Binary Image Classification Using Machine Learning and Deep Quantum Neural Networks

*Vaishali Mehta
CSE Dept., MMDU, Mullana,
Ambala, Haryana, India
drvaishaliwadhwa@gmail.com

Avinash Kumar
CSE Dept., DCRUST, Murthal
Sonepat, Haryana, India
avikumar.research@gmail.com

Kanchan Nahar
CSE Dept., Geeta University,
Panipat, Haryana, India
kanchancse@geeta.edu.in

Poonam
CSE Dept., LNTCE,
Panipat, Haryana, India
poonam1520.jp@gmail.com

Dolly Sharma
CSE Dept., Amity University,
Greater Noida, India
dolly.azure@gmail.com

Rohak Tiwari
DPS, Rkpuram,
Greater Noida, India
rohak0503@gmail.com

***Abstract*—This paper helps to explore the intricate task of natural and precise image grouping for effective organization and retrieval. High precision in image classification is challenging due to the complexity of images and the vast array of defining features. Deep learning-based artificial intelligence, a rapidly progressing field, plays a crucial role in various industries such as image classification, computer vision, text mining, voice recognition, and medical scan analysis. Deep convolutional neural networks (CNNs) excel in advanced image categorization and processing, particularly for high-resolution images. This study introduces a deep quantum neural network (QNN) technique for binary image categorization, delving into the latest research on image classification using cross-entropy functions, deep learning, and convolutional neural networks.**

Keywords—Deep Neural Network, Quantum Computing, Deep Learning Algorithms

I. INTRODUCTION

Having the option to group pictures naturally and precisely is significant for both compelling picture association and recovery. Accomplishing high picture order precision, notwithstanding, is very difficult. This is mostly on the grounds that pictures are broadened and each can be described by a huge arrangement of various elements, and somewhat in light of the fact that semantically related pictures may not live constantly (and subsequently, may not be directly distinct) in the component space.

Deep learning-based artificial intelligence has seen great progress in a multitude of industries today and is rapidly gaining new functions. In several academic fields, such as classification of images, computer vision , text mining, voice recognition, , and analysis of medical scans, the effect of deep learning is crucial. Deep learning takes into account a large number of features, parameters, and functions in order to resolve complex issues, make judgments, or identify links between various dataset groups. Datasets are managed by deep learning by being mapped to high-dimensional spaces.

The deep convolutional neural network offers extraordinary help with cutting-edge methods for picture categorization and processing. The enhanced convolutional neural networks provide strong support for the categorization of high-resolution images. Deep neural networks are often used for models with bigger input datasets. When training deep neural networks with an image input dataset, a number of parameters and image feature sets with a high number of pictures are used. To identify the provided pictures, deep neural networks extract semantic characteristics from the image collection and network-fuse those features [14][20].

In order to improve the generalized performance of machine learning models, Convolutional neural networks are widely used by utilizing the dropout and batch normalization techniques. In fact, the performance of the generalization may be enhanced by the dataset with a high number of training examples. Convolutional neural networks also perform better when using data improvement techniques like cropping, translating, flipping, and rotation on training samples.

The cross-entropy loss approach is applied to quantify and gauge the effectiveness of image categorization models. The cross-entropy loss function's probability output value ranges from 0 to 1. When the expected probability of image to be classified matches to the actual class [22][23], the cross-entropy loss rises. The present image classification model may be identified as the poor classification model since it would result in a significant loss value if the projected probability diverges close to zero. The aim of the prediction is either 1 or 0, making the binary cross-entropy a specific kind of cross-entropy. Deep neural networks are used with sigmoid activation for the prediction. In certain cases when the target variable is not a probability vector, the cross-entropy may still be applied.

In this study, a deep quantum neural network (QNN) technique for binary image categorization is developed. The remaining sections of the essay are structured as follows. The latest research on image classification employing cross entropy function, deep learning, and convolutional neural networks is discussed in Section 2 of this study. The following sections discuss the suggested procedures and the findings of the experiments.

II. LITERATURE REVIEW

In this work, [3] another group of computationally basic surface descriptors, alluded to as parallel slope shapes (BGC), is introduced. Utilizing the BGC system, eight parallel inclinations are processed between sets of pixels considering a shut way around the focal pixel of a binary valued picture fix. A solitary circle highlight, a twofold circle include, and a triple-circle highlight were created. An outfit of surface grouping tests was led more than 10 different datasets to evaluate the viability of the proposed approach quantitatively. In view of the got results, the single-circle adaptation of the BGC family is the best entertainer. Moreover, the notable LBP surface administrator is beated by the single-circle BGC surface administrator. A Wilkoxon marked rank test has shown the factual meaning of the accomplished exactness improvement.

To tackle the multi-class picture order issue, [4] join SVM-based paired classifiers. The outfit plans we review are OPC (one for every class), PWC (pairwise coupling), and ECOC (blunder adjustment yield coding), pointed toward further developing mistake rectification through overt repetitiveness. Creator proposed techniques that support the edges (i.e., sureness) of SVM-based double classifiers and eliminate the commotion that is produced by immaterial classifiers from class forecast in these gathering plans. Utilizing observational review, creators exhibited that our edge supporting and sound decrease strategies lead to higher arrangement precision than troupe plans intended for most extreme blunder remedy.

As examined in this paper, [2] utilizes a novel brain network model invigorated through a procedure that has improved the field of PC vision i.e. the pixel-wise picture order that is joined with parallel cross-entropy misfortune and an autoencoder by prior-training of the CNN (Convolutional Neural Network). This procedure straightforwardly gauges the picture source names for each time-recurrence (T-F) container in our picture, disposing of the requirement for pre-and postprocessing. Convolutional brain networks are prepared involving twofold covers as the objective result marks. By taking into account every T-F canister of the extent spectrogram of a combination signal as a pixel with a multi-name, the parallel cover distinguishes the prevailing picture source in every T-F container. A paired cross entropy is utilized as a goal for preparing to limit the typical likelihood blunder between the objective and anticipated name. Initiation V3 design is utilized to additionally further develop ImageNet grouping precision. Results show that the proposed calculation is the most reliable.

As per [5], the strategy for utilizing arbitrary woodlands with proposed neighborhood wavelet-based negligible paired design (LBP) further developed picture arrangement execution and diminished preparing and testing time. Most regularly, nearby twofold examples as well as their changes, including focus symmetric neighborhood double examples (CS-LBP), are concentrated on utilizing picture pixels. The wavelet-based surface attribute of X-beam pictures is first depicted by extricating the descriptors based upon neighborhood wavelet CS-LBP (WCS-LBP) from explicit areas of pictures. Our following stage is to apply the separated component vector to choice trees with the goal that we can build irregular woods, which are troupes of arbitrary choice trees. One test picture was ordered to the classification with the most noteworthy back likelihood utilizing irregular woods with a WCS-LBP. A correlation of the proposed technique with other component descriptors and order strategies uncovers better execution and quicker handling.

Although convolutional neural networks (CNNs) [19] are effective at solving troublesome picture grouping problems, they are challenging to plan. Subsequent to examining the impediments of conventional Particle Swarm Optimization (PSO), we utilize quantum acted Particle Swarm Optimization with twofold encoding (BQPSO) to work on the quest interaction for the ideal engineering. This is achieved by proposing a novel and vigorous paired encoding procedure that doesn't expect clients to be know about CNNs. To guarantee the viability of developed CNN structures, a quantum-acting developing methodology is suggested. Our calculation's presentation is estimated by its order exactness on a few benchmark datasets regularly utilized in profound learning. Our trial results proves that our model is more powerful and performs better compared to conventional strategies. A totally programmed calculation for advancing CNN designs utilizing quantum acted PSOs has been created here interestingly.

It has become well known to address a picture utilizing the neighborhood parallel examples (LBP) descriptor in the field of clinical picture characterization [7]. Nonetheless, most existing LBP-based strategies disregard the spatial connections among nearby examples for encoding parallel examples in a proper neighborhood range. For complex examples, for example, clinical pictures acquired by magnifying lens, the disregarding of spatial connections in the LBP will bring about terrible showing. In this paper, we propose a versatile neighborhood span for every pixel to further develop neighborhood parallel examples. These versatile nearby parallel examples are utilized to encode miniature designs for picture portrayal in light of a two-layered contiguous histogram procedure. The proposed strategy performs altogether better compared to a few other winning LBP methods after broad assessments on four clinical datasets.

Utilizing MobileNet binarization at enactment capability and model loads, [8] presents a straightforward yet powerful plan. On account of MobileNet, it isn't trifling and can be inclined to dissimilarity to prepare a twofold organization without any preparation. We propose an original brain network engineering, in particular the MoBi-Net - Mobile Binary Network, in which skip associations are controlled to keep away from data shortfall and evaporating slopes, and consequently work with preparing. Further, while existing parallel brain networks frequently utilize lumbering spines, for example, Alex-Net, ResNet, VGG-16 with pre-prepared loads, MoBi-Net spotlights on binarizing as of now packed brain organizations, for example, MobileNet without expecting earlier preparation, while keeping the exactness tantamount to existing ones. Probes ImageNet datasets show the capability of the MoBiNet as it accomplishes 54.40% top-1 precision and emphatically lessens the computational expense with advanced administrators. .The proposed MoBi-Net engineering has the accompanying design: Each convolutional layer is trailed by two skip associations, one to the info layer and another interfacing with a secret layer. The organization likewise incorporates three layers of units that don't partake in handling data sources and results, meant as "skip", "dropout" and “result."

Early sickness determination as often as possible purposes programmed clinical picture investigation (like clinical picture grouping). PC helped conclusion (CAD) frameworks consider the exact identification and treatment of sicknesses. Profound learning (DL)- based CAD frameworks can now accomplish amazing results in most of medical care applications. Besides, vulnerability measurement in existing DL strategies has gotten deficient concentration in the field of clinical examination. To overcome this issue, [1] proposed a novel, straightforward, and compelling combination model called Binary Residual Feature Fusion (BRFF), with a vulnerabilities module for medical care picture order (BARF). To make up for vulnerability, we have utilized Monte Carlo (MC) dropout strategy during deduction to ascertain the standard deviation and mean of the expectations. The recommended system utilizes two essential methodologies immediate and cross approval, which are tried on four separate medical care picture datasets. Our discoveries show that the proposed model is appropriate for arrangement of clinical pictures in certifiable clinical settings.

In applications, for example, face acknowledgment and surface picture arrangement, the neighborhood twofold example (LBP) and its variations have demonstrated to be compelling. The majority of these LBP strategies, notwithstanding, just consider the recurrence circulation of LBP designs and disregard the fleeting logical data between LBP designs. To accomplishing fleeting logical data, [9] proposed a 2D-LBP strategy that counts the weighted event number of revolution invariant uniform LBP design matches using sliding window technique. At the point when the range of the 2D-LBP is changed, multi-goal 2D-LBP highlights can be acquired. At long last, a binary classifier is utilized as an outfit learning move toward accomplish a precise characterization by joining the expectations on each 2D-LBP with a solitary goal. Hypothetical confirmation shows that the proposed 2D-LBP is an overall system that can be applied to other LBP variations to create new element extraction strategies. The proposed strategy accomplishes 99.71%, 97.09%, 98.48%, and 49.00% arrangement precision on the public surface picture data sets 'Brodatz,' 'CUReT,' 'UIUC,' and 'FMD,' individually. In contrast with the first LBP and its variations, the suggested approach accomplishes higher characterization exactness in different cases while making some lower memories intricacy.

A pre-training convolutional neural network was proposed in [10] with both binary weight values and activations, resulting in a quantized model particularly designed for moving devices having limited computational resources power capacity. Researchers working on quantizing CNNs introduced value approximation which using a set of discrete values and assuming the same full-precision network architecture, preserves the floating-point information contained in the dataset. However, present study proposes a novel quantization approach based on "structure-based approximation"— quite different architecture to be incorporated for better performance. Specifically, we propose Group-Net, a "network decomposition" model that divides the network into groups. In this model, every full-precision group is reconstructed effectively by simply aggregating a set of homogeneous binary branches. Furthermore, the model learns the effective links between groups in order to improve the overall representation capability. The proposed Group-Net has a high degree of generalization to other tasks. For example, the Group-nets are extended for optimal semantic segmentation by embedding the rich context into binary representation. Experiments on classification and semantic segmentation tasks show that the proposed methods outperform numerous prevalent architectures. The performance over existing best binary neural networks is obtained in terms of accuracy and minimized computational cost.

In [6] authors addressed challenges in designing efficient Convolutional Neural Networks (CNNs) using quantum-acted Particle Swarm Optimization. They introduced quantum-acted PSO with binary encoding for optimizing CNN architecture. Experimental results demonstrate the model's robustness and improved performance over traditional methods. In [11], authors presented a hybrid quantum-classical convolutional neural network for image classification, highlighting the synergy of quantum and classical computing. Proposes an algorithm that leverages quantum entanglement for improved image classification accuracy. A quantum computing-based accelerated model for image classification is presented in [12]. It utilizes a parallel pipeline encoded Inception module, showcasing the potential of quantum computing in enhancing classification speed and accuracy. [13] provides a comprehensive survey of advances in quantum machine learning and deep learning for image classification. Summarizes key trends, challenges, and achievements in the field, serving as a valuable reference for researchers and practitioners.

Authors in [15] proposed nonnegative/binary matrix factorization for image classification using quantum annealing. Demonstrates the effectiveness of quantum annealing in solving image classification problems with nonnegative constraints. In [21] authors investigate the training of deep quantum neural networks, addressing challenges and opportunities in the quantum domain. Explores the dynamics of quantum neural networks and their potential applications in image classification. In [18] a neural network model for accurate multi-class image classification with a quantum entanglement approach has been proposed. Authors highlighted the incorporation of quantum entanglement for improved classification accuracy. Authors in [16] introduced quantum convolutional neural networks with hybrid quantum-classical learning for multiclass classification. Investigates the model's performance in comparison to classical counterparts, emphasizing quantum advantages. In [17], a variational quantum deep neural networks for image recognition is developed. It explores the potential of variational quantum circuits in enhancing image recognition tasks.

III. METHODOLOGY

Quantum computing is the future of computers. It is a new revolution in computation that performs extremely fast calculations using the fundamental ideas of quantum physics. The performance guarantee of quantum computation lies in its ability to efficiently perform numerous tasks such as search optimization, quantum simulation, prime factorization, and machine learning applications; computations that are too large for even the most powerful conventional computers. The strength of quantum computing mainly comes from the two cornerstones of quantum physics namely entanglement and interference that are based on the wave and particle aspects of quantum computation.

A quantum computer, like a traditional computer, works in Q-bits. While classical bits can only exist in the states 0 and 1, a Q-bit (or qubit) on the other hand can represent not only the binary values, but a linear combination of both as well. Such linear combinations are referred to as superposition states.

The second quantum mechanics concept that can be applied to quantum computation is the phenomena of entanglement. The combined state of two or more qubits (or particles in general) that contains more data than the qubits do separately is referred to as entanglement. Multi-qubit quantum states are a significant resource since they are entangled in the vast majority of cases. For instance, the quantum teleportation utilizes the entangled states between qubits, in which information can be shared between two qubits irrespective of their physical proximity. In fields like quantum simulation and quantum chemistry, where the solution commonly comes from the entangled multi-qubit states, entangled states play a crucial role.

A. Procedure

Quantum image processing follows similar workflows to classical image processing. In conventional image processing techniques, the image is encoded in various ways, such as encoding each image pixel according to the color intensity. Once encoded, we process the image — we can make any changes to the original using a variety of computations, such as cropping, filtering, enhancing, etc. Once completed, there are various post processing techniques we can leverage such as edge detection, object and pattern recognition, to name a few.

For processing, a quantum computer requires data in a quantum state. Devices known as NISQ (Noisy Intermediate Scale Quantum) include a finite number of stable qubits that last for a finite amount of time. Encoding classical data into the state of the qubits is the initial stage in a quantum machine learning system. This procedure in preparing a quantum state is often known as quantum data encoding or embedding. The design and effectiveness of the QML (Quantum Machine Learning) algorithm depend critically on the use of classical data encoding for quantum computation.

To use current NISQ devices, a compact representation is required that uses only a few qubits and quantum gates. Qubits not only decay quickly, but quantum gates are also very prone to errors, which in turn limits the operations needed to prepare the quantum state which is supposed to be very small. Encoding is categorized as:

1) *Digital encoding - the representation of **data in the form of qubit strings***
2) *Analogue encoding – data representation in the form of **amplitudes of a state***

When performing arithmetic operations on data, a digital encoding is preferred. While mapping of data into the quantum device's vast Hilbert space is required for machine learning algorithms, analogue encoding is recommended.

The computational cost of converting classical data into qubits is **Logarithmic** or **linear** in input size. Each encoding is essentially associated following aspects:

- The number of qubits should be minimal.
- The number of parallel operations should be minimal to minimize the width of the quantum circuit
- The data must be represented appropriately for further calculations

Typical Quantum Machine Learning will involve 3 steps:

*1) **Encoding:** This article is all about this step where classical data is loaded into a Quantum state*

*2) **Processing:** This is the stage where the Quantum device process the embedded input, which can be a variational circuit or a quantum routine*

*3) **Measurement:** The expected outcome is measured in this step, and then it becomes the prediction for QML.*

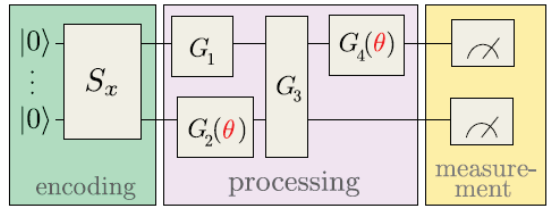

Fig1: Typical Quantum Machine Learning Steps

Let's zoom into the overall encoding process in figure 1, to prepare input for a quantum algorithm as a quantum state, a quantum circuit has to be performed that prepares the corresponding state. This circuit can be generated in classical preprocessing steps and then generate the circuit for state preparation, as shown below.

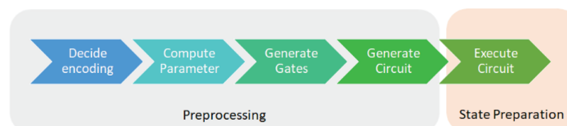

Fig2: Classical Preprocessing Steps

B. Implementation and Results

The proposed models in simulated using google quantum AI tool. Implementation of quantum computer machine learning is somewhat similar to classical machine learning models. Figure 3 given below shows the different steps of implementation.

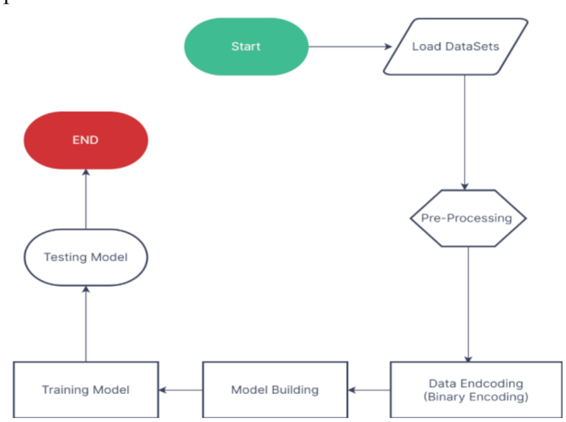

Fig3: Process Flow Chart

a) Datasets : For this experiment, MNIST dataset has been used in this paper. MNIST is most popular dataset of handwritten digits. This dataset contains 60000 images of training and 10000 images of test set.

b) Pre-Processing: In MNIST dataset, there are total 10 classes but in this paper, only binary classification is considered. Hence, some preprocessing step need to perform. In preprocessing, firstly images are filtered out in two classes, then converted into grayscale image. As images are to be passed to quantum circuit, so these are resized into 2x 2 matrix.

c) Data Encoding: For encoding images into quantum inputs, images are reshaped into 1x4x1 matrix. Then binary encoding technique is applied with threshold value 0.5 and finally converted into quantum input using quantum circuit of grid qubit of size 2 x 2.

d) Model Building: For building quantum model, single qubit and two qubit gates are used in this paper. X gate is used for input and H gate is used for measurement. Hidden layers of XX and ZZ gates are also added into the circuit. After building circuit, circuit is looks like as shown below in figure 4:

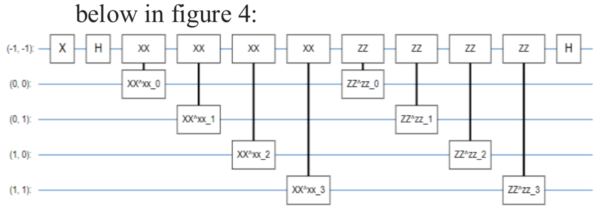

Fig4: Typical Quantum Circuit

e) Training and testing: For training and testing, hinge accuracy and hinge loss are taken as major parameter and RMSprop optimizer is used to optimize the losses. For training and validation data, 30% split is performed.

f) Evaluating results: Hinge loss leads to some (not guaranteed) sparsity on the dual, but it doesn't help at probability estimation. Instead, it punishes misclassifications (that's why it's so useful to determine margins): diminishing hinge-loss comes with diminishing across margin misclassifications. Hinge loss leads to better accuracy and some sparsity at the cost of much less sensitivity regarding probabilities.

Hinge loss result obtained by proposed model is shown in figure below:

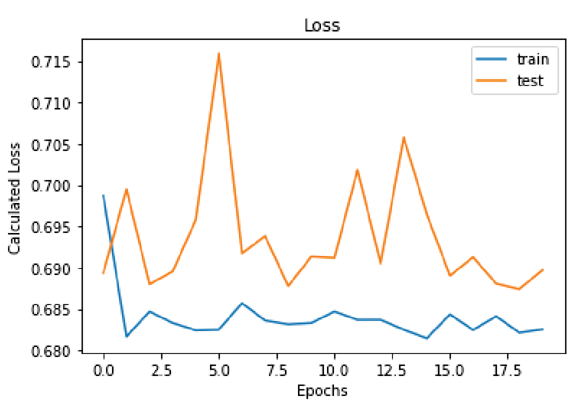

Fig5: Epochs vs Loss Curve

IV. Conclusion

Presents study introduces a deep quantum neural network for binary image classification, leveraging quantum entanglement and interference. While achieving a 70% accuracy rate, the model exhibits notable fluctuations and high loss values, indicating the need for ongoing improvements in quantum computing methods. This research contributes to quantum machine learning, highlighting both the potential and challenges in quantum image classification. Future work should focus on refining these methodologies for a more robust quantum-enhanced machine learning paradigm.

References

1. Abdar, M., Fahami, M. A., Chakrabarti, S., Khosravi, A., Pławiak, P., Acharya, U. R., Tadeusiewicz, R., & Nahavandi, S. (2021). BARF: A new direct and cross-based binary residual feature fusion with uncertainty-aware module for medical image classification. Information Sciences, 577, 353–378. https://doi.org/10.1016/j.ins.2021.07.024
2. Dr.A, .Usha Ruby. (2020). Binary cross entropy with deep learning technique for Image classification. *International Journal of Advanced Trends in Computer Science and Engineering*, *9*(4), 5393–5397. https://doi.org/10.30534/ijatcse/2020/175942020
3. Fernández, A., Álvarez, M. X., & Bianconi, F. (2011). Image classification with binary gradient contours. *Optics and Lasers in Engineering*, *49*(9–10), 1177–1184. https://doi.org/10.1016/j.optlaseng.2011.05.003
4. Goh, K.-S., Chang, E., & Cheng, K.-T. (2001). *SVM binary classifier ensembles for image classification*. 395. https://doi.org/10.1145/502585.502652
5. Ko, B. C., Kim, S. H., & Nam, J. Y. (2011). X-ray image classification using random forests with local wavelet-based CS-local binary patterns. *Journal of Digital Imaging*, *24*(6), 1141–1151. https://doi.org/10.1007/s10278-011-9380-3
6. Li, Y., Xiao, J., Chen, Y., & Jiao, L. (2019). Evolving deep convolutional neural networks by quantum behaved particle swarm optimization with binary encoding for image classification. *Neurocomputing*, *362*, 156–165. https://doi.org/10.1016/j.neucom.2019.07.026
7. Liu, D., Wang, S., Huang, D., Deng, G., Zeng, F., & Chen, H. (2016). Medical image classification using spatial adjacent histogram based on adaptive local binary patterns. *Computers in Biology and Medicine*, *72*, 185–200. https://doi.org/10.1016/j.compbiomed.2016.03.010
8. Phan, H., Huynh, D., He, Y., Savvides, M., & Shen, Z. (2020). MoBiNet: A mobile binary network for image classification. *Proceedings - 2020 IEEE Winter Conference on Applications of Computer Vision, WACV 2020*, 3442–3451. https://doi.org/10.1109/WACV45572.2020.9093444
9. Xiao, B., Wang, K., Bi, X., Li, W., & Han, J. (2019). 2D-LBP: An Enhanced Local Binary Feature for Texture Image Classification. *IEEE Transactions on Circuits and Systems for Video Technology*, *29*(9), 2796–2808. https://doi.org/10.1109/TCSVT.2018.2869841
10. Zhuang, B., Shen, C., Tan, M., Liu, L., & Reid, I. (2019). Structured binary neural networks for accurate image classification and semantic segmentation. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, *2019-June*, 413–422. https://doi.org/10.1109/CVPR.2019.00050.
11. Wei Li, Peng-Cheng Chu, Guang-Zhe Liu, Yan-Bing Tian, Tian-Hui Qiu, Shu-Mei Wang, "An Image Classification Algorithm Based on Hybrid Quantum Classical Convolutional Neural Network", Quantum Engineering, vol. 2022, Article ID 5701479, 9 pages, 2022. https://doi.org/10.1155/2022/5701479.
12. Alsubai, S.; Alqahtani, A.; Binbusayyis, A.; Sha, M.; Gumaei, A.; Wang, S. A Quantum Computing-Based Accelerated Model for Image Classification Using a Parallel Pipeline Encoded Inception

Module. Mathematics 2023, 11, 2513. https://doi.org/10.3390/math11112513.

13. Ruba Kharsa, Ahmed Bouridane, Abbes Amira, Advances in Quantum Machine Learning and Deep Learning for Image Classification: A Survey, Neurocomputing, Volume 560, 2023, 126843, ISSN 0925-2312, https://doi.org/10.1016/j.neucom.2023.126843.
14. Beer, K., Bondarenko, D., Farrelly, T. et al. Training deep quantum neural networks. Nat Commun 11, 808 (2020). https://doi.org/10.1038/s41467-020-14454-2.
15. Asaoka, H., Kudo, K. Nonnegative/Binary matrix factorization for image classification using quantum annealing. Sci Rep 13, 16527 (2023). https://doi.org/10.1038/s41598-023-43729-z.
16. Bokhan, Denis, Mastiukova, Alena S., Boev, Aleksey S., Trubnikov, Dmitrii N., Fedorov, Aleksey K.(2022) Multiclass classification using quantum convolutional neural networks with hybrid quantum-classical learning, Frontiers in Physics, vol. 10, ISSN 2296-424X, doi. https://doi.org/10.3389/fphy.2022.1069985.
17. Yunqian Wang, Yufeng Wang, Chao Chen, Runcai Jiang, Wei Huan g (2022). Development of variational quantum deep neural networks for image recognition. Neurocomputing, volume 501, pp 566-582.
18. Riaz F, Abdulla S, Suzuki H, Ganguly S, Deo RC, Hopkins S. Accurate Image Multi-Class Classification Neural Network Model with Quantum Entanglement Approach. Sensors (Basel). 2023 Mar 2;23(5):2753. doi: 10.3390/s23052753. PMID: 36904951; PMCID: PMC10007163.
19. Li W, Chu PC, Liu GZ, Tian YB, Qiu TH, Wang SM. An image classification algorithm based on hybrid quantum classical convolutional neural network. Quantum Engineering. 2022 Jul 14;2022.Alsubai, S., Alqahtani, A., Binbusayyis, A., Sha, M., Gumaei, A. and Wang, S., 2023. A Quantum Computing-Based Accelerated Model for Image Classification Using a Parallel Pipeline Encoded Inception Module. Mathematics, 11(11), p.2513.
20. Kharsa R, Bouridane A, Amira A. Advances in Quantum Machine Learning and Deep Learning for Image Classification: A Survey. Neurocomputing. 2023 Dec 1;560:126843.
21. Asaoka H, Kudo K. Nonnegative/Binary matrix factorization for image classification using quantum annealing. Scientific Reports. 2023 Oct 2;13(1):16527.
22. Wang Y, Wang Y, Chen C, Jiang R, Huang W. Development of variational quantum deep neural networks for image recognition. Neurocomputing. 2022 Aug 28;501:566-82.
23. Riaz F, Abdulla S, Suzuki H, Ganguly S, Deo RC, Hopkins S. Accurate image multi-class classification neural network model with quantum entanglement approach. Sensors. 2023 Mar 2;23(5):2753.