

Based on quantum optical neural networks, smart, understandable artificial intelligence provides sustainable, safe healthcare applications.

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Abstract

Managing expanding urbanisation, energy use, environmental preservation, citizen economic and living standards, and people's ability to effectively use and adopt modern information and communication technology (ICT) are all objectives of smart cities. A branch of machine intelligence engineering known as explaining artificial intelligence (XAI) makes complex techniques approachable and adaptable for efficient decision-making in the sciences and technologies. The quantum uncertainty problem may be applied to the network state, which consists of several states and dimensions and requires real-time information. Specifically pertinent are the linkages between the emerging paradigms of machine learning (ML), quantum computing (QC), and quantum machine learning (QML), and traditional communication networks. This study provides a new method in explainable deep learning for analysing healthcare data in multimedia for long-term quantum photonic applications. Input has been collected from multimedia healthcare data and processed for noise removal and normalization.

Keywords Explaining artificial intelligence · Deep learning · Multimedia healthcare · Data analysis · Sustainable quantum optical application

1 Introduction

Disordered quantum methods, such as quantum optics and random field spin methods, exhibit a variety of fascinating properties as a result of quantum fluctuation. On critical behaviour, periodicity, and dynamics of such disordered systems, the impact of quantum fluctuation is significant. In disordered methods, quantum fluctuation can create novel phases that are crucial for development of new methods related to quantum processing. These phases are crucial for both theoretical research and practical application [1]. In the presence of quantum fluctuation, dynamical characteristics of many body systems are significantly altered, and such quantum dynamics are crucial for precisely addressing combinatorial optimisation issues. Quantum information theoretic measures have recently developed into very useful instruments for studying quantum phase transverse in both pure and disordered methods [2]. Accuracy of most computer vision applications has dramatically increased as a result of the advancements made over the past ten years in the field of artificial intelligence

(AI). One application where advancements have ensured human-level accuracy in the classification of many forms of medical data is medical picture analysis (e.g., chest X-rays [3-5]). Nevertheless, automated medical imaging is rarely used in clinical settings despite these technological advancements. Zachary Lipton claims that the solution to this apparent paradox is simple: without understanding an algorithm's decision-making process, clinicians will never be able to trust its results.

2.Related works

Artificial intelligence explainability research is not a recent field of study. There is no consensus on a concept of explainability, notwithstanding recent frequent publications on the subject of XAI [6]. For the sake of this survey, we distinguish explainable systems, which offer insight into the system's operational logic, from interpretable systems, which enable users to analyse the (mathematical) mapping from inputs to outputs. According to a study [7-8], in order to produce explanations that are both human-understandable and objective, truly explainable systems must include components of reasoning that draw on knowledge bases.

2 System model

This section discusses a novel technique in explainable deep learning based on sustainable quantum optical application. Input has been collected from sustainable quantum optical application and processed for noise removal and normalization. Processed data features have been extracted using a gradient quantum NN, and classification is carried out using an attention based GNN. Proposed architecture is represented in Fig. 1.

In order to achieve the Sustainable Development Goals (SDGs), energy generation and management practises must be improved and modernised. By monitoring and managing energy transmission and promoting efficient communication between utilities and end users, the smart grid enhances user experience. Vast amount of energy data handled by the smart grid is ineffective as a result of inadequate methods for data collection, processing, monitoring, and decision-making. Together with smart grid, big data analytics make it possible to better visualize the grid and help achieve sustainability. The sustainability of smart

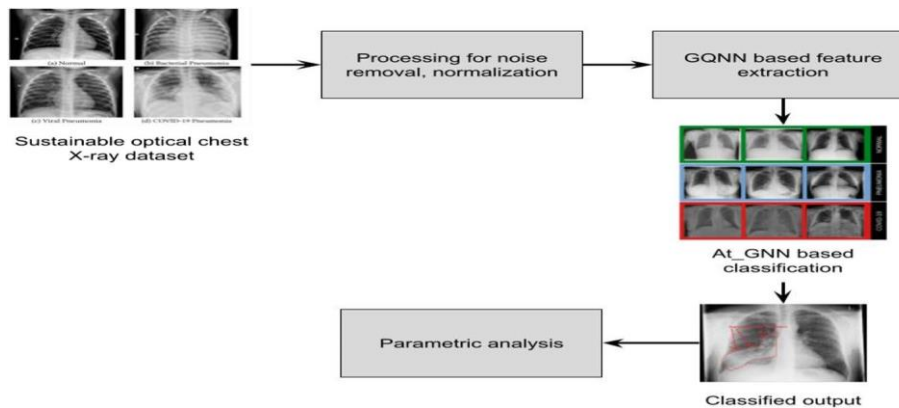


Fig. 1 Overall proposed sustainable quantum optical architecture

grid and effective data management with big data analytics, which has social, economic, technical, and political repercussions, are the focus of the current research.

2.1 Gradient quantum neural network (GQNN) based feature extraction

The formula for gradient descent is as follows. The objective function that one wants to minimise is $f: \mathbb{R}^N \rightarrow \mathbb{R}^t$. One iteratively updates an initial point, $\mathbf{z}^{(k)} \in \mathbb{R}^N$, using the steepest descent of the objective function at the current point, as shown by Eq. (1),

$$\mathbf{z}^{(t+1)} = \mathbf{z}^{(t)} - \eta \nabla f \mathbf{z}^{(t)} \quad (1)$$

where, $\eta > 0$ is a hyperparameter that, in general, may be step-dependent (referred to as the learning rate in a machine learning environment). By factoring in information about the curvature, or the second derivatives of the objective function, at each step, Newton's method improves on this approach. The quantum optical NN is shown in Fig. 2.

The goal function by Eq. (2) Hessian matrix H is consequently included in the iterative update,

$$\mathbf{z}^{(t+1)} = \mathbf{z}^{(t)} - \eta H^{-1} \nabla f \mathbf{z}^{(t)} \quad (2)$$

Without any nonlinearity, each unitary gate in the GQNN system sequentially affects the output of the one before it. In order to allow side

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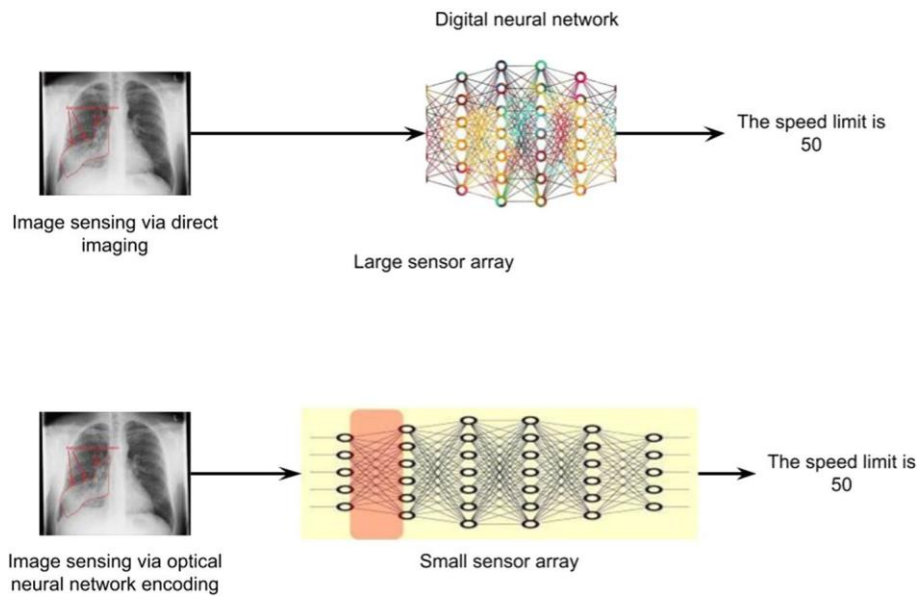


Fig. 2 Proposed quantum optical neural network

2.2 Attention-based graph neural network in classification

Figure 3 displays a broad view of the suggested model architecture. The framework is thoroughly explained in the following subsections. We use a graph attention technique that monitors the area around I and gives each j ($j \in Ni$) a score for importance based on their

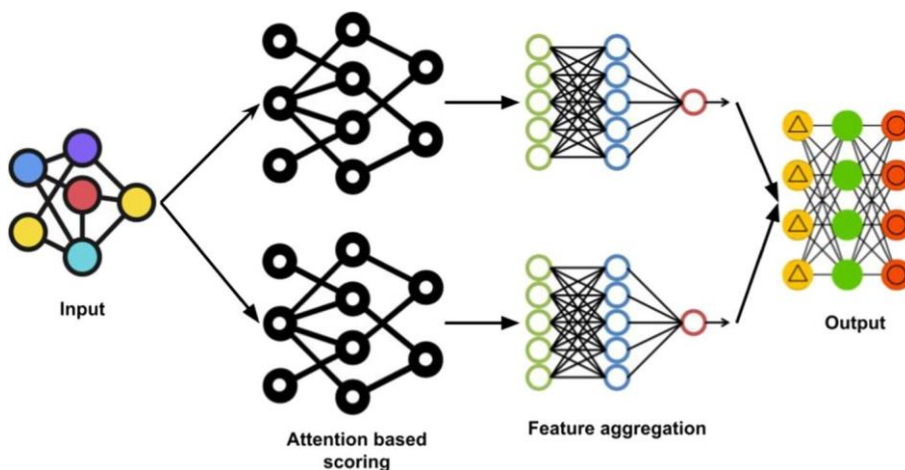


Fig. 3 Architecture overview

trust qualities. To perform a linear transformation, each node is first given a parameterized weight matrix (W). Equation (38) represents unnormalized trust score between I and j .

$$e_{ij} = a \quad , \quad \begin{matrix} W & W \\ Tr, & Trj \end{matrix} \quad (38)$$

3 Performance analysis

We used a variety of open-source libraries to develop every application as part of the proof-of-concept phase, including pysim5G, fiona, shapely, PyTorch, Tensorflow, Keras, Pandas, CV2, Openpose, NumPy, flirimageextractor, nodejs, docker, sklearn, matplotlib, flask, Django, nginx, react. Additionally, we developed object identification models and GPU- optimized them for Nano using TFOD_API. Additionally, we made advantage of Jupyter, a web-based Python environment, and Flask, a Python micro web server. To work with either a PiCamera or a USB camera, we set up NVIDIA Jetson Nano camera. Additionally, the environment required to train unique Caffe and TensorFlow methods for Movidius Neural Compute Stick 2 was added.

3.1 Dataset description

The chest anatomical region is covered by the IU Chest X-ray, Chest X-ray 14, and CheXpert datasets with regard to X-ray imaging. Additionally, the PadChest, MIMIC-CXR, and IU Chest X-Ray datasets provide free-text radiology reports. With the exception of the Pad-Chest dataset, all of the reports are written in English. The largest datasets, MIMIC-CXR and CheXpert, contain 377,110 and 224,316 radiographs, respectively. The raw free-text reports are not provided by CheXpert, but it does offer an automatic rule-based labeller for extracting keywords from medical reports that are in line with the Fleischner Society's suggested lexicon. The labels from the radiology reports were also extracted using this method and added to the MIMIC-CXR dataset. The most popular dataset in the literature, UI Chest X-Ray, has 3,955 free-text reports and 7,470 chest X-ray images.

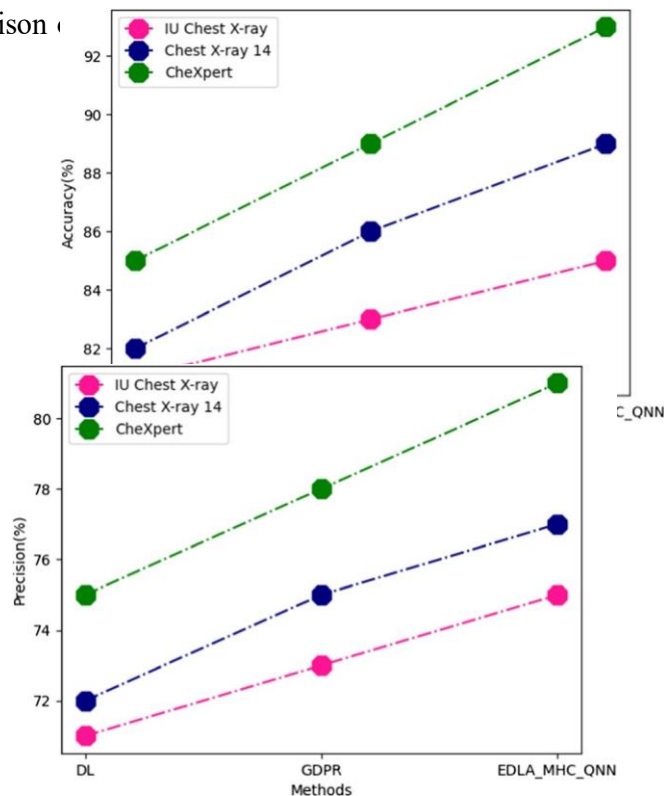
The above Table 1 shows a analysis based on various healthcare datasets. Here the data-set analysed are IU Chest X-ray dataset, Chest X-ray 14 dataset, CheXpert dataset. Parametric analysis is carried out in terms of accuracy, precision, recall, F-1 score, NSE, MAP, and Jaccard index.

Figures 4, 5, 6, 7, 8, 9, and 10 shows a analysis for IU Chest X-ray dataset, Chest X-ray 14 dataset, CheXpert dataset. Proposed technique attained an accuracy of 89%, a precision of 79%, a recall of 70%, an F-1 score of 55%, NSE of 45%, MAP of 42%, and Jaccard index of 48%; while CNN attained an accuracy of 85%, a precision of 75%, a recall of 66%, an F-1 score of 52%, a NSE of 42%, a MAP of 35% and a Jaccard index of 42% and GANN attained an accuracy of 88%, a precision of 77%, a recall of 68%, an F-1 score of 53%, a NSE of 43%, a MAP of 38% and a Jaccard index of 45% for IU Chest X-ray dataset. For Chest X-ray 14 dataset attained an accuracy of 90%, a precision of 85%, a recall of 77%, an

Table 1 Analysis based on various healthcare datasets

Dataset	Techniques	Accuracy	Precision	Recall	F1-Score	NSE	MAP	Jaccard index
IU Chest X-ray	DL	81	71	65	61	55	51	45
	GDPR	83	73	68	63	59	53	48
	EDLA_MHC_	85	75	71	65	61	55	51
Chest X-ray	DL	82	72	68	62	58	52	46
	GDPR	86	75	72	64	62	54	49
	EDLA_MHC_	89	77	75	66	65	56	52
CheXpert	DL	85	75	72	64	61	54	48
	GDPR	89	78	75	68	63	56	52
	EDLA_MHC_	93	81	79	71	65	58	53

QNN

Fig. 4 Comparison of accuracy**Fig. 5** Comparison of precision

3.2 Discussion

We wrap off our discussion of AI's potential impact on healthcare systems by pointing out some of the wider implementation challenges facing artificial intelligence. Some of the problems that prevented the effective use of AI in the medical field were concerns about data privacy, societal difficulties, ethics, hacking, and developer troubles. Artificial intelligence's most glaring and immediate flaw in the healthcare sector is the potential for a breach of data privacy and security. Due to its information-driven development and expansion, it is particularly vulnerable to having its accumulated data misused or stolen.

4 Conclusion

This research proposes a novel technique in explainable deep learning based on multimedia healthcare data analysis sustainable smart nano-grid application. The input data features have been extracted using a gradient quantum neural network, and classification is carried out using an attention-based graph neural network. Additionally, to raise accuracy as well as reduce both false-positive and false-negative outcomes, each application needs to be tested with a large number of training and test datasets. The proposed technique attained an accuracy of 96%, a precision of 86%, a recall of 79%, an F1-score of 67%, an NSE of 55%, a MAP of 56%, and a Jaccard index of 61%. Big data analytics and the smart grid, which involves both the public and commercial sectors, inspire prosumers to work towards sustainable goals. By utilising real-time data gathered from various industries and consumer behaviour,

References

1. Alanazi, S.A., Kamruzzaman, M.M., Alruwaili, M., Alshammari, N., Alqahtani, S.A., Karime, A.: Measuring and preventing COVID-19 using the SIR model and machine learning in smart health care. *J. Healthcare Eng.* (2020)
2. Casiraghi, E., Malchiodi, D., Trucco, G., Frasca, M., Cappelletti, L., Fontana, T., et al.: Explainable machine learning for early assessment of COVID-19 risk prediction in emergency departments. *IEEE Access* **8**, 196299–196325 (2020)
3. Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A., & De Felice, F. (2020). Artificial intelligence and machine learning applications in smart production: Progress, trends, and directions. *Sustainability*, 12(2), 492.
4. Gill, S. S., Tuli, S., Xu, M., Singh, I., Singh, K. V., Lindsay, D., ... & Garraghan, P. (2019). Transformative effects of IoT, Blockchain and Artificial Intelligence on cloud computing: Evolution, vision, trends and open challenges. *Internet of Things*, 8, 100118.
5. Raju, K., Pilli, S. K., Kumar, G. S. S., Saikumar, K., & Jagan, B. O. L. (2019). Implementation of natural random forest machine learning methods on multi spectral image compression. *Journal of Critical Reviews*, 6(5), 265-273.

6. Saba, S. S., Sreelakshmi, D., Kumar, P. S., Kumar, K. S., & Saba, S. R. (2020). Logistic regression machine learning algorithm on MRI brain image for fast and accurate diagnosis. *International Journal of Scientific and Technology Research*, 9(3), 7076-7081.
7. Saikumar, K. (2020). RajeshV. Coronary blockage of artery for Heart diagnosis with DT Artificial Intelligence Algorithm. *Int J Res Pharma Sci*, 11(1), 471-479.
8. Saikumar, K., Rajesh, V. (2020). A novel implementation heart diagnosis system based on random forest machine learning technique *International Journal of Pharmaceutical Research* 12, pp. 3904-3916.