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Classifying Binary Images with the Use of DLNNs and Machine Learning

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Abstract—

In order to better organize and retrieve images, this research delves into the complex problem of natural and accurate picture grouping. Because pictures are complex and include a wide variety of distinguishing elements, achieving high accuracy in image categorization is tough. A number of sectors rely heavily on deep learning-based AI, which is a quickly developing area. These include medical scan analysis, picture categorization, computer vision, text mining, and voice recognition. When it comes to processing and classifying high-resolution pictures, deep convolutional neural networks (CNNs) really shine. By exploring current research on picture classification utilizing cross-entropy functions, deep learning, and convolutional neural networks, this paper presents a deep quantum neural network (QNN) method for binary image categorization. Using Convolutional Neural Networks with Dropout and Batch Normalization, Machine Learning Models Can Achieve Better Generalized Performance. The generalization's performance could be improved using a dataset that has a large number of training instances. Using data optimization methods such as cropping, translating, flipping, and rotating on training samples also improves the performance of convolutional neural networks.

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

INTRODUCTION

For effective image association and recovery, the ability to spontaneously and accurately group photos is crucial. Regardless, it is very challenging to achieve great image order accuracy. This is due, in large part, to the fact that images are complex and may be defined by a myriad of different aspects, and, to a lesser extent, to the fact that images with similar semantic content may not exist in the component space at all times, making them difficult to distinguish. Many different businesses are now benefiting greatly from AI that is based on deep learning, and this kind of AI is quickly expanding its capabilities. The impact of deep learning is critical in several academic domains, including picture categorization, computer vision, text mining, speech recognition, and medical scan analysis. Deep learning uses a plethora of characteristics, parameters, and functions to solve complicated problems, make decisions, or find connections between different groups of datasets. One way that deep learning handles dataset management is by mapping them to high-dimensional spaces. Using state-of-the-art techniques for image processing and classification, the deep convolutional neural network provides outstanding assistance. Classification of high-resolution photos is greatly aided by the improved convolutional neural networks. Models that take in larger datasets often use deep neural networks. Deep neural networks are trained using image input datasets that include a large number of photographs and a large number of parameters. Deep neural networks network-fuse semantic attributes extracted from image collections in order to recognize the supplied photographs [14][20]. To measure and assess how well picture classification models work, the cross-entropy loss method is used. There is a probability output value between 0 and 1 for the cross-entropy loss function. There is an increase in the cross-entropy loss when the actual class matches the estimated likelihood of the picture to be categorized [22][23]. Because it would lead to a substantial loss value if the predicted probability diverged near to zero, the current picture classification model may be deemed as the bad classification model. Because every prediction may only take one of two possible outcomes, the binary

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cross-entropy is a subset of cross-entropy. The prediction is made using deep neural networks activated with sigmoid function. The cross-entropy may still be used in certain situations even if the target variable isn't a probability vector. The authors of this article created a method for binary image classification using deep quantum neural networks (QNNs). Following this introduction, the essay is organized into the following parts. Section 2 of this article discusses the most recent research on picture categorization using deep learning, convolutional neural networks, and cross entropy functions. The proposed methods and experimental results are detailed in the sections that follow.

LITERATURE REVIEW

Also presented in this study is a new class of computationally simple surface descriptors called parallel slope shapes (BGC) [3]. The BGC algorithm takes a binary-valued image fix and processes eight parallel inclinations between groups of pixels while considering a closed path around the focus pixel. Three round highlights were made: one with a single circle, two with two circles, and a triple with three circles. More than ten datasets were used to statistically assess the suggested approach's feasibility using a suite of surface grouping tests. The findings show that the BGC family's single-circle adaption is the most entertaining. Finally, the one-circle BGC surface administrator beats out the famous LBP administrator. The significance of the achieved precision increase has been shown by a Wilkoxon marked rank test.

Combine paired classifiers based on support vector machines (SVMs) to address the problem of images ordered by multiple classes [4]. We take a look at three outfit plans—OPC, which stands for "one for every class," PWC, for "pairwise coupling," and ECOC, which stands for "blunder adjustment yield coding"—that aim to improve error correction by obvious repetition. To alleviate the chaos caused by irrelevant classifiers in these ensemble plans, the creator offered methods that bolster the edges (i.e., certainty) of SVM-based double classifiers. Our edge supporting and sound reduction tactics outperform troupe approaches for severe error repair in terms of arrangement accuracy, as shown by observational evaluation. In this paper, we look at how [2] uses a new model of a neural network that has been enhanced by a method that has advanced computer vision: the pixel-wise picture order combined with parallel cross-entropy loss and an autoencoder via CNN prior training. Without any pre- or post-processing, our method directly measures the picture source names for each time-frequency (T-F) container in our image. The objective result markings in convolutional brain networks are created using twofold coverings. The parallel cover determines the dominant image source in each T-F container by considering each T-F container's extend spectrogram of a combination signal as a multi-named pixel. An aim for preparation is to minimize the usual probability mistake between the target and expected name, and a paired cross entropy is used for this purpose. To further improve ImageNet grouping accuracy, the Initiation V3 design is also used. According to the findings, the suggested method of calculation is the most trustworthy. According to [5], the method of using random woods with the suggested neighborhood wavelet-based tiny paired design (LBP) improved image arrangement performance and reduced training and testing time. Focus symmetric neighborhood double examples (CS-LBP) and neighboring twofold examples are often the main topics when it comes to using image pixels. The descriptors based upon neighborhood wavelet CS-LBP (WCS-LBP) are extracted from certain portions of images in order to illustrate the wavelet-based surface attribute of X-ray images. Step two involves constructing irregular woodlands, or troupes of arbitrary choice trees, by applying the separated component vector to choice trees. The group most likely to experience back pain when using uneven woods with a WCS-LBP was given one test photo. The suggested method reveals faster handling and better execution when correlated with other component descriptions and order schemes. Convolutional neural networks (CNNs) are difficult to design, yet they are good at tackling difficult photo grouping issues [19]. After reviewing the problems with traditional PSO, we use BQPSO, or quantum-acted particle swarm optimization with two-fold encoding, to the search for optimal engineering. An innovative and robust paired encoding approach is proposed to do this, which does not assume any prior knowledge of CNNs on the part of the clients. The 812th recommendation is for a quantum-acting development technique to ensure the feasibility of constructed CNN structures. The order exactness on a few benchmark datasets often used in deep learning is

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used to estimate the presentation of our approach. The outcomes of our trials demonstrate that our model outperforms more traditional approaches. Curiously, a fully programmed algorithm for improving CNN architectures using quantum acting PSOs has been developed here. In the realm of clinical image characterisation, it has became popular to handle a picture using the neighborhood parallel examples (LBP) descriptor [7].

However, when it comes to encoding parallel instances in the correct neighborhood range, the majority of current LBP-based algorithms ignore the spatial linkages among close examples. Ignoring spatial relationships in the LBP will result in a bad display for complicated cases, such as clinical photos collected with a magnifying lens. We provide an adaptable neighborhood span for each pixel in this study to advance neighborhood parallel instances. Using a two-layered continuous histogram approach, these adaptable neighboring parallel instances are used to encode small patterns for visual depiction. Overall, the suggested approach outperforms a handful of previous successful LBP approaches in extensive evaluations across four clinical datasets. A simple but effective strategy is shown in [8] that makes use of MobileNet binarization at enactment capabilities and model loads. Due to MobileNet, it isn't simple and could be misguided to throw up a two-pronged structure on the go. Specifically, we suggest the MoBi-Net - Mobile Binary Network as a novel approach to brain network architecture that controls skip connections to avoid data shortage and evaporating slopes while simultaneously working with preparation. As an added note, current parallel brain networks like Alex-Net, ResNet, and VGG-16 often make use of sluggish spines with pre-loaded data, whereas MoBi-Net focuses on binarizing densely packed brain organizations like MobileNet without requiring prior preparation, while maintaining accuracy comparable to existing networks. With enhanced administrators, MoBiNet achieves 54.40% top-1 accuracy and significantly reduces computational cost, as seen in Probes ImageNet datasets. It is with this architecture that the planned MoBi Net engineering is accompanied: There are two skip associations after each convolutional layer; one connects to the information layer, and the other is for a secret layer. The company also has three tiers of units called "skip," "dropout," and "result" that aren't involved in processing data sources or outcomes. Programed clinical image investigation is often used for early illness diagnosis (such as clinical picture grouping). Computer-aided diagnosis (CAD) systems take precise disease diagnosis and therapy into account. In most medical care applications, CAD frameworks built on deep learning (DL) may currently achieve outstanding outcomes. Furthermore, there has been a lack of emphasis on vulnerability evaluation in clinical examination-related current DL techniques. Binary Residual Feature Fusion (BRFF), with a specific module for medical care image order (BARF), was suggested by [1] as a new, simple, and convincing combination methodology to address this problem. During the deduction to expectations, we have used the Monte Carlo (MC) dropout approach to compensate for the susceptibility. Tested on four different healthcare image datasets, the suggested solution makes use of two crucial methodologies: instantaneous and cross approval. The results of our investigation validate the suggested model for use in certified clinical settings for the purpose of clinical image organization.

Local bipartite pattern recognition (LBP) and its variants have shown promising results in scenarios such as face recognition and surface image layout. However, most of these LBP solutions overlook the transitory logical data between LBP designs in favor of focusing on the recurring circulation of LBP designs. In order to get temporary logical data, a 2D-LBP approach was suggested by [9] that uses the sliding window technique to count the weighted event number of revolution invariant uniform LBP design matches. It is possible to get multi-goal 2D-LBP highlights by adjusting the 2D-LBP's range. By combining the expectations on each 2D-LBP with a single objective, a binary classifier is finally used as an intermediate learning step toward achieving an accurate characterisation. Theoretical validation demonstrates that the suggested 2D-LBP provides a general framework for developing novel element extraction algorithms for use with other LBP variants. On the publicly available surface image datasets 'Brodatz,' 'CUReT,' 'UIUC,' and 'FMD,' respectively, the suggested method achieves 99.71%, 97.09%, 98.48%, and 49.00% arrangement accuracy. Compared to the original LBP and its variants, the proposed method achieves better characterisation accuracy in many scenarios while reducing memory complexity to a certain extent. In order to create a quantized model that is optimized for mobile devices with low processing power, the authors of [10] suggested a pre-training convolutional neural network that uses binary weight values and activations. The quantization of convolutional neural networks (CNNs) led to the development of value approximation, a technique that maintains the dataset's floating-point information by using a set of discrete values while assuming the same full precision network architecture. However, in order to improve efficiency, the current work suggests a new quantization method based on "structure based approximation"—a completely different design. Our proposed model, Group-Net, is a "network decomposition" strategy that partitions the network into subsets. This approach successfully reconstructs all full precision groups by only aggregating a collection of homogeneous binary branches. To top it all off, the model improves its representational capacity by learning the effective linkages between groups. There is a high level of task generalizability in the suggested Group-Net. To achieve effective semantic segmentation, for instance, Group-nets are enhanced by including rich context into binary representation. Several popular designs are beaten out by the suggested strategies in experiments conducted on semantic segmentation and classification problems. In comparison to the top binary neural networks currently available, we get better results with less computing overhead. The difficulties of developing effective Convolutional Neural Networks (CNNs) via the use of quantum-assisted Particle Swarm Optimization were discussed in [6]. In order to optimize the design of CNNs, they proposed quantum-acted PSO with binary encoding. The model's enhanced performance and resilience are shown by the experimental findings, which surpass those of older techniques. The authors of [11] demonstrated the complementary nature of quantum and classical computing by presenting a convolutional neural network for picture categorization that was both hybrid and based on quantum and classical principles. Introduces a method to enhance picture categorization accuracy by using quantum entanglement. In [12], the authors provide a paradigm for picture categorization that is accelerated using quantum computing. It uses an Inception module encoded in a parallel pipeline, demonstrating how quantum computing might improve classification accuracy and speed. A thorough overview of recent developments in deep learning and quantum machine learning as they pertain to picture categorization may be found in [13]. It provides a useful summary of the discipline's important developments, problems, and successes for academics and professionals in the field. In order to classify images using quantum annealing, the authors of [15] suggested nonnegative/binary matrix factorization. This proves that quantum annealing works for nonnegative constraint image classification issues. By tackling problems and possibilities in the quantum environment, the authors of [21] explore deep quantum neural network training. Delves into the inner workings of quantum neural networks and how they may be used for picture categorization. For precise multi-class picture classification using a quantum entanglement method, a neural network model is suggested in [18]. To boost classification accuracy, the authors emphasized using quantum entanglement. For multiclass classification, the authors of [16] presented quantum convolutional neural networks that combine quantum and classical learning methods. Examines the model's efficiency in contrast to its classical equivalents, with a focus on the quantum benefits. For picture identification, the authors of [17] create variational quantum deep neural networks. It investigates how variational quantum circuits may improve picture recognition.

METHODOLOGY

A computer's future lies in quantum computing. It is a paradigm shift in computing that applies the principles of quantum physics to do computations at the speed of light. Quantum computation's performance guarantee is based on its efficiency in performing search optimization, factorization, quantum simulation, prime applications of machine learning, and other calculations that even the most powerful conventional computers struggle with. Entanglement and interference, the two pillars of quantum physics that underpin quantum computation's wave and particle components, respectively, are quantum computing's primary sources of strength. Like classical computers, quantum computers use Q-bits to store and process information. A Q-bit, also known as a qubit, may represent a linear combination of binary values and more, in contrast to traditional bits, which can only exist in the states of 0 and 1. Superposition states describe these linear combinations. The phenomenon of entanglement is the second principle of quantum mechanics that may be used in quantum computing. Entanglement refers to the situation when two or more quantum bits (or particles) have a combined

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state that holds more information than each qubit has on its own. Because they are entangled in most circumstances, multi-qubit quantum states are a great resource. If two qubits are in an entangled state, they may exchange information regardless of how close they are to one other; this is how quantum teleportation works. Entangled states are fundamental in quantum simulation and quantum chemistry, where solutions are often derived from entangled multi-qubit states. A. Methodology There is little difference between the procedures used by conventional and quantum image processing. Traditional methods of image processing include encoding the picture in a number of ways, one of which is by assigning a color intensity value to each pixel. After the picture is encoded, it undergoes processing, whereby several calculations allow us to alter the original in any way we like (cropping, filtering, boosting, etc.). After that is done, we may use a variety of post-processing algorithms, including object and pattern recognition, edge detection, and many more. Data must be in a quantum state for a quantum computer to process it. Noisy Intermediate Scale Quantum (NISQ) devices have a limited number of stable qubits with a finite lifetime. The first step of a quantum machine learning system is to encode classical data into the qubit states. One common name for this process of getting a quantum state ready is quantum data embedding or encoding. Quantum Machine Learning's (QML) architecture and performance are highly dependent on quantum computation's ability to leverage conventional data encoding. Using existing NISQ devices necessitates a succinct representation with minimal qubits and quantum gates. In addition to qubits' rapid decay, quantum gates are notoriously error-prone, reducing the number of operations required to produce the supposedly tiny quantum state. One way to classify encoding is as: 1) Digital encoding, which involves expressing data using strings of qubits 2) Analogue encoding, which employs state amplitudes as a means of data representation Digital encoding is the way to go when working with data that requires mathematical computations. Analogue encoding is suggested, however data mapping into the enormous Hilbert space of the quantum gadget is necessary for ML algorithms. Converting classical data to qubits incurs computational costs that are either linear in input size or logarithmic in logarithmic terms. The following characteristics are fundamentally linked to each encoding: We recommend using as few qubits as possible. For the quantum circuit to have the smallest possible footprint, the number of parallel processes must be kept to a minimum. Proper representation of the data is required for further computations. There are typically three stages to quantum machine learning: 1) Keying in: The process of loading classical data into a quantum state 814 is the focus of this essay. 2) Analyzing: Here, the embedded input—a variational circuit or a quantum routine—is processed by the quantum device. Thirdly, evaluation: In this stage, we measure the predicted result, which will later serve as the QML prediction.

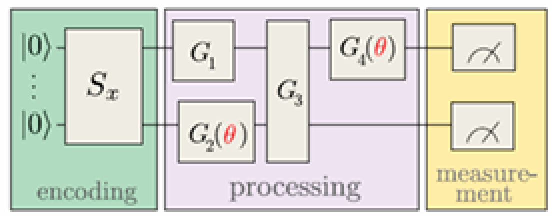


Fig1: Typical Quantum Machine Learning

Steps See figure 1 for a closer look at the complete encoding process. In order to get the input for a quantum algorithm ready as a quantum state, a quantum circuit has to be executed. As seen below, this circuit may be created via traditional preprocessing processes followed by the generation of the state preparation circuit.

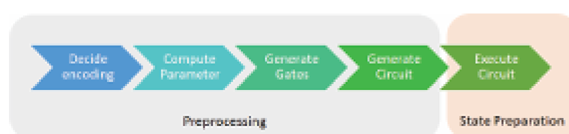


Fig2: Classical Preprocessing Steps

Section B: Results and Application Using Google's Quantum AI tool, we ran simulations of the suggested models. There are several similarities between classical and quantum computer machine learning models in terms of implementation. Below, you may see Figure 3, which illustrates the various stages of implementation.

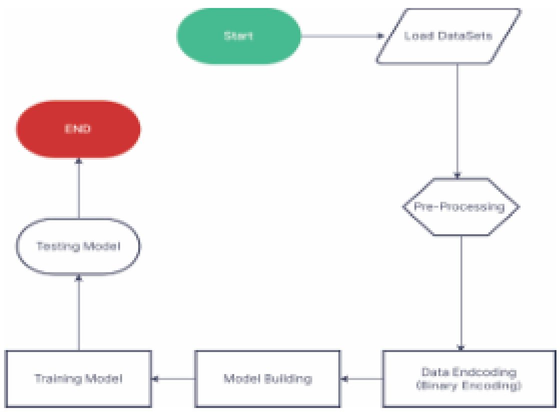


Fig3: Process Flow Chart a) Datasets :

This study uses the MNIST dataset for its experiments. When it comes to handwritten numbers, MNIST is the most used dataset. Sixty thousand photos make up the training set, whereas ten thousand images make up the test set. The MNIST dataset has a total of ten classifications, however, for the purposes of this work, only binary classification is taken into account. Therefore, a preprocessing step must be carried out. Preprocessing involves converting photos to grayscale and then filtering them into two groups. The photos are downsized to a 2x2 matrix before being sent to the quantum circuit. c) Encoding Data: By transforming pictures into a 1x4x1 matrix, images may be encoded into quantum inputs. Next, a threshold value of 0.5 is used in the binary encoding approach. Lastly, a 2 × 2 grid qubit quantum circuit is used to turn the input into quantum form. d) Model Construction: This study employs both single qubit and two qubit gates in its construction of quantum models. Both the X-gate and the H-gate are input/output gates. It also has hidden layers of ZZ and XX gates. Figure 4 shows the final product of the built circuit:

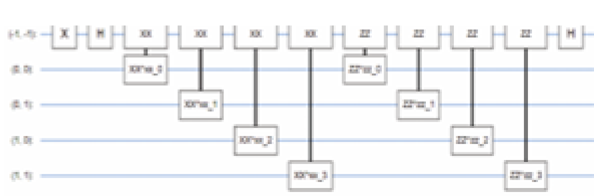
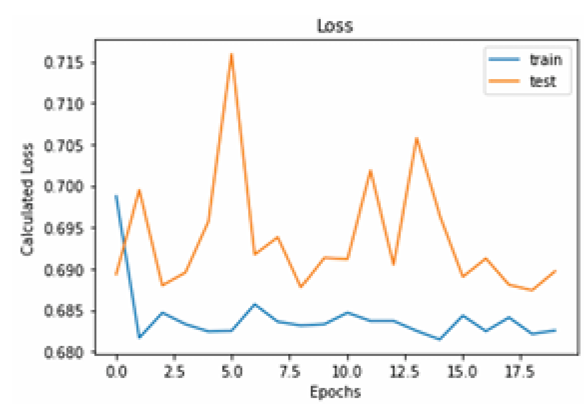


Fig4: Typical Quantum Circuit e) Training and testing:

The main parameters for training and testing are hinge accuracy and hinge loss, with the losses optimized using RMSprop optimizer. A 30% split is applied to the data used for training and validation. f) Assessing the outcomes: Although hinge loss may (but is not guaranteed to) produce sparsity on the dual, it is of little use for estimating probabilities. In fact, it's great for figuring out margins since it punishes misclassifications: reducing misclassifications across margins leads to less hinge-loss. While hinge loss improves accuracy and sparsity to a certain extent, it significantly reduces sensitivity to probability. The figure below displays the hinge loss result achieved using the suggested model:



Conclusion

In this research, we present a deep quantum neural network that uses quantum interference and entanglement to classify binary images. The model showcases significant oscillations and large loss values, even if it achieves a 70% accuracy rate, suggesting that quantum computing technologies need continuous refinement. Bringing attention to the possibilities and difficulties of quantum picture categorization, this study adds to the field of quantum machine learning. Improving these approaches to create a stronger paradigm for quantum-enhanced machine learning should be the goal of future research.

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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/2020/17594 2020

[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 Goh,

[4]. 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.2018.28698 41 10.

[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.

[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]. 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

[13]. Module. https://doi.org/10.3390/math11112513.

[14]. 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 https://doi.org/10.1016/j.neucom.2023.126843.

[15]. Beer, K., Bondarenko, D., Farrelly, T. et al. Training deep quantum neural 0925-2312, networks. Nat Commun 11, 808 (2020). https://doi.org/10.1038/s41467-020-14454-2.

[16]. 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.

[17]. 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.

[18]. 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.

[19]. 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.

[20]. 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.

[21]. 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.

[22]. 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.

[23]. 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.

[24]. 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.