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State of the Art: A Pandemic Big HealthCare Analytics Solution: Image Data Classification Using Quantum MAML

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Abstract

The modern age is facing many pandemic healthcare problems, e.g., covid 19, infections, inflammations, and many more, leading to critical, deadly situations. Survival rate can be increased with proper diagnosis of such data. We have proposed one of the implementations based on a medical image dataset for classification using deep reinforcement learning (RL) with quantum computing. Deep RL is the combination of DL (deep learning), generative adversarial network (GAN), and RL. The final classification is made by an ensemble classifier. The GAN is used for generating synthetic, original, and qualitative fame image data like original data. The RL is used for minimizing losses in the classification work. The GANRL method is found to be effective for such noisy, unclear image data of pandemic deadly diseases earlier. The ensemble classifier extreme gradient boosting (XGBoost) is used for classification with high accuracy. Computation can be more effective if quantum circuits are used for such work in terms of CPU cycle time (execution time) and power consumption for the processing. Quantum SVM is found to be more effective for medical data in terms of power consumption and execution time when simulated with quantum simulator than circuit.

Keywords: Deep learning, generative adversarial network, model agnostic meta learning, reinforcement learning, quantum computing

INTRODUCTION

Machine learning has been proved to be one of the effective solutions for healthcare big data analytics. Technology needs input data for training the model, and then only make them useful for solving unknown problems. This process contains data preprocessing for selecting relevant features [1], presentation of data for real-time healthcare applications [2], as the medical data is imbalanced and raw form by nature. ML tools with different computing systems are used for processing the input data. Deep learning (DL) [3], models are used for medical image data classification. They are analog system, digital system, Vedic computing system, and quantum computing system. Quantum computing is a new approach for calculation that uses principles of fundamental physical for solving extremely complex healthcare big data analytics challenges [4], very quickly. A quantum qubit with its state is represented as a block sphere. It is an emergent field of cutting-edge computer science using the unique qualities of quantum mechanics to solve problems beyond the ability of even the most powerful classical computers. There are four key principles of quantum computing [5–10]. They are superposition, entanglement, coherence, and interference. Quantum computers use quantum

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bits called qubits that can behave like a bit and store either a zero or one, and a combination of zero and one at the same time. Qubits can scale exponentially, making the computation, calculation faster. Quantum algorithms work by storing and manipulating information in a way inaccessible to classical computers, which can provide speedups for certain problems. Quantum computing process data logically and sequentially than digital computers. It is used by specialized and experimental quantum mechanics-based quantum hardware, which can be effectively implementable for big data analytics. It also processes data with quantum logic at parallel instances, relying on interference. Medical image data are usually found in an imbalanced nature, unclear or missing in value, and less qualitative or noisy in content. The performance of traditional medical image data recognizers is less due to such nature as shown above. DL [11, 12], with CNN architecture and transfer learning, is used effectively for image data processing. They give average performance for medical image data processing, especially for smaller dataset for classification, segmentation, localization, and detection. Henceforth, we propose one of the MAML approaches using reinforcement learning (RL) method for minimizing loss for higher accuracy to predict by a classifier along generative adversarial network for creating new synthetic data to remove imbalance nature in the data. Quantum computing is used for faster computation of the proposed MAML approach. Meta learning [13] is a self-learning approach for effective use in many fields like astronomy, healthcare, biomedical, sophisticated artificial intelligence tools, gaming applications, and many more. The meta learning tools use RL methods that teach the environment to take actions. It is usually used for unpredicted problems. Meta learning is the learning of machine learning tools. The different types of meta learning are first order model agnostic meta learning. Healthcare big data analytics algorithms are used for effective implementations on healthcare big data for prediction work. RL has gained significant attention in the field of image classification due to its ability to learn and adapt to its complex environments. RL [11–30], offers a promising approach to address these challenges through trial and error to maximize a reward signal. RL algorithms use many samples, for which we use GAN [31], generated synthetic data for RL information environment space. Hence, it reduces the classification loss by improving its performance for image classification. We have used a support vector machine for the classification of the image. We have used lung cancer image data, which has 735 images. Quantum computing reduces the space of features, which is used by the next phase, enhancing performance in terms of time and power consumption.

REVIEW

DL is one type of convolutional neural network architecture with many hidden layers. It is used for in-depth examination of data. In the CNN model, preprocessing of data, e.g., feature extraction, following image processing for classification using hidden layers with convolution, ReLU layer, and pooling layers. Finally, it can be used for image classification using a flatten layer as the output. It is an independent machine learning model. The difficulty with the model is that it takes more computational time and processing power. Therefore, we have used the VGG transfer learning (one of the DL convolutional neural network architectures) model only for feature extraction in this model. GAN works on data distribution modeling, which has a generator and a discriminator. GAN generator function is based on zero sum game where the generator and discriminator continue to play against the game, and the generator learns the distribution of real data. GAN does not premodel but rather understands the distribution of original data and accordingly generate new data with a bias of a Gaussian distribution noise value. It collects information from different images in the same scene and then reorganizes by fusing the extracted information from different images in the same scene to get a new image. Low light image enhancement technology aims to restore original low-quality image scene information through technical means and methods by improving overall and partial contrast of the image, denoising, adjusting the image background, and edges. It facilitates subsequent intelligent analysis of computer vision, leads to the study of how to more effectively improve the quality of low luminance images [30]. The attenuation difference between the channels can be compared with the maximum value of the red channel and the maximum value of blue-green channel for the new color image [31]. The GAN value function is as follows.

$$\min_{G}\max_{D} V\,(D,G) = E_{x\approx p_{data(z)}}\left(log\left(1-D\big(G(z)\big)\right)\right) \quad (1)$$

An RL agent may be directly or indirectly trying to learn a policy, value function, and the model. Policy represents the agent's behavior function. The value function represents how good each state and action. The model represents the environment.

$$S_0, a_0, r_0, S_1, a_1, r_1, ------ S_{n-1}, a_{n-1}, r_n, S_n \quad (2)$$

While interacting with the world, the agent collects data of the form

$$D = \{(s(t), a(t), r(t), s(t+1)\}_{t=1}^{T} \quad (3)$$

(state, action, immediate reward, and next state).

Healthcare bigdata analytics use model-based RL for MAML models. Model-based MAML learns to predict the unpredicted and random data from a small dataset. It works using the rules next state as estimate P(s'|s,a) used for learning to predict with immediate reward as estimate P(r|s,a).

SURVEY

Lee et al. [32] introduces a new way to improve PQCs by using a classical neural network inspired by MAML. The learner neural network finds better starting values for the PQC, thus making it faster and more accurate. After training, the learner provides good initial parameters for various problems, thus reducing the number of updates required. This method is well-suited for various quantum tasks, such as optimizing Hamiltonians, and promises good results in experiments. Trigka et al. [33] explores how DL has progressed from early methods to the latest advances in image processing, covering better model designs, improved efficiency, and ways of measuring performance. It also examines future trends: the use of DL with new technologies, such as quantum computing, edge computing, and explainable AI to make systems faster, smarter, and more secure. Gadu et al. [34] introduces a new method called GAN-Q-Unet that comes up to improve the conversion of 2D spine X-ray images into 3D models for the diagnosis of scoliosis and planning surgeries. It uses a special type of neural network to enhance the image quality and alleviate issues created by implants, which may hamper accuracy. It enhances bone details using synthetic data along with an advanced image-filling technique for better outcomes. The tests show that this method works better than the existing ones, hence useful for medical purposes. Panfilo et al. [35] explores how businesses are hesitant to share their data with service providers while searching for machine learning (ML) services due to privacy concerns. Authors suggest the use of synthetic data that will allow service providers to test the design of their ML models without giving their real data. They emphasize developing synthetic data for various kinds of datasets using advanced DL models, such as Variational Autoencoders. Tests demonstrated that synthetic data can assure privacy while at the same time providing useful results, thus contributing to the further opening of ML service markets. Yadav et al. [36] looks at how meta-learning techniques can be implemented for improving medical image segmentation with transfer learning. It outlines review methods for different transfer learning methods, such as using pretrained models and adapting to new domains. Then, it pushes forth through different meta-learning approaches, like RL and model ensembles. In testing these methods on three medical image datasets, the study finds that meta-learning indeed brings better performance, especially on datasets with large differences. Han et al. [37] introduces a meta-learning way to automatically discover quantum scars in chaotic systems. Quantum scars refer to patterns within wave functions concentrating on specific periodic orbits. Manuals do not apply manual detection techniques but train the neural network based on a massive image dataset with fine-tuning using a tiny amount of data related to quantum scars. This approach successfully identifies quantum scars without human intervention; it can also be applied to other fields, such as micro-lasing and quantum-dot devices. Such detection is significant in these fields. Allen et al. [38] demonstrates how meta-learning can improve machine learning models for quantum mechanical calculations in molecular and material systems. In contrast to the standard approach that depends on consistent QM data, the meta-learning framework allows the training of models with data from various QM methods. The authors demonstrated this approach by enhancing performance by decreasing errors and resulting in smoother potential energy surfaces. This opens a door for making pretrained models for interatomic potentials based on diverse QM datasets. Yang et al. [39] reviews the challenges and solutions of federated learning in medical image analysis. There are two levels to it. both at the task and meta levels. Task-specific quick knowledge acquisition requires a base model, while meta-level learning, also known as slow knowledge, requires a meta-model. Task level and meta level are the two stages of meta learning. The support task Sb was stated as follows.

$$\Theta_i^b = \Theta_{i-11}^b - \alpha \nabla_\Theta L_{S_b}\left(f \Theta_{i-1}^b\right) \tag{4}$$

Where α is the learning rate, Θ_i^b the base network weights after i step towards task b. $L_{S_b}(f_{\Theta_{i-1}})$ is the loss on support set of task b after (I-1) steps.

$$L_{meta}(\Theta_0) = \sum_{b=1}^{B} L_{T_b}\left(f_{\Theta_N^b}(\Theta_0)\right) \tag{5}$$

Meta level objective function:

$$\Theta_0 : \Theta_0 = \Theta_0 - \beta \nabla_\Theta \sum_{b=1}^{B} L_{T_b}\left(f_{\Theta_N^b}(\Theta_0)\right) \tag{6}$$

Update for meta parameters where β is a learning rate L_{T_b} is the loss on target set and b is the task. The thesis paper in [40], discusses MAML for image data processing. Hendryx et al. [41] discussed the first-order model-agnostic meta-learning algorithms for the task of few-shot image segmentation. They have shown the model's sensitivity to hyperparameters during test time. They found that meta-learning initializations could be equivalent in performance to traditional transfer learning with extra data. Paper [41], suggested a sign-based MAML technique based on stochastic gradient descent for efficient use of health data. Balakrishnan et al. [42] introduced a fast-learning framework for deformable registration of medical image analysis. It uses a CNN that maps images to a deformation field that aligns the images. The framework is trained on unsupervised learning and then performs segmentation using supervised learning. It gives excellent state-of-the-art accuracy at a faster rate. Ma et al. [43] explored its potential in risk-sensitive domains. Applications of measures, such as CVaR and Sharpe Ratio, are noted in finance. They have found the key trade-off between average waiting time and fairness in queuing systems constitutes other areas where uncertainty appears as variance across a spectrum due to renewable energy systems' related power fluctuations impacting local grids. A RL algorithm is proposed by Schwarting et al. in [44] for competitive visual control policies using self-play using an imagined environment. The agent of the algorithm uses a multi-agent world model to predict its opponent's behavior with imagined interactions in a compact latent space. The agent shows consistent multi-agent predictions in a continuous racing environment by optimizing behavior through the gradients of the back-propagated values. It outperforms independent agents with ground-truth observations. The increasing menace of cancer and related increased research are discussed by Padmanabhan et al. [15] for the increase in survival rates due to effective treatments. It shows proper scheduling is important for chemotherapy with safety and effectiveness. They designed an effective Q-learning algorithm for a model-free RL approach, which is provided for closed-loop control of chemotherapy drug dosing and an optimal controller design. Berner et al. [19] have proposed an advanced RL technique to get superhuman performance in competitive sports games. The key parameters are increasing batch size and total training for higher computation scale. Scaling becomes more important for current methods as challenges grow. This can work in zero-sum environments, and tasks grow in complexity. Cassirer et al. [21] proposed Reverb, which is a very efficient and simple data storage and transfer system designed specifically for machine learning research. It enables an API that can scale a single server from one to hundreds of concurrent clients easily with difficult conditions and handle loads of around 100,000 QPS and at least 11 GB/s of compressed data. This flexibility, along with robust scaling capabilities, allows researchers to run experiments with one process or thousands of machines with the same Reverb setup. This flexibility naturally explains why Reverb is currently being used by hundreds of researchers to conduct a wide diversity of RL experiments. Siu et al. [45] measured game performance and human response to Various teammates: a cooperative card game team consisting of both humans and artificial intelligence. The results of playing Hanabi with a rule-based agent and a reinforcement-learning-based “Other-Play” agent that maximizes zero-shot coordination were compared. When both teams had identical scores, they favored the rule-based agent. They have explained reasons and agreements for trust, comfort, and perceived good performance in the game. Suggest that even the best RL agents are a failure in being perceived as being good teammates. Hendryx et al. [41] have found the optimal hyperparameter configuration for the update routine at test time could be different from the one used during meta-training. This shows MAML-type algorithms can minimize empirical risk over a given update routine and initialization but cannot guarantee optimality of the hyperparameters of the update routine. The previous work has found that MAML-type algorithms suffer from overfitting in a high dimension of the parameter space due to an insufficient amount of regularization and a lack of empirical risk minimization for the update routine’s hyperparameters. The designed MAML algorithms have intelligently gotten to comfortably integrate small and large datasets in an effective manner by becoming experts and learning new things as they develop, just like human beings. The following Figure 1 shows implemented proposed MAML methods with accuracy found from their papers. The highest accuracy is found to be 64%. The MAML approach improves DL computation speed for complicated tasks. This is overcome by MAML method improving computational time.

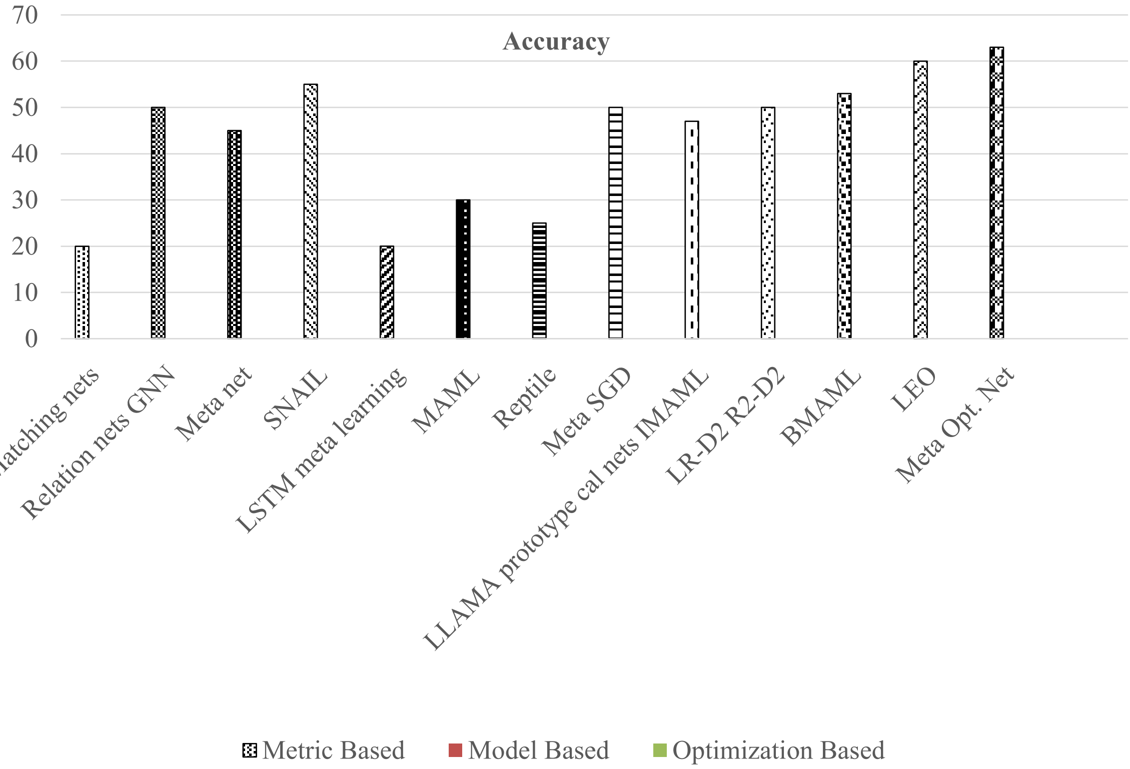

Figure 1. Comparison of MAML models accuracy % proposed in different papers [46].

PROPOSED WORK

Value Functions

i. Quantum Kernel: Quantum circuit

$$|\phi(x)\rangle = \bigcup(x)|0^{\otimes_n}\rangle = \left(\otimes_{q=1}^{n} R_z(x_q)\right)\bigcup_{2^n}^{ent}\left(\otimes_{q=1}^{n}\left(R_y(x_q)R_z(x_q)H\right)\right)|0^{\otimes_n}\rangle ..(1)$$

ii. GAN

$$\min_G \max_D V(D,G) = E_{x\approx p_{data(z)}} (\log(1-D(G(z)))] \cdots (3)$$

iii. RL for action

$$S_0,a_0,r_0,S_1,a_1,r_1,\ S_{n-1},a_{n-1},r_n,S_n\ (2)$$

iv. SVM Classifier

$$w = i \to m\sum \alpha itiK(xi,x) + bti(wTxi - b) = 1 \Leftrightarrow b = wTxi - ti \qquad (4)$$

Proposed Algorithm

Step 1. Implement feature extraction using VGGNet deep learning model.
Step 2. Generate quantum simulator with given data set.
Step 3. Generate GAN synthetic dataset.
Step 4. Map combined data from quantum simulator and GAN for the RL state space.
Step 5. Compile XGBoost with the data from RL minimizing loss value of the classifier.
Step 6. Evaluate the Classifier.
Step 7. Exit.

The workflow diagram of the proposed work is as follows (Figures 2 & 3).

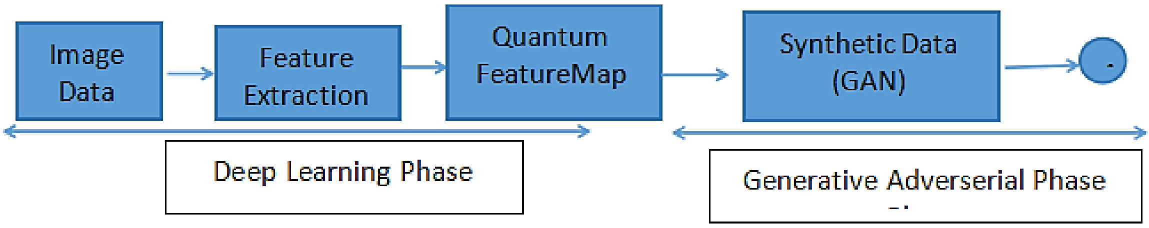

Figure 2. First phase for training machine learning models.

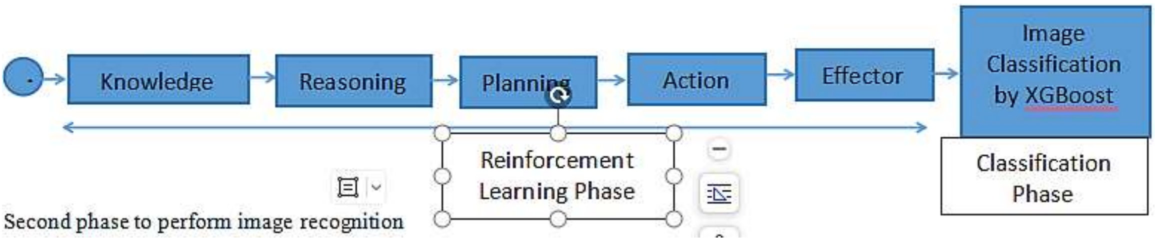

Figure 3. Second phase to perform image recognition.

RESULT ANALYSIS

We have used PyTorch for the implementation of the model. Quantum simulator works effectively than quantum circuit along the DL, GAN and RLarchitectures with XGBoost as the classifier. This is made using pytorch programming with quiskit package for quantum functions and DL, GAN, RL programs in python using google drive. The lung cancer image dataset from Kaggle is used for this research work. We have proposed DGDRE (Deep Learning Generative Adversarial Network

Reinforcement Learning Ensemble Classifier) for medical image data. The first phase is the feature extraction phase that uses VGG Net to reduce feature dimension from (sample size*256*256*3) to (sample size*32676) for less complexity in computation. The feature size is reduced by a sixth fraction. GAN architecture is used to generate some similar images more qualitatively than the original images. Then DL architecture VGG Net is used to extract features from the generated images with reduced dimension and feature size of the generated data. Now the RL method is used to consider all the features (original and generated), finding the number of episodes that give the least penalties to train the extreme gradient boosting classifier for classification with higher accuracy. The RL method is used to reduce loss that occurred due to information received from the image features. The DL and XGB classifiers have an accuracy of 64.49%, whereas the accuracy of this model is 83.59%, which is quite high. This model acts as a robust model for image classification with proper decision-making, though the computation cost is higher than a simple CNN architecture.

CONCLUSIONS AND FUTURE WORK

We have implemented the healthcare medical data for classification with high performance using quantum computing. The machine learning tool used here is one of the methods for meta learning using DL, GAN and RL. The effectiveness of RL is to reduce loss in diagnosis of the small size image dataset. This is used in the work for the optimum result. This model can be used for large size image dataset replacing GANRL with Deep GANRL. The proposed work can effectively use for image registration in neuroscience effectively. The proposed model can be effectively used for critical situations like noisy or partial dataset taken in pandemic time as it uses its own generated data for more clarity in the data analysis.

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