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Parkinson, Chaos & Quantum Computing

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Parkinson, Chaos & Quantum Computing

Dissertação apresentada como parte dos requisitos para obtenção do título de Mestre em Ciência da Computação junto ao Programa de Pós-Graduação Interunidades em Ciência da Computação da Universidade Estadual Paulista "Júlio de Mesquita Filho" - Campus de São José do Rio Preto.

Orientador: Prof Dr Rodrigo Capobianco Guido

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São José do Rio Preto
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DEDICATÓRIA

Ao meu tio.

ABSTRACT

Signal processing models and artificial intelligence algorithms have benefited from the advance of Quantum Computing. Nevertheless, just modest possibilities have been seen in that sense for speech and voice analysis. Thus, the intention of the author of this dissertation is to investigate whether Quantum Machine Learning models might perform well in classifying Parkinsonian speech. Particularly, since the speech database used in the experiments produced just a few features, available current quantum models are feasible for the proposed approach. The results, up to this point, stimulate further investigation and suggest prominent perspectives.

Key-words: Quantum machine learning. Parkinson's disease. Digital signal processing. Voice analysis

RESUMO

Modelos de processamento de sinais e algoritmos de inteligência artificial se beneficiaram com o avanço da Computação Quântica. No entanto, apenas possibilidades modestas foram vistas nesse sentido para a análise da fala e da voz. Assim, a intenção do autor desta dissertação é investigar se os modelos de Aprendizado de Máquina Quântica podem ter um bom desempenho na classificação da fala parkinsoniana. Particularmente, como o banco de dados de fala utilizado nos experimentos contém poucas características, os modelos quânticos atuais disponíveis são viáveis para a abordagem proposta. Os resultados, até aqui, estimulam futuras investigações e sugerem perspectivas proeminentes.

palavras-chave: Aprendizado de máquina quântica. Doença de Parkinson. Processamento de sinais digitais. Análise de voz

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SUMMARY

Chapter 1

Introduction

Since Parkinson's disease was discovered in 1817 by James Parkinson, the first doctor who profoundly studied it, there has been a tremendous progress. As mankind's scientific knowledge gradually evolved, neuroscience has been able to incorporate different ideas coming from multiple areas. With novel digital speech processing (DSP) and machine learning models, new and non-invasive diagnoses for neurodegenerative diseases have become possible, as shown in [1, 2, 3]. In those papers, we observe that handcrafted feature extraction strategies can detect Parkinson successfully.

Concomitantly with the deep learning revolution, the new field of quantum physics emerged, originating the quantum computation and the quantum information theory. They expanded previous possibilities, including new ways of transmitting, storing, and processing information [4, 5, 6]. In spite of the considerable growth of that field, processing large amounts of quantum information is still a difficult task. Indeed, environments interact with data and, thus, sustainably blocking undesirable interactions for thousands of qubits is still a pursuit of the scientific community. Given this scenario, a new promising possibility have arisen recently: the noisy intermediate-scale quantum (NISQ) devices [7]. In contrast to early quantum algorithms, when dealing with NISQ devices, only hundreds of noisy qubits are required. Although universal quantum computing for NISQ devices does not yet exist, specific computing tasks can be operated on such platforms. An important example is the method adopted in this dissertation, i.e., the variational quantum algorithms (VQA) [8] that can deal with practical problems such as combinatorial optimization and machine learning. VQA is built through a properly parameterized operation whose parameterization is obtained by means of a classical computer.

Consequently, the author of this dissertation is inspired by recent results suggesting a connection between alpha-synuclein (αsyn) [9, 10] and deterioration of some speech parameters, considering a zebra finch (a bird breed) neural model [11], which is similar to the human pathway. This could lead to the possibility of early Parkinson's diagnosis with non-invasive methods that require only ordinary speech recordings, by using smartphones, for instance. We specifically discuss how VQAs compare against classical machine learning methods, when features coming from nonlinear dynamical systems theory are used.

Chapter 5

Conclusion and Future Work

In this work, quantum machine learning for parkinsonian speech detection was explored with good and comparable results to classical machine learning. In modern approaches, the speech feature extraction is usually automated using deep neural networks, trading many times explainability for generalization. Despite the limitations of current quantum computers, the results represent a first step, demonstrating useful medical applications of this new class of models. As quantum computing technologies continue to scale up the number of high fidelity qubits, improving critical factors, like coherence time and error correction, we posit hope that this new generation of models will have great results, potentially surpassing classical ones.

Regarding the main difficulties, since the field of quantum computing is in its birth and large-scale access to quantum hardware is not still available, we have to stick to simulators, which require high time complexity, and hence a low number of qubits for the experiments. On the good side, lots of frameworks are constantly being developed, which began with low-level ones - just like the beginning of classical computing, when Assembly and C were the top languages, used for almost every application - and now other frameworks that allow for higher-level implementations, like Pennylane.

For conclusion and future directions of work, one interesting approach to see is when a post-NISQ era comes, and with this, robust hardware with large number of qubits to use. Then, much wider/deeper quantum models could be used for the new task at hand, possibly removing the need for handcrafted feature engineering. Other line of research is to tackle possible symmetries in speech data as an effective inductive bias in the parametrized circuits, or even to discover hidden symmetries with them.

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