

Impact of Quantum Computing on Artificial Intelligence

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Abstract

Artificial intelligence is just one of the domains that quantum computing has the potential to revolutionise. It has emerged as a promising technology. This paper aims to explore the impact of quantum computing in artificial intelligence, such as improving computational tasks within AI and enhancing machine learning algorithms. Additionally, quantum computing can provide effective solutions to complex optimization problems and offer resource-efficient computations. Furthermore, we took a reasonable example on this research to conduct a comprehensive comparison between the performance of Quantum Support Vector Classifier (QSVC) and classical Support Vector Classifier (SVC) by leveraging Fidelity Quantum Kernels.

Keywords: Quantum Computing, Artificial Intelligence, Support Vector Machine (SVC), Quantum Support Vector Machine (QSVC), Quantum Kernel, ZZFeatureMap.

I. Introduction to Quantum Artificial Intelligence

At the nexus of artificial intelligence and quantum physics lies the developing field of quantum artificial intelligence. This area seeks to apply the ideas of quantum computing to enhance artificial intelligence's computational tasks, particularly its subfields of machine learning. The two main domains of quantum artificial intelligence are as follows: using principles of quantum information and computation within artificial intelligence models, or using artificial intelligence for processing quantum information to advance research in quantum technologies.[7]

The potential of quantum computing in artificial intelligence is found in its capacity to improve data storage and processing speed as well as to handle computationally challenging subroutines. This is particularly significant in the context of machine learning, where complex algorithms are used to analyze immense volumes of data. Current machine learning algorithms, although capable of handling large data sets, often require significant time and computational resources to process and analyze the data. [\(Kietzmann et al., 2021\)\[1\]\[2\]](#)

II. Intersection of Quantum Artificial Intelligence

The convergence of artificial intelligence with quantum computing presents significant opportunities for the advancement of both domains. The next major advancement in computing speed, known as quantum computing, will allow advances in a number of fields, including artificial intelligence. By manipulating multi-valued bits with quantum gates, it provides a new paradigm by permitting the creation of an infinite number of logical states through linear combinations of a set of base states. By combining principles from quantum computing with artificial intelligence

models such as neural networks, researchers aim to enhance computational power and achieve more efficient and accurate computations. This convergence opens up exciting possibilities for optimizing complex systems, drug discovery, and addressing important problems across various domains. ([Quantum Computing | IBM Research, n.d](#)) [5][6]

III. Major Challenges & Limitations of SVC (literature review)

Support Vector Machine (SVM) algorithm, including the Support Vector Classifier (SVC) for classification tasks, is a machine learning algorithm that falls under the category of artificial intelligence (AI). Support Vector Classifier (SVC) is like a smart line-drawer in machine learning. It figures out the best way to separate different groups in data, creating a boundary with the most space between them. It pays extra attention to certain key points, called support points, to draw this line in the best possible way. SVC is handy for sorting things into categories, and it works well for different types of sorting challenges.[3]

- **Major Challenges**

1. SVMs are sensitive to noise and outliers which are situated in the data. Outliers may significantly affect where the decision border is, which could result in less-than-ideal outcomes.
2. It usually chooses a limited number of support vectors for big training sets, therefore (SVM), especially with a linear Kernel like SVC, is generally not suitable for large Datasets due to their computational complexity and memory requirements.[8]

IV. Methodology

This methodology aims to compare the performance of Quantum Support Vector Classifier (QSVC) with classical Support Vector Classifier (SVC) using Fidelity Quantum Kernels. The Support Vector Machine (SVM) algorithm, which includes the Support Vector Classifier (SVC) for classification tasks, is a machine learning algorithm that falls under the umbrella of artificial intelligence (AI). The first step involves defining the classification problem and selecting an appropriate Dataset, followed by preprocessing steps such as handling missing values and splitting the data into training and testing sets. For the classical SVC, scikit-learn is utilized to implement and train the model on the training data. The Quantum Feature Map, particularly ZZFeatureMap, is chosen for the QSVC, along with the Fidelity Quantum Kernel from Qiskit.

The QSVC is then trained using both simulators and real quantum hardware when available. The evaluation of both models involves comparing performance metrics, and statistical tests are applied to assess the significance of any observed differences. Hyperparameter tuning is performed for both classical and quantum models to optimize their performance. The results and analysis section discusses the impact of the fidelity quantum Kernel on QSVC performance, and potential advantages are explored. Future work is outlined, suggesting areas for improvement in quantum algorithms and highlighting the importance of staying abreast of the latest developments in quantum computing and machine learning libraries. The documentation and reporting phase emphasizes thorough documentation of methodology, code, and results for transparent and replicable research.

V. Result Analysis

Using the Qiskit Machine Learning library, this code snippet compares the performance of a classical Support Vector Classifier (SVC) and a Quantum SVC (QSVC). The classical SVC is trained on a linear Kernel, while the QSVC employs a linear ZZFeatureMap (parameterized quantum circuit) in its Fidelity Quantum Kernel, showcasing the potential advantages of quantum approaches in capturing complex data relationships.

Output:

Algorithm	Accuracy
Classical SVC	0.35
QSVC Classification	0.8

Table 1: Results

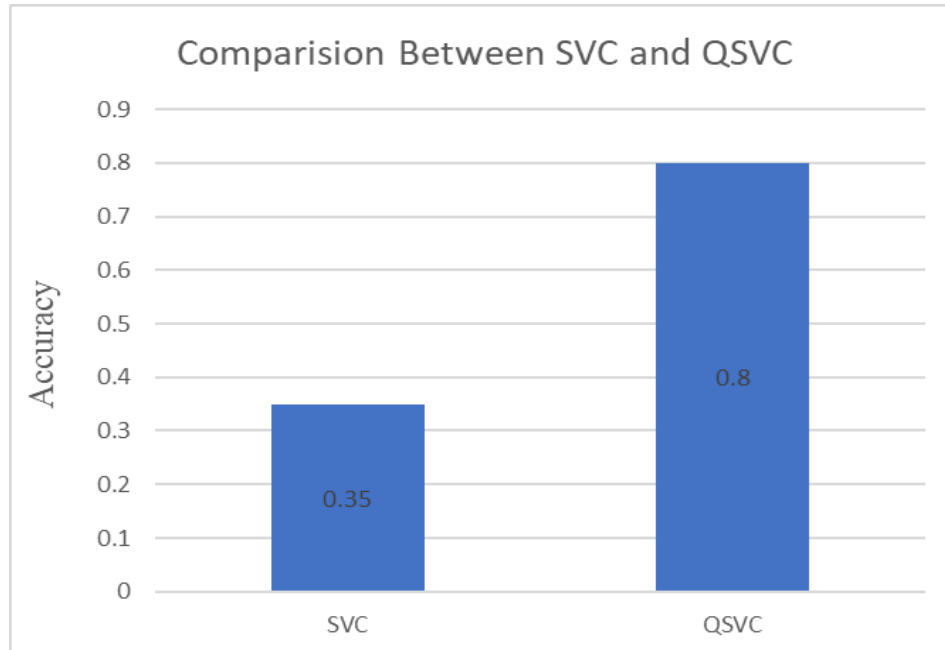


Figure 1

This experiment was done in the IBM quantum lab using Jupyter Notebook. using 3D AD-HOC Dataset with training size 100 and test size 10 showed that QSVC performed better than SVC

using linear approach and using with SVC Kernel and QSVC fidelity Kernel it shows QSVC outperforming the classical support vector classifier (SVC) on the provided Dataset. The classification accuracy of 0.8 for QSVC indicates that it correctly predicted the labels for 80% of the test samples. QSVC achieved an improvement of approximately 128.57% over SVC on the given Dataset. So as we increased our Dataset size we needed more hardware resources but we only had limited memory so we took 100 size for the Dataset.

Code for Reference : <https://gitfront.io/r/RiteshKoul/XU1mbENRtYMW/MyRepo/>

VI. Advantages of QSVC over SVC

- **Fidelity Quantum Kernels:** Focus on the use of Fidelity Quantum Kernels, a unique quantum approach to Kernel methods. Discuss how fidelity-based approaches differ from traditional Kernels in capturing quantum correlations and may lead to more effective representations of complex relationships in the data.
- **Quantum Feature Map Selection:** Emphasize the choice of the ZZFeatureMap or PauliFeatureMap in the quantum approach. Discuss why this specific quantum feature map is chosen, its properties, and how it contributes to the overall performance of the QSVC. Compare and contrast it with classical feature maps.
- **Entanglement in Quantum Feature Mapping:** Highlight the use of entanglement in the quantum feature mapping process. Discuss how the entanglement strategy impacts the ability of the QSVC to capture intricate patterns in the data and provide a non-linear advantage.

VII. Conclusion

To sum up, QSVC is better than SVC when it comes to handling large Datasets in higher dimension using quantum Kernel where SVC cannot, the experiment we performed showed that QSVC had 0.8 accuracy over SVC with 0.35. QSVC achieved an improvement of approximately 128.57% over SVC on the given Dataset. Quantum intelligence is at the cutting edge of technology and has the potential to revolutionize artificial intelligence just like we seen in the experiment for example. The efficiency boost provided by quantum computing, combined with the transformative effect of quantum algorithms such as Shor's on cryptography and optimization, opens up new possibilities for AI capabilities. The ongoing pursuit of quantum computing advances and AI integration is imperative to drive us into a new age of computing power and problem solving potential [8]

VIII. Quantum Artificial Intelligence's Future

Quantum artificial intelligence's (QAI) future appears exceptionally promising, heralding a transformative era in computing. Quantum computers, with their ability to process vast Datasets and solve complex problems exponentially faster than classical counterparts just like we examined in the experiment, hold immense potential for revolutionizing fields such as optimization, cryptography, drug discovery, and machine learning. As quantum technologies mature, we anticipate breakthroughs in tackling previously insurmountable challenges, pushing the boundaries

of computation, and opening new avenues for innovation. QAI is poised to reshape industries, offering solutions to problems that were once deemed intractable and paving the way for advancements with profound societal impact. [\(Google Quantum AI, n.d\)\[9\]](#)

References

- [1] Kietzmann, J., Demetis, D S., Eriksson, T., & Dabirian, A. (2021, July 1). Hello Quantum! How Quantum Computing Will Change the World. <https://scite.ai/reports/10.1109/mitp.2021.3086917>
- [2] Yu, Y., Qiu, D., & Yan, R. (2020, January 1). A Quantum Entanglement-Based Approach for Computing Sentence Similarity. <https://scite.ai/reports/10.1109/access.2020.3025958>
- [3] Carrasquilla, J. (2020, January 1). Machine learning for quantum matter. <https://scite.ai/reports/10.1080/23746149.2020.1797528>
- [4] Botsinis, P., Ng, S X., & Hanzo, L. (2013, January 1). Quantum Search Algorithms, Quantum Wireless, and a Low-Complexity Maximum Likelihood Iterative Quantum Multi-User Detector Design. <https://scite.ai/reports/10.1109/access.2013.2259536>
- [5] Quantum Computing | IBM Research. (n.d). <https://research.ibm.com/quantum-computing>
- [6] Shi, R., & Zhang, M. (2019, May 20). Privacy-preserving Quantum Sealed-bid Auction Based on Grover’s Search Algorithm. <https://scite.ai/reports/10.1038/s41598-019-44030-8>
- [7] Gao, X., Zhang, Z., & Duan, L. (2018, December 7). A quantum machine learning algorithm based on generative models. <https://scite.ai/reports/10.1126/sciadv.aat9004>
- [8] Overview on Quantum Computing and its Applications in Artificial (n.d). <https://ieeexplore.ieee.org/document/9355449>
- [9] Zhu, S., Yu, T., Xu, T., Chen, H., Dustdar, S., Gigan, S., Gunduz, D., Hossain, E., Jin, Y., Lin, F H., Liu, B., Wan, Z., Zhang, J., Zhao, Z., Zhu, W., Chen, Z., Durrani, T., Wang, H., Wu, J., Pan, Y. (2023, January 1). Intelligent Computing: The Latest Advances, Challenges, and Future. <https://scite.ai/reports/10.34133/icomputing.0006>
- [8] Wang, J., Guo, G., & Shan, Z. (2022, October 14). SoK: Benchmarking the Performance of a Quantum Computer. <https://scite.ai/reports/10.3390/e24101467>
- [9] Google Quantum AI. (n.d). <https://quantumai.google/> HYPERLINK "<https://quantumai.google/>" HYPERLINK "<https://quantumai.google/>" HYPERLINK "<https://quantumai.google/>" HYPERLINK "<https://quantumai.google/>" HYPERLINK "<https://quantumai.google/>" HYPERLINK "<https://quantumai.google/>" HYPERLINK "<https://quantumai.google/>"
- [10] Richhariya, Bharat & Gupta, Dr. Deepak & Prasad, Shakti & Acharjee, Kamalini. (2017). A

review on support vector machine for classification problems. Artificial Intelligent Systems and Machine Learning. 9. 130-139.

<https://www.researchgate.net/publication/322068632> A review on support vector machine for classification prob