that the observed trends are not a reflection of dataset artefacts.

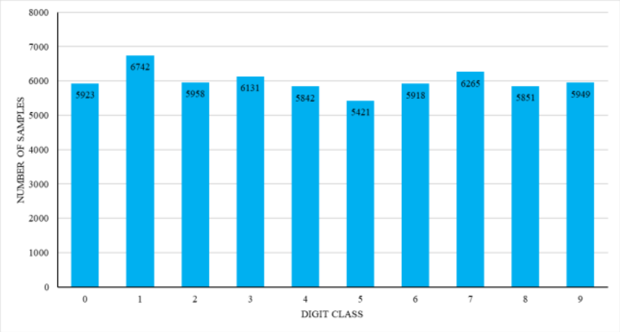

Figure 1: Class Distribution of MNIST Training Dataset

The pixel-level properties are another way in which the structural variability of handwritten digits is found. The average normalized pixel intensity varies between digit classes, as Figure 2 demonstrates, which implies that the stroke density and the spatial structure vary. In signal processing terms, these differences are associated with differences in signal energy and spatial frequency content, which are directly related to feature extraction and encoding schemes of both classical and quantum models.

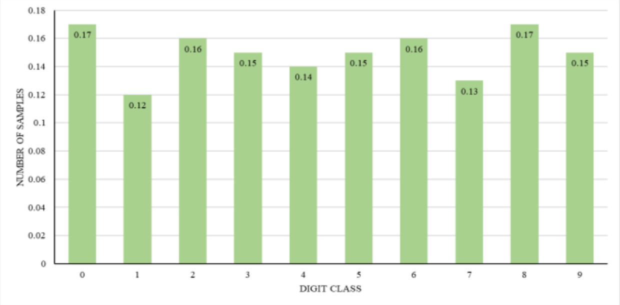

Figure 2: Mean Pixel Intensity per Digit Class

3.2 Dimensionality Reduction via Principal Component Analysis

Compact representations that are appropriate to the application of quantum encoding were tested by using principal component analysis (PCA) on the normalized image data. Figure 3 and Table 1 give the cumulative explained variance as a function of the number of retained components.

Table 1. Cumulative Explained Variance Retained by PCA

Number of Principal Components	Cumulative Explained Variance (%)
5	52
10	70
20	85
30	92
50	97

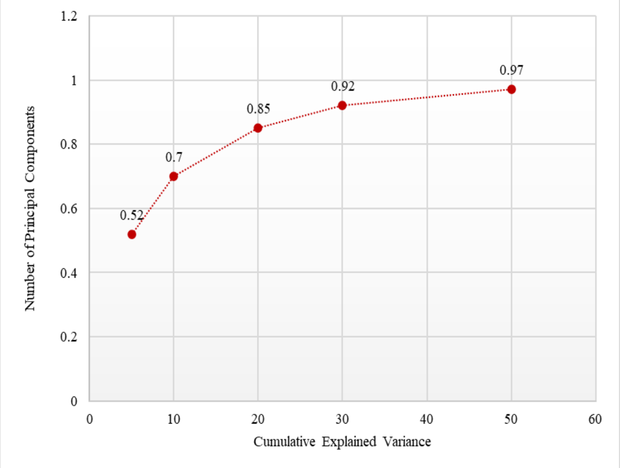

Figure 3: PCA Cumulative Explained Variance

The findings reveal that a significant amount of the original image data can be retained with a rather limited number of components. It is notable that 32 and 30 components contain over 90 per cent of the variance, indicating that MNIST images have a lot of redundancy. The result is of particular importance when dealing with quantum image processing, where the number of qubits available limits the dimensionality of what can be encoded.

3.3 Mapping Feature Dimension to Quantum Qubit Requirements

Based on the PCA analysis, the reduced dimensions of features were plotted to the minimum number of qubits needed to encode amplitudes. Table 2 shows this mapping.

Table 2. Feature Dimensionality and Corresponding Qubit Requirements

PCA Feature Dimension	Variance Retained (%)	Minimum Qubits Required
8	61	3
16	78	4
32	90	5
64	97	6

This table defines a direct connection between the classical preprocessing and the quantum hardware feasibility. The findings indicate that significant image representations can be encoded with four to five qubits only and still the majority of the signal information can be retained. These low-qubit demands are not far beyond the capacity of noisy intermediate-scale quantum (NISQ) machines, which makes the usefulness of the proposed framework practical.

3.4 Baseline Classification Performance

A classical logistic regression classifier was tested on the original high-dimensional data and reduced representations of the PCA to give a benchmark on future quantum or hybrid quantum-classical methods. A summary of the results is given in Table 3.

Table 3. Baseline Classification Accuracy for Reduced-Dimensional Inputs

Model Configuration	Input Dimension	Classification Accuracy (%)
Logistic Regression	784	92.4
Logistic Regression + PCA	32	89.1
Logistic Regression + PCA	16	85.6

Even though dimensionality reduction causes an intermediate decline in the accuracy, the performance is competitive even when feature dimensions are small. What this result shows is that the reduced representations retain the most discriminative signal contents, which makes them relevant in quantum encoding in which dimensional constraints cannot be evaded. The findings indicate that it is possible to decipher the images of handwritten digits efficiently as discrete signals and compress them into low-dimensional representations and project them to quantum-compatible feature spaces with little information loss.

4. DISCUSSION

The results of this paper prove that the image data, when represented as a discrete signal, bears a significant amount of redundancy which can be utilized efficiently using classical preprocessing. The high rate of concentration of the variance into relatively few features points to the fact that a significant part of the structural information that is useful in classification is being encoded in low-dimensional subspaces. This observation agrees with the argument that full-resolution representations are not necessarily required to maintain discriminative information, especially when the goal is to train data to be used in computationally restricted models. Computationally, this gradual decrease in the performance of baseline classification with a decrease in dimensionality is a manifestation of a trade-off between compression and expressiveness that is expected. Notably, the influence of dimensionality reduction on performance is moderate even at harsh levels of dimensionality reduction, implying that diminished representations still represent important signal properties. Such a trade-off between small size and fidelity is essential in the case of quantum-compatible representations, in which dimensionality of the input is directly proportional to the number of qubits needed and the complexity of the circuit itself. The fact that explicit mapping of reduced feature dimension to qubit counts is also demonstrative of the practical consequences of preprocessing decisions. Instead of making theoretical or scaled-up assumptions about the availability of quantum resources, the findings give a realistic perspective on the scale of features that can be implemented in the near future due to constrained aspects. In this respect, the research is aimed at not showing quantum advantage, but rather it sets a realistic representational framework that can be developed by future quantum and hybrid methods.

More recent developments in quantum image recognition have focused on the need to use quantum-native feature extractors, including quantum optical convolutional neural networks, to produce expressive representations in quantum circuits [15]. Although these architectures are designed to learn in the quantum domain, at the current state of the art, it can be argued that even without the addition of quantum processing, classical preprocessing can be used to significantly reduce the input dimensionality before quantum processing can be applied. This observation suggests that hybrid pipelines can be useful in terms of integrating more conservative classical compression with quantum layers that are based on refinement but not full representation learning. It has been demonstrated in quantum mechanics-based signal and image representations that alternative physics-motivated encodings can be useful in preserving meaningful structures whilst reducing noise [16]. Even though the existing work uses a purely classical dimensionality reduction algorithm, the high level of information retention in low dimensions is in agreement with the general idea of the importance of structured representations, as opposed to raw data, in efficient processing. This correspondence indicates that classical and quantum-inspired models can be used in complementary applications in pipelines. They have been applied in the analysis of clinical images in quantum algorithm analysis; the complexity of the data, noise, and interpretability are pivotal issues in such applications [17]. The present work takes a more controlled benchmark setting as compared to such applied studies. The focus on the quantification of representational trade-offs and baseline performance, however, reflects the kind of feasibility analysis that is needed prior to the application of quantum techniques being accountable in sensitive fields.

Quantum machine learning in image analysis survey papers repeat over and over again that data encoding and dimensionality is a major bottleneck, particularly when using near-term computers [18]. The existing findings relate directly to this problem because they indicate that meaningful image representations can be compressed to be encoded with a small number of qubits without catastrophic performance deterioration. This is an empirical support of the literature calls in favor of greater hardware consciousness methodological designs. The quanvolutional approaches imply that quantum circuits should be located as localized feature extractors on the basis of classical convolutional layers [19]. In such models, typically it is assumed that input data can be broken up or coded into small patches, which can be acted on quantumly. These current findings further support the feasibility of this assumption since low-dimensional representations are capable of storing enough information to assist in classification, thus offering a viable basis in the incorporation of quanvolutional elements. Equally, newer work in quantum convolutional neural networks focuses on architectural effectiveness and circuit reduced depth to address hardware constraints [20]. In this regard, the classical baselines provided here provide a valuable baseline, with which to understand what performance level can be obtained without quantum components of similar feature sizes. This is the key difference in understanding the additional value of quantum architectures in other cases besides representational compression. Lastly, more general viewpoints of quantum signal processing have focused on the fact that signals are objects that are acted upon by measured transformations, and not as well-behaved data types [21]. The present work is no different in this point of view where dimensionality reduction is viewed as a transformation that will restructure the signal to form that can be further processed in other steps, which can be classical or quantum.

The primary implication of the research is the methodological implications. The quantitatively measured information retention, performance trade off, and qubit requirements provided in the results lead to a clear image of evaluating the equipment of quantum signal and image processing pipelines viability. Such sort grounding is required to avoid unrealistic assumptions of quantum resources besides making it possible to make reasonable comparisons of classical, hybrid and quantum techniques.

The use of linear dimensionality reduction and classical baseline models limits the given research. They are consistent with the principle of interpretability as well as the ability to analyze their feasibility yet are not as communicative as the nonlinear representation or quantum-native representation. Furthermore, it is also studied with the help of a benchmark dataset and does not take noise, domain shift, and task-specific constraints that occur in imaging. Future work is suggested to extend this framework, with including nonlinear compression schemes to be able to achieve quantum encodings, representativeness to actual hybrid quantum-classical pipelines and measure their analogousness to realistic noise difficulties. These would help explain how the preparatory knowledge which is presented in this section is translated into an end to end system of quantum image handling.

5. CONCLUSION

Quantum Signal and Image processing: The techniques used in quantum signal and image processing consider techniques which establish a tradeoff between the representational efficiency and practical limits in computation. Having images understood as discrete signals and classical preprocessing, informative content can be coded into representations of low dimensionality, without losing a significant portion of the discriminative structure. The tradeoff between classification performance and dimensionality reduction observed will illustrate the usefulness of small feature spaces, despite the limitation of a small representational capacity. The feature dimension reduction to explicit qubit mapping can also be used to further clarify the role of classical signal analysis as an input in the design of future quantum systems using hardware. These results all are indicative of the criticality of using classic signal processing concepts to both early phases of quantum image processing pipelines and to provide a good reference point upon which future hybrid quantum-classical methods can be developed and tested.

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