Incorporating quantum machine learning for the analysis of alterations in cloud droplet dimensions: A Novel Approach

Ms. Mukta Nivelkar[1] , Dr. S. G. Bhirud[1] , Ms. Nikitabahen Makwana[2],Dr. Bipin Kumar[2]

[1] Department of Computer Engineering and Information Technology, Veermata Jijabai Technological Institute, Mumbai, India.
[2] Ministry of Earth Science, Indian Institute of Tropical Meteorology,Pune, India.

E-mail: [1]mmnivelkar_p19@ce.vjti.ac.in, [1]sgbhirud@ce.vjti.ac.in, [2]makwana.nikita@tropmet.res.in, [2]bipink@tropmet.res.in

Abstract. Clouds are composed of an endless number of very small water droplets that are accumulated over time. The diameter of these water droplets can range anywhere from 5 to 50 microns, and they are available in a broad variety of characteristics. A number of different processes that are associated with clouds exert a considerable degree of emphasis on the distribution of sizes for clouds. For instance, a greater variety of sizes will frequently result in the formation of water droplets that are the size of raindrops occurring at a pace that is considerably faster. The cloud will evaporate more slowly along its edges and will be less reflective of shortwave radiation if the cloud droplet population has a wider variety of sizes. This results in the cloud being less reflective of shortwave radiation. Even if the average size of cloud droplets does not change, this is still consistent with the findings. These examples explain why it is vital to have an understanding of the weather and climate by demonstrating the significance of being aware of the mechanisms that govern the variety of cloud droplet sizes. The proposed work utilizes a model called DNS (Direct Numeric Simulation) to get precise droplet data. The dataset comprises the velocities of the droplets and the mixing ratio. Vorticity in a cloud is the measure used to characterise spins. Vorticity zones are identified inside a designated DNS domain. Quantum machine learning techniques are utilised to investigate the numerical data of cloud droplets, aiming to get insights into the size changes that occur in droplet data. This is done to enhance comprehension of cloud droplet data and the intricacies linked to its highly dynamic nature.

1. Introduction

Improved weather forecasting would be very beneficial to many industries, including those that deal with land slide, earthquake prediction, and disaster preparedness. The usual method is less effective in this situation due to the volume and complexity of the data. Quantum computing can help us develop more precise climate models, which can help us prepare for natural disasters and sudden acts of violence. Quantum computers are capable of modelling for both static and real-time analyses of climatic data. The initial goal of this paper is to use machine learning to assess atmospheric cloud data. Managing odd data patterns and computational complexity have been addressed in previous research on traditional computers. Traditional computers have limited capabilities for handling and analysing complex data. In order to obtain results that are superior to those of conventional computations, quantum computing can handle the complicated nature of the data and be used for extra analysis. Climate change is to blame for the complexity and rapid change in atmospheric cloud droplet data. These atmospheric cloud data observations span in distance from a few metres to many miles. Analysis of cloud data measures changes in the cloud's droplet properties over time. The second goal is to use quantum computation in climate science studies to help with future weather predictions. Upcoming real-time forecast data processing will surely be more accurate and quick owing to quantum computing's capacity to make accurate static weather forecasts. In the proposed project, machine learning models will be used to analyse data on atmospheric cloud droplets using quantum computing. Quantum techniques like superposition and entanglement are used to manage data complexity and locate deeper data to get more accurate results [1][2][3]. Fault-tolerant quantum devices will soon be used for data processing. the creation and use of parameterized models or quantum variational circuits on classical data. A quantum machine learning algorithm requires encoded classical input to create a parameterized model, which is then applied to a variational circuit and circuit measurements are taken. The use of variational quantum circuits to process quantum information and model quantum machine learning is demonstarted and documented in this work [5][6].

2. Simulation Data

The Direct Numeric Simulation(DNS) model treats droplets as Lagrangian point particles, and the Eulerian framework is used to trace their velocity, radius, and location. Eulerian variables include the mixing ratio, temperature, and velocities of the droplets fluid. The values of these variables are provided at each point in the domain with a grid spacing of 1 millimetre (128 points in each direction, namely x, y, and z). It may be concluded that the total number of points in the entire volume is 128×128×128. The forces of gravity, inertia, and Stokes drag all have an impact on the mobility of droplets. When calculating the expansion of the droplets, the local value of supersaturation is taken into consideration. Droplets that have a radius that is less than 0.05 micrometres are considered to be weightless tracer particles to be addressed [5]. Two distinct categories of data are produced by the simulation: (Credit: Dr. Bipin Kumar, Senior Scientist , IITM Pune, Maharashtra, India.)

(i) In the Eulerian model, the flow velocities, temperature, water vapour mixing ratio are some of the quantities that are kept in these files. The NETCDF (Network Common Data Form) file format is also used.

(ii) Lagrangian: These files provide information on the properties of droplets, such as their velocity, position, local supersaturation, and temperature. The SION format, which is a binary format, was used to retain this data.

A time step of 5×10-4 seconds is being used. On the basis of flow characteristics, in particular in accordance with the Courant–Friedrichs–Lewy (CFL) condition, the time step for the data that is created is determined.

3. Primary Goal

The primary target that we have set for ourselves is to compare the features of droplets and fluids in sections of the simulation domain that are exceedingly vortical with parts that tend to be less vortical. Quantum machine learning and quantum computations are performed on given data for classification of droplets into high and low vorticity regions using qauantum devices[4].

4. Objectives

Objectives are defined as follows:

(i) Investigation of flow characteristics of droplets in high and low vorticity region.

(ii) Analysis of variations in mixing ratio and velocity on droplets in high and low vortex region.

(iii) Statistical analysis of droplet characteristics such droplet number concentration, volume mean radius, spectral width, supersaturation and standard deviation in two different vorticity regions.

(iv) analysis of mixing scenarion on droplet growth.

The stages that are involved in processing droplet data in the high and low vortex regions are broken out in further detail in Figure [1]. Architecture depicts two distinct continents, each of which is seen individually. Within the first section of the diagram, the primary emphasis is placed on the traditional components of data modelling, processing, and conversion. whereas the second portion focuses on the quantum counterpart of the system. Specifically, this model adheres to the classical-quantum approach to machine learning.

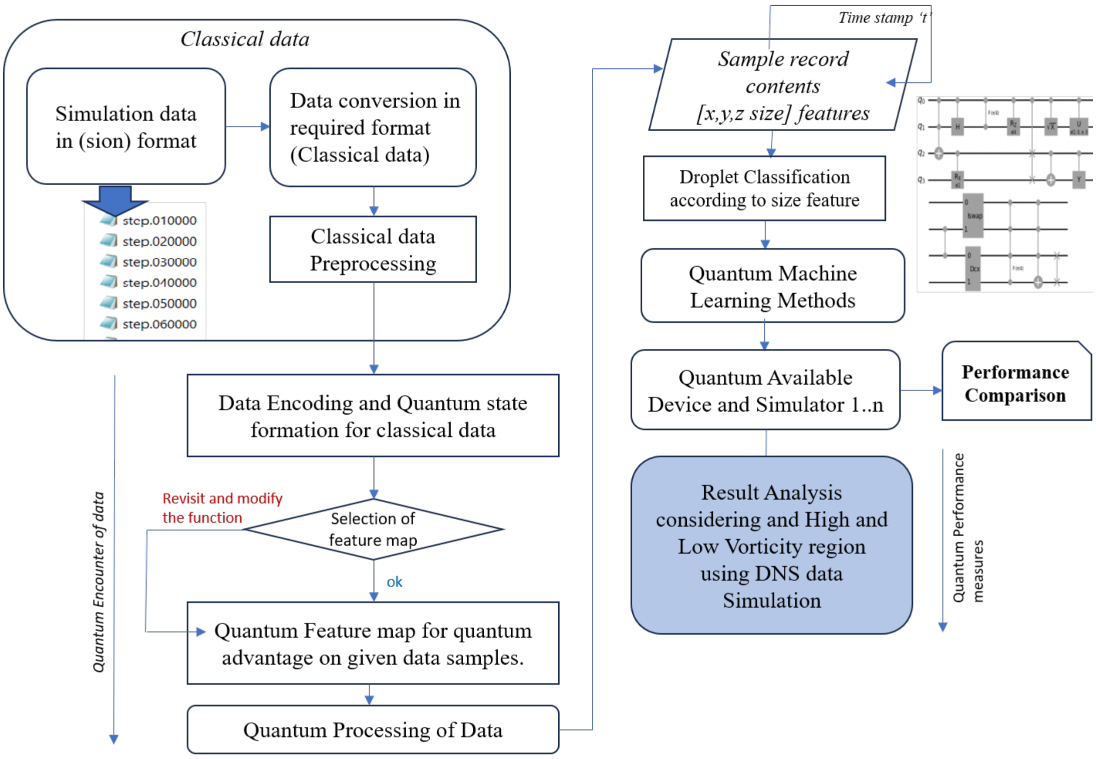

Figure 1. Proposed System Architecture for Droplet Data Analysis

5. Methodology

There are many different tools and subroutines that are utilised in the process of putting the quantum algorithm into action. With the assistance of a wide variety of quantum tools, the Qiskit platform allows for the implementation and testing of both supervised and unsupervised machine learning tasks. In this study, the droplet and DNS[5] datasets are taken into consideration from the implementation point of view, and an experiment is carried out using quantum hardware. Due to the fact that cloud droplets are both small and complex in nature, quantum machine learning models have been proposed as a means of analysing this data. Time and measurement complexity will be the focal focuses of additional study, and a proposal will be made regarding how quantum technology might be utilised to exceed the operational capability of conventional machines on several fronts.

6. Conclusion

In this abstract work, we are attempting to persuade the cloud physics hypothesis by utilising the quantum computing method. In each country's weather forecasting model, clouds and the processes that they undergo play a significant influence. Improvements may be made to cloud operations through the utilisation of a number of characteristics to analyse cloud droplet data. In order to separate the findings of conventional computers from those of quantum computers, quantum machine learning approaches and quantum computers have been developed. The work that is being proposed would be evaluated on a number of quantum devices by gaining access to resources, and the functionality would be compared.

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