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"Comprehensive Analysis of Quantum-Inspired Technique for Cloud Detection"

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Certificate

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Candidate's Declaration

I hereby declare that the work presented in this thesis titled ***"Comprehensive Analysis of Quantum-Inspired Technique for Cloud Detection"*** by **KOMAL** is in partial fulfillment of the requirements for the **M.Sc. (Data Science)** degree submitted to the **Amity Institute of Integrative Sciences and Health**, **Amity University Haryana**.

This work is an original record of my own efforts, conducted under the guidance of **Dr. Amar Arora** and **Dr.Amrit Pal Singh**. The content in this thesis has not been submitted by me to any other University or Institute.

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I am profoundly indebted to my dear family for their unwavering patience, prayers, blessings, and relentless efforts to uplift my spirits. Their support has been my source of strength and has enabled me to endure throughout this journey.

Most importantly, I extend my deepest thanks to Almighty God, whose divine guidance has illuminated my path. This study would not have come to fruition without His grace.

Finally, I would like to thank my friends who, in various ways, have supported me in the completion of this thesis.

Komal

Abstract

The growing accessibility of satellite imagery has created new opportunities for monitoring the environment, allowing for a comprehensive analysis of atmospheric conditions on a global scale. Nevertheless, obtaining valuable insights from this data, specifically for tasks such as identifying clouds and categorizing weather, continues to pose significant challenges due to the data's high dimensionality, spectral diversity, and noise in remote sensing images. By combining classical and quantum machine learning methods, this thesis aims to address these problems, focussing on kernel-based models.

The research is divided into two primary areas. The goal of the first section, which concentrated on cloud detection in multispectral satellite data, is to precisely divide and categorise cloud-covered regions. Traditional support vector machines (SVMs) with linear and radial basis function (RBF) kernels are tested for their ability to distinguish between cloud-based and non-cloud-based pixels. Quantum Support Vector Machines (QSVMs) are being studied as a cutting-edge substitute in parallel. Quantum kernel estimation is used by QSVMs to transform classical data into a high-dimensional Hilbert space using parameterised quantum circuits.Standard classification metrics are used to evaluate each model's performance, and the results demonstrate that QSVMs can occasionally reach accuracy that is on par with or better than that of traditional SVMs. The second section centres on classifying weather photos, where satellite imagery is arranged according to pre-established weather classifications such as cloudy, sunny, wet, and foggy. Applications in meteorology, agriculture, emergency preparedness, and transportation all depend on this classification. This quantum-assist The research again contrasts classical SVMs (both linear and RBF) with QSVMs to assess their performance. Publicly accessible weather image datasets are utilized for both training and testing, and findings show that classical SVMs excel with larger datasets, while QSVMs provide a promising option when dealing with high-dimensional, low-sample datasets. The incorporation of quantum kernels adds a new dimension of expressiveness, which may enhance the model's ability to generalize on complex classification boundaries.

This thesis not only illustrates the effectiveness of kernel-based techniques in analyzing satellite images but also adds to the expanding research on quantum machine learning by implementing QSVMs in practical remote sensing applications. The comparative assessment yields valuable insights into the moments and contexts where quantum-enhanced models might outperform traditional methods. As quantum technology continues to advance, such hybrid frameworks that combine classical and quantum approaches show considerable potential for future applications in Earth observation and environmental monitoring.

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1 Introduction

Satellite imaging is crucial in modern science and technology, influencing a wide range of areas including meteorology, environmental monitoring, national security, urban growth, agriculture, and climate change studies [8]. As satellite sensors and remote sensing technologies improve, a vast amount of data is produced each day. These satellites, particularly those with high-resolution optical and multispectral cameras, gather extensive raw imaging data from the Earth's surface, oceans, and atmosphere[8]. This information is essential for making informed decisions in areas such as disaster response, food production, urban planning, and weather forecasting. For example, satellites can monitor changes in vegetation, track snow accumulation, follow storm systems, and evaluate urban sprawl - all in nearly real time .

However, the primary challenge is handling and extracting meaningful insights from the terabytes of imaging data generated regularly. The sheer size and complexity of this information make manual analysis impractical, thus highlighting the need for automated, intelligent data processing methods[8].An efficient algorithm should retain any useful evidence, yet still be able to filter through, process and analyze only the relevant portions of the data. Especially when the resolution and frequency of satellite imaging is increasing, the problems of storage and processing are also aggravated, what calls for smart data selection and classification methods used right from the beginning of the analysis[8].

Cloud detection and elimination is one of the vital pre-processing steps in satellite image interpretation. For scientists and analysts who are focused on things that happen on the surface of the earth, clouds can obscure surface features. Identifying cloud is significant for two reasons. First, in research concerning agriculture, deforestation, and monitoring infrastructure, obtaining clear images is vital for precise observation and interpretation. Areas covered by clouds can create gaps in the data and lead to misinterpretations if not addressed appropriately [8]. Second, clouds are themselves significant meteorological elements that must be analyzed for climate modeling, weather forecasting, and storm tracking. Therefore, it is critical to differentiate between clouds that obscure important ground data and those that are of meteorological significance [8].

Identifying and removing cloud-covered areas from large image datasets manually is not only tedious but also prone to human error. Traditional image processing methods, while effective in certain contexts, often struggle to maintain accuracy when applied on a large scale. Consequently, the need for efficient, automated cloud detection algorithms has increased markedly. The use of machine learning, particularly deep learning, has made advancements in this field, allowing for the classification and segmentation of clouds based on labeled training datasets. Nevertheless, even the most advanced classical machine learning models may underperform when faced with complex, high-dimensional data or when the computational load becomes excessive [8].

Beyond cloud detection, I have built upon this research by investigating weather classification using image datasets. This involves categorizing satellite and ground-level images into five different weather types: sunny, cloudy, rainy, foggy, and snowy. Precise weather classification is essential for automated environmental monitoring systems, intelligent transportation networks, agricultural planning, and real-time weather prediction. Each of these weather categories exhibits distinct visual characteristics—for example, foggy conditions tend to obscure image textures, while snowy landscapes are often bright and reflective. By integrating weather classification with cloud detection, a more thorough understanding of environmental patterns can be achieved, potentially enhancing the reliability of climate-related applications.

As data volumes and complexity is growing, quantum computing stands out as a best solution to enhance and speed up data analysis tasks. Quantum computing uses the ideas of quantum mechanics,Especially superposition and entanglement, to process information in ways that traditional computers cannot. Unlike classical bits, which can only represent 0 or 1, quantum bits or qubits, can exist in both states simultaneously due to superposition. This characteristic allows quantum computers to execute many calculations at once, which will speeds up certain problem types. Also, because of their entanglement, qubits can be connected in a way that improves computational efficiency and accuracy.

Data science could undergo a revolution because to of these quantum properties, especially in handling high-dimensional data processing and optimisation problem[1].

When it comes to analyzing satellite images, quantum computing has several compelling advantages. First, quantum algorithms reduce the dimensionality of image data than classical techniques - a major benefit in hyperspectral imaging because every pixel carries data over hundreds of spectral bands. Second, emerging quantum algorithms aim to boost classification accuracy by identifying optimal boundaries in complex and nonlinear datasets. One promising approach, known as Quantum Machine learning, combines the power of Quantum computing with traditional machine learning to build more reliable models for task like pattern recognition, image classification and clustering[1].

Quantum Machine Learning have combined to create the fast developing fields of quantum information science and artificial intelligence. A number of techniques have shown great promise. Quantum Support Vector Machines (QSVM) use quantum-enhanced kernel methods in order to categorize data points, operating in Exponential larger Hilbert spaces than those used by traditional kernels. These kernels can reveal deeper data structures that classic models might miss. Similarly, Quantum Principal Component Analysis (QPCA) helps reduces the dimensionality of large datasets while preserving key features, providing a quantum-based approach to high-resolution satellite photography. Other state-of-the-art methods include Quantum Convolutional Neural Networks (QCNNs), which can adapt classical CNN architectures to fit quantum circuits, and VQCs, which use hybrid quantum-classical system to imporve classification performance[1].

My research explore how Quantum Machine learning(QML) algorithms can be used for cloud detection and weather classification using satellite imagery datasets. By Comparing quantum-enhanced models with classical algorithms is intended to determine whether quantum techniques can offer faster inference times or or improved accuracy in real-world scenarios. Another reason for this work is the growing accessibility of limited-access quantum hardware and quantum simulators from firms such as IBM Quantum and PennyLane, which allow for the current testing with small-scale quantum algorithms. [1].

In conclusion, as the amount and complexity of satellite imagery continue to increase, the application of quantum computing and quantum machine learning techniques may open the door to new levels of efficiency and accuracy in the interpretation of environmental data. Merging quantum techniques with conventional image processing workflows could result in significant advancements in weather prediction, climate modeling, and immediate disaster response. By exploring the applications of QSVMs and associated quantum algorithms, this research contributes to the ongoing effort to make satellite imaging analysis more intelligent, scalable, and impactful [8].

2 Related work

Quantum machine learning (QML) has recently attracted interest due to its ability to tackle intricate pattern recognition challenges with the help of quantum-enhanced algorithms. In the field of remote sensing, particularly in the detection of clouds within multispectral satellite images, several investigations have focused on the use of classical machine learning methodologies such as Support Vector Machines (SVMs). Nevertheless, recent research has started to explore quantum-inspired methods to boost efficiency and generalization.

One particular study outlined in [A1] examines the application of quantum kernel-based Support Vector Machines for identifying clouds in multispectral Landsat-8 satellite images. The researchers introduce a hybrid quantum-classical approach where the pixels of satellite images are mapped into a Hilbert space through parameterized quantum feature maps. These maps are fine-tuned to enhance kernel-target alignment, which effectively improves classification performance[8]. Importantly, the findings indicate that quantum-enhanced SVMs can obtain accuracy levels similar to those of classical SVMs, even when utilizing relatively straightforward quantum kernels. The study also offers useful details on estimating quantum resources, such as the quantity of T-gates required for practical implementation on high-performance or quantum computing systems.[A2] presents SEUNet++, a deep learning framework designed especially for accurate cloud segmentation in Landsat-8 satellite images, building on sophisticated models for cloud analysis. By incorporating a lightweight channel attention mechanism into the decoder, this model enhances the U-Net++ architecture and makes it possible for it to highlight pertinent features more successfully. After carefully observing scientist found that Resnet-50 was the most effective backbone for this task. Also, Using transfer learning greatly boosted the model's performance. SEUNet++ achieved a impressive Intersection over Union (IoU) score of 91.8%, outperforming the original U-Net++ and traditional models in accuracy, precision, and recall. This improvement resulted in clearer cloud boundary detection and better identification of delicate cloud formation[2]. The authors use the IARPA fMoW dataset to demonstrate a deep learning-based classification strategy for evaluating high-resolution multispectral satellite pictures with an emphasis on facility and object identification. The system combines metadata with convolutional neural networks (CNNs) like DenseNet, ResNet, Inception, and Xception. By combining the CNN outputs with the additional information, the model reaches an overall accuracy of 83% and an F1 score of 0.797. Impressively, it performs even better in certain cases, achieving a 95% accuracy by correctly identifying 15 different classes. Methods like transfer learning, data augmentation, and ensemble averaging greatly improves the outcomes. The technique also addresses problems specific to satellite images, like variations in object sizes and orientations and interference from cloud cover.This work show how deep learning can be used to automate the analysis of satellite images to support important areas like environmental monitoring, disaster relief, and law enforcement[12]. In [A4], the authors investigate how quantum computing can be applied to satellite image processing, especially for Earth observation tasks. They focus on breaking down parameterized quantum machine learning (QML) models into Clifford+T gate sets to evaluate quantum system, The study emphasizes the importance of models that can break weight symmetry and generalise well to new data by calculating the number of T-gates needed to achieve quantum advantage. They also highlighting the value of hyperspectral images, like those from EnMAP, because of their rich spectral information and lower quantum resource demand. Additionally, the authors propose a hybrid computing approach that combines high-performance computing and Quantum Computing, They suggest that more complex QMLs model benefits from quantum systems, while simpler models with fewer T-gates work better on classical High -performance computing. This analysis helps bridge the gap between current quantum hardware limitation an the practical use of QML models.[11]. In [A5], the authors introduce an innovative quantum communication protocol that uses CubeSats and drones to create a reliable way to distribute entangled photons between distant locations on Earth, tackling challenges caused by weather disruptions. Their research aims to improve the robustness of satellite-based quantum communication by simulating the protocol using IBM Q Experience hardware. Unlike traditional image-based datasets, the work focus on quantum teleportation and entanglement distribution. This study represents the first phase of a five-stage project, mainly evaluating feasibility.But, it relies heavily on simulations and hasn't been tested in real-world applictions, its practical impact is currently limited.[13].

The authors of [A6] investigate using quantum kernel estimation (QKE) alongside support vector machines (SVMs) to detect clouds in satellite images. To improve how well the kernel align with the data, they introduce hybrid SVMs that map pixel information into a Hilbert space using parameterised ZZ-feature maps. This approach blends traditional SVM training with quantum kernel calculations. Tests on the Landsat-8 dataset show that these hybrid models achieve classification accuracy similar to classical methods. using of quantum-enhanced models for practical Earth observation applications is highlighted in this study[7].

In [A7], the authors describe a weather image classification model that combines a dual augmented-attention module with a Vision Transformer (ViT) to strengthen feature extraction. This model tackels the shortcomings of conventional deep learning methods in recognising different weather patterns. The dual attention module, which combines convolutional and Atrous self-attention to captures both detailed and broad information, while a pre-trained ViT is used to extract basic semantic features. These features are then combined and sent through a linear layer for the final classification. Experiments conducted on public datasets (MWD and WEAPD) show that this model outperforms recent deep learning approaches in terms of F1 scores.[6]. The authors of[A8] developed a scalable system for automated weather image classification using transfer learning with pre-trained deep convolutional neural network(CNNs). Their goal is to reduce reliance on costly sensors and manual observation . Built on the Spark platform, this model is designed to efficiently process large weather datasets. The Inception V3 combined with a Logistic Regression classifier achieved the highest accuracy of 97.77% among the models that were evaluated. This solution shows strong potential for practical use in areas like agriculture, transportation, and outdoor monitoring [9]. In [A9], the authors ivestigate the application of nnU-Nets, a self-configuring deep learning model, to detect clouds in multispectral satellite images. Designed especially for segmentation tasks, nnU-Nets adapt automatically to different datasets and it doesn't needed manual adjustments in model's design . Tests conducted on Sentinel-2 and Landsat-8 images demonstrate exceptional performance, achieving a Jaccard index of 0.882 on previously unseen Sentinel-2 patches, thereby surpassing U-Net with ResNet-34 and traditional thresholding approaches. The framework was positioned in the top 7% of the "On Cloud N" challenge. This research highlights the capability of nnU-Nets to streamline cloud detection across a range of satellite missions[4]. In [A10], the authors address the challenge of cloud segmentation in high-resolution multispectral images by presenting the CloudPeru2 dataset and a comprehensive segmentation technique. The CloudPeru2 dataset is made up of 22,400 manually annotated image patches (512×512) sourced from PERUSAT-1 satellite imagery. The method proposed utilizes a CNN based on the Deeplab v3+ architecture to facilitate automated cloud identification. Experimental results demonstrated impressive performance, achieving an accuracy of 96.62%, precision of 96.46%, specificity of 98.53%, and sensitivity of 96.72%. This technique surpassed existing approaches, showcasing its efficacy for processing large-scale satellite data[10].

The examination of cloud detection in satellite images is essential and has been approached using various methods. Deep learning algorithms are now a leading force in image analysis, with multiple studies confirming their success in identifying clouds. For example,[A2] investigates U-Net, SeU-Net++,ResNet variants, and DenseNet264 architectures[2], while[A3, A8, A9,A10] employs CNNs with specific implementations, including DenseNet161,ResNet152, Inception-V3, Xception, ResNet-50, VGG16, VGG19, and DeepLab V3[12, 9, 4, 10].

Table 1: Reviews of Cloud Detection Research Papers

Sr.no	Authors	Research Gaps/Motivation	Problem Statement	Techniques Used	Data Sets	Research Objectives	Results/Strength/Weaknesses
A1	Artur Miroszewski et al.[8]	Quantum-kernel SVMs in remote sensing remain under-explored.	Can quantum-kernel SVMs outperform classical SVMs in cloud detection?	Quantum Kernel SVMs, Kernel Target Alignment Optimization	Landsat-8 multispectral images	Compare QKSVMs with classical SVMs in cloud detection	Quantum ML works for cloud detection. Simulated models only.
A2	Preetpal Kaur Buttar, Manoj Kumar Sachan [2]	Clouds hinder the accurate analysis of land objects in satellite imagery.	Develop an algorithm to accurately segment clouds from satellite images.	SEUNet++, U-Net++, ResNet variants, DenseNet-264	Landsat 8, 95-Cloud	Propose deep learning-based cloud segmentation (SEUNet++)	91.8% IoU achieved, robust even with limited ground truth.

Sr.no	Authors	Research Gaps/Motivation	Problem Statement	Techniques Used	Data Sets	Research Objectives	Results/Strength/Weaknesses
A3	Mark Pritt, Gary Chern [12]	Existing DL models struggle with accuracy.	Boost classification accuracy using deep learning.	CNNs, DL architectures	Multispectral + Hyperspectral	Improve land cover mapping with DL models	Effective features, limited generalization across regions.
A4	Soronzonbold Otgonbaatar et al.[11]	Classical computing struggles with large EO data.	Enable scalable quantum processing for EO datasets.	PQC, Clifford+T gates, hybrid QC-HPC	Hyperspectral (e.g., EnMAP)	Estimate QC resources and hybrid strategies	High T-gate usage is impractical, insights into scaling.
A5	Syed Masiur Rahman et al. [13]	Quantum comms must be resilient to weather disruptions.	Enable robust CubeSat-drone quantum communication.	Entangled photon teleportation via drones	IBM Q simulator	Design CubeSat-drone quantum protocol	Weather-resilient QComms possible; early-stage feasibility.
A6	Artur Miroszewski et al. [7]	Quantum kernels for cloud detection are understudied.	Improve cloud detection using QKE and ZZ-feature maps.	Hybrid SVMs + Quantum Kernel Estimation	38-Cloud dataset (Landsat-8)	Design hybrid SVM for cloud detection	Comparable with classical SVMs; theoretical, simulated.

Sr.no	Authors	Research Gaps/Motivation	Problem Statement	Techniques Used	Data Sets	Research Objectives	Results/Strength/Weaknesses
A7	Jing Li, Xueping Luo [6]	Weather classification models lack accuracy.	Enhance classification via attention-based ViT.	Vision Transformer, Dual Attention Module	5-Class Weather Image Set	Develop high-accuracy, generalizable weather classifier	High F1 scores; dataset diversity limits generalization.
A8	Shweta Mittal, Om P. Sangwan [9]	Automate weather classification for scalable systems.	Weather classification using DNN with transfer learning.	Deep CNN (e.g., Inception V3)	5-Class Weather Dataset	Scalable cloud-based framework using Spark + TL	97.77% accuracy (Inception V3 + LR); dataset-specific.
A9	Bartosz Grabowski, Maciej Ziaja, Michal Kawulok [4]	The study aims to make cloud detection algorithms flexible and smooth for new satellite missions.	The paper tackles cloud detection using a fully data-driven AutoML approach.	Self-configuring nnU-Net	95-Cloud Dataset	The objective is to develop a fully automated cloud detection method for satellite images.	nnU-Nets deliver state-of-the-art cloud segmentation autonomously, but their large size may limit on-board satellite deployment.

Sr.no	**Authors**	**Research Gaps/Motivation**	**Problem Statement**	**Techniques Used**	**Data Sets**	**Research Objectives**	**Results/Strength/Weaknesses**
A10	Giorgio Morales, Alejandro Ramírez, Joel Telles [10]	Cloud detection across diverse geographies is tough.	Segment clouds in high-res multi-spectral imagery.	CNN, Deeplab v3+	CloudPeru2 dataset	CloudPeru2 release + end-to-end CNN segmentation	96.62% accuracy; some false positives at boundaries.

Additionally, [A7] leverages Vision transformers and dual attention models[6]. Concurrently, research into the use of quantum computing for image classification has been underway. Quantum Support Vector Machines(QSVMs) and quantum kernel methods have been introduced to tackle this classification challenge [A1][8], showcasing techniques like kernel target optimization and quantum feature map simulation. Researchers have also delved into hybrid quantum-classical methods, which include hybrid SVMs using quantum kernel estimation and ZZ-feature maps [A6][7], alongside studies of parameterized quantum circuits and resource estimation [A4][11]. Furthermore, research into quantum information processing—such as the use of drones and CubeSats to distribute and transfer entangled photons—highlights the expanding importance of quantum technology in remote sensing.

3 Methodology

3.1 Support Vector Machines: A Foundation for Classification

Backing SVMs are a popular and dependable class of supervised machine learning algorithms for binary classification problems[3]. In these cases, the main goal is to accurately classify data points, each described by unique attributes, into one of two separate classes, usually expressed as $\{-1, +1\}$[8]. Finding the best decision boundary in the feature space that efficiently divides the data points into different classes is what geometry says this means[3].

Finding the optimal hyperplane to maximise the margin while concurrently separating data points of distinct classes is the basic concept underlying support vector machines (SVMs). The margin for each class is the distance, measured perpendicularly, between the nearest data points and the hyperplane[3]. Enhancing this margin is crucial because it typically results in better generalisation performance, which enables the model to categorise fresh, unknown data more successfully.

3.1.1 Hard-Margin SVM: The Case of Linearly Separable Data

Examine a training dataset consisting of N data points, represented as $\{(v_i, z_i)\}_{i=1}^{N}$, where v_i represents the feature vector for the i-th data point and $z_i \in \{-1, +1\}$ indicates its corresponding class label[3]. When dealing with linearly separable datasets, a hard-margin SVM looks for a hyperplane that is defined by a normal vector w and an offset b so that every training data point satisfies the following requirement:

$$z_i(w \cdot v_i - b) \geq 1$$

All data points classified as positive ($z_i = +1$) are guaranteed to be on one side of the hyperplane ($w \cdot v_i - b \geq 1$) by this condition, while all data points classified as negative ($z_i = -1$) are guaranteed to be on the opposite side ($w \cdot v_i - b \leq -1$). The geometric margin of this separating hyperplane is written as$\frac{2}{||w||_2}$. The aim of hard margin SVM is to maximize the margin which is mathematically equivalent to minimizing the squared Euclidean norm of the weight vector, $\frac{1}{2}||w||_2^2$. This leads to a constrained optimization problem[8]:

$$\begin{aligned} \text{minimize} \quad & \frac{1}{2}||w||_2^2 \\ \text{subject to} \quad & z_i(w \cdot v_i - b) \geq 1, \quad i = 1, ..., N \end{aligned} \tag{1}$$

The resolution of this optimization issue shows that the ideal hyperplane is defined by a selection of training data points referred to as *support vectors*. These specific data points are those that are situated nearest to the hyperplane and fulfill the conditions $w \cdot v - b = 1$ or $w \cdot v - b = -1$. The function used to classify a new data point v with the hard-margin SVM is determined by the sign of the following function:

$$f(v) = \text{sgn}(w \cdot v - b)$$

Nonetheless, a notable drawback of the hard-margin SVM is its ineffectiveness in managing datasets that are not linearly separable, which is a frequent issue in practical scenarios such as cloud image classification.

3.1.2 Soft-Margin SVM: Addressing Non-Linear Separability

To tackle the challenges presented by non-linearly separable data in hard-margin SVMs, the concept of a *soft-margin SVM* is proposed[3]. This method loosens the rigid margin constraints by permitting certain data points to breach the optimal margin. This is accomplished by incorporating non-negative *slack variables* $\xi_i \geq 0$ for each data point v_i. The required condition now transforms into:

$$z_i(w \cdot v_i - b) \geq 1 - \xi_i$$

The slack variables ξ_i measure how much the i-th data point diverges from the perfect margin. An increased ξ_i signifies a larger infraction. The goal of the soft-margin SVM is not only to maximize the margin (achieve minimization of $\frac{1}{2}||w||_2^2$) but also to reduce the total of the slack variables, thereby penalizing misclassifications and those points within the margin. This balance is influenced by a non-negative *regularization parameter* $C \geq 0$ [3]. A smaller value of C emphasizes a wider margin, which might lead to more margin infringements, whereas a larger value of C imposes stricter penalties on violations, striving for fewer misclassifications. The optimization problem for the soft-margin SVM in its primal form is:

$$\begin{aligned} \text{minimize} \quad & \frac{1}{2}||w||_2^2 + C\sum_{i=1}^{N}\xi_i \\ \text{subject to} \quad & z_i(w \cdot v_i - b) \geq 1 - \xi_i, \\ & \xi_i \geq 0, \quad i = 1, ..., N \end{aligned} \tag{2}$$

This fundamental issue can be converted into its *dual form*, which is frequently easier to address and naturally gives rise to the concept of kernel functions:

$$\begin{aligned} \text{maximize} \quad & \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{N}\alpha_i\alpha_j z_i z_j \langle v_i, v_j\rangle \\ \text{subject to} \quad & \sum_{i=1}^{N} z_i\alpha_i = 0, \\ & 0 \leq \alpha_i \leq C, \quad i = 1, ..., N \end{aligned} \tag{3}$$

Here, α_i are the Lagrange multipliers associated with each data point. The solution to this dual problem yields the optimal values of α_i. The decision function for classifying a new data point v in the soft-margin SVM is then given by:

$$f(v) = \text{sgn}\left(\sum_{i=1}^{N} z_i\alpha_i\langle v, v_i\rangle + b\right)$$

Notice that the decision function relies on the *inner product* $\langle v, v_i\rangle$ between the new data point v and the training data points v_i. This observation is crucial for the introduction of kernel functions.

3.1.3 The Kernel Trick: Enabling Non-Linear Decision Boundaries

The true capabilities and flexibility of Support Vector Machines (SVMs) are revealed through the *kernel trick*. Understanding that the SVM formulation, in both the dual optimization problem and the decision function, relies only on the inner product of data points enables us to perform non-linear transformations of the input data into a higher-dimensional (potentially infinite-dimensional) *feature space* without needing to explicitly compute these transformations[3].

By selecting a *kernel function* $k(v_i, v_j)$ that corresponds to the inner product in this elevated-dimensional space, i.e., $k(v_i, v_j) = \langle \phi(v_i), \phi(v_j) \rangle$, where ϕ indicates the non-linear transformation, we can train an SVM that identifies a linear separating hyperplane within this higher-dimensional space. This linear hyperplane in the transformed space translates into a non-linear decision boundary in the original input space. The dual optimization problem becomes with the kernel trick:

$$\begin{aligned} \text{maximize} \quad & \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_j z_i z_j k(v_i, v_j) \\ \text{subject to} \quad & \sum_{i=1}^{N} z_i \alpha_i = 0, \\ & 0 \leq \alpha_i \leq C, \quad i = 1, ..., N \end{aligned} \tag{4}$$

And the decision function for a new data point v is:

$$f(v) = \text{sgn}\left(\sum_{i=1}^{N} z_i \alpha_i k(v, v_i) + b \right)$$

3.2 Classical Kernel Functions

Classical SVMs in this research utilize three fundamental kernel functions:

- **Linear Kernel:** The most basic kernel is characterized by the inner product of input feature vectors ($k(v_i, v_j) = v_i^T v_j$). Its goal is to identify a linear hyperplane that differentiates between classes. This kernel acts as a reference point and performs well when the data is naturally linearly separable or when working with high-dimensional datasets where linear models can yield unexpectedly good results[8]

- **Radial Basis Function (RBF) Kernel:** This is a commonly utilized non-linear kernel defined as $k(v_i, v_j) = \exp(-\gamma ||v_i - v_j||^2)$. The RBF kernel effectively maps input data into an infinite-dimensional space, facilitating the learning of intricate, non-linear decision boundaries. The parameter γ dictates the range of the kernel's impact[8].

These traditional kernels are widely recognized and have demonstrated success in different image classification applications. Their effectiveness frequently hinges on the unique features of the dataset and the precise adjustment of their hyperparameters.

3.3 Custom-Designed Quantum Kernel

Besides classical approaches, this study investigates the capabilities of quantum kernel methods by utilizing a specially designed quantum kernel[1, 5]. This kernel utilizes quantum computation principles to establish a feature map and then calculate the kernel values. The particular quantum kernel design applied in this research includes:

- **Angle Embedding:** The classical characteristics of the superpixels are translated into the rotation angles of the qubits, utilizing Y-axis rotations. This approach assigns each feature to a distinct quantum state[5].
- **Strongly Entangling Layers:** After the angle embedding, a series of strongly entangling gates is implemented. This layer of variational quantum circuits introduces controlled interactions (entanglement) among the qubits. The gate parameters are randomly initialized and remain unchanged during the kernel evaluation process. These layers are designed to establish intricate correlations within the quantum state, potentially resulting in a more comprehensive feature space[14].
- **Probability-Based Kernel Value:** The kernel value between two data points is determined by the overlap of their quantum states following the application of the feature map and entangling layers. Specifically, the kernel value is defined as the likelihood of measuring the all-zero state at the output of a quantum circuit that sequentially applies the feature map for one data point and the adjoint of the feature map for the other.

This tailored quantum kernel seeks to utilize the expansive Hilbert space available to quantum systems to possibly uncover complex patterns in cloud imagery data that classical kernels might struggle to detect with similar computational power. The efficiency of this quantum kernel is evaluated by adjusting the number of qubits in the quantum circuit, thereby altering the dimensionality of the quantum feature space. The findings are then contrasted with the results achieved using classical SVMs employing various kernel functions[1, 5].

4 About the dataset

4.1 Dataset

This study employs two separate datasets to tackle the dual goals of detecting clouds and classifying weather conditions using both satellite and ground-level images. Each dataset has a specific focus and presents distinct structural, formatting, and challenges that affect the preprocessing and modeling approaches adopted in this research.

The initial dataset is specifically assembled for cloud detection and consists of 38 images from Landsat 8 satellite scenes, paired with manually marked pixel-level ground truth masks[8]. These scenes have been divided into smaller segments of 384×384 pixels, which enhances their suitability for deep learning-focused semantic segmentation methods. The dataset offers a strong framework for evaluation since it is divided into a training set of 8,400 patches and a test set of 9,201 patches. There are four spectral bands on each patch: Near-Infrared (Band 5), Blue (Band 2), Green (Band 3), and Red (Band 4). Such spectral bands are stored independently in different directories rather than being combined into a typical RGB image [8]. Compared to standard RGB images, multispectral data provides more detailed information, which is in line with the particular needs of remote sensing tasks. With the use of convolutional neural networks or other pixel-wise classification techniques, the spatial resolution and band separation provide important insights into the properties of clouds and enable precise segmentation[12]. The ability to distinguish clouds from surface features

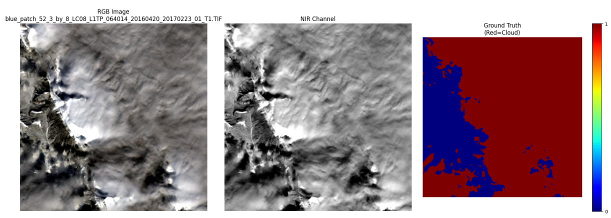

Figure 1: RGB image of cloud

like snow or bright sand, which commonly present difficulties for traditional RGB-based models, is also enhanced by the addition of Near-Infrared (NIR) data.

Five meteorological classes—sunny, cloudy, foggy, rainy, and snowy—are represented in the second dataset used for weather classification. This dataset contains a total of 18,039 images, with the distribution among classes being uneven: sunny (6,702), cloudy (6,274), foggy (1,261), rainy (1,927), and snowy (1,875). Such imbalance is a common challenge in real-world classification scenarios, which could influence the efficacy of models if not adequately managed through strategies like class weighting, oversampling, or data augmentation[9]. In contrast to the cloud detection dataset, the images in this collection come from a variety of sources, leading to different resolutions, although all images are at least 200×200 pixels[9]. In the preprocessing stage, systematic indexing and labelling are required because the filenames of the photographs do not follow a consistent naming pattern, despite the fact that the images are arranged into five distinct folders called after the various weather kinds. This dataset is a valuable reference point for evaluating classification algorithms in a variety of weather and lighting scenarios, mirroring actual circumstances found in transportation, climate monitoring, and outside surveillance systems. To sum

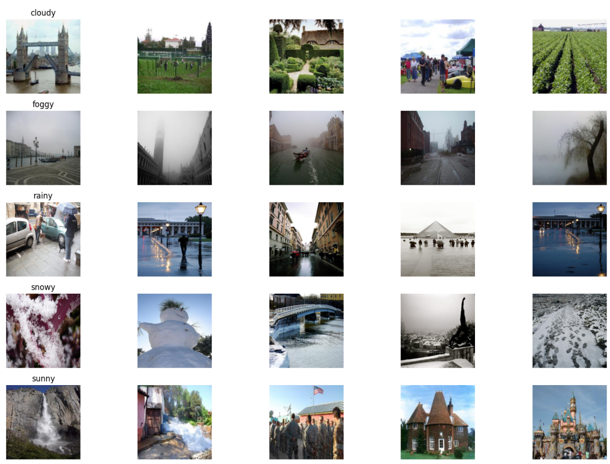

Figure 2: sample images from weather Dataset

up, both datasets provide important insights: RGB photos taken at ground level for in-depth weather state classification and multispectral satellite photography for accurate cloud detection. A more thorough understanding of meteorological events is made possible by the integration of different datasets, which also helps to build scalable and reliable machine learning models for environmental study.

5 Experimental Setup

5.1 Computational Environment

5.1.1 Hardware Configuration

Google Colab Pro was used in a cloud-based setting for all tests in order to guarantee consistent performance and take use of GPU acceleration.The specifications used were as follows:

- **CPU:** Intel Xeon @ 2.20GHz (2 cores)
- **RAM:** 25.51 GB
- **GPU:** NVIDIA Tesla P100 (16 GB VRAM)
- **Storage:** 166.8 GB (temporary runtime disk)

This setup provided sufficient resources to meet the computational demands of classical SVMs on large datasets and the simulation requirements for QSVM implementations.

5.1.2 Software Framework

The experiments used the following software stack to support classical machine learning and quantum computing simulations:

- **Operating System:** Ubuntu 18.04.6 LTS
- **Programming Language:** Python 3.10.12
- **Libraries and Dependencies:**
  - `JAX, JAXlib (v0.4.28)` – High-performance numerical computing
  - `PennyLane (v0.33.1)` – Quantum circuit simulation
  - `Scikit-learn (v1.2.2)` – Classical SVM and metrics
  - `NumPy (v1.25.2), Pandas (v1.5.3)` – Data handling
  - `Matplotlib (v3.7.1), Seaborn (v0.12.2)` – Visualization
  - `TensorFlow (vX.Y.Z)` – CNN feature extraction (via Keras API, e.g., ResNet50)

5.2 Cloud Detection Task

5.2.1 Data & Feature Engineering

Dataset: The dataset comprises multispectral satellite imagery, including the Red, Green, Blue, and Near-Infrared (NIR) bands, along with corresponding ground truth cloud masks. A total of 50 images were used to generate the training and testing datasets.

Preprocessing:

- Each spectral band is scaled using percentile-based normalization.
- RGB channels are merged and converted to the LAB color space.
- The `skimage.segmentation.slic` algorithm is applied to the LAB image to segment it into superpixels.

Feature Extraction: For each superpixel, the average intensity values of the Red, Green, Blue, and NIR channels are computed. A binary cloud label is assigned depending on whether the mean value of the ground truth within that segment exceeds 0.5.

5.2.2 Model Architectures

Classical SVM: A custom Support Vector Machine implementation is used, supporting both linear and RBF kernels. The model is trained using a simplified Sequential Minimal Optimization (SMO) algorithm with a regularization parameter $C = 1.0$.

Quantum SVM (QSVM): Implemented using PennyLane's `default.qubit` simulator with 12 qubits.

- **Feature Embedding:** Each qubit undergoes a Hadamard gate, followed by RY and RZ rotations parameterized by feature vectors.
- **Entanglement:** Consecutive CNOT gates are applied between neighboring qubits.
- **Kernel Computation:** The quantum kernel is computed from the output state probability distributions.

- **Optimization:** Kernel-based SVM trained using SMO with $C = 1.0$.

5.2.3 Data Handling

- The superpixel dataset is split into training (80%) and testing (20%) subsets using stratified sampling.
- For QSVM:
  - StandardScaler is applied.
  - Features are zero-padded and reduced to 12 dimensions using PCA.

5.2.4 Training & Comparison Protocol

- Models are evaluated across sample sizes: 20, 40, 80, 160, and 320.
- **Class Imbalance:** SMOTE is applied to each training subset.
- All three models—Linear SVM, RBF SVM, and QSVM—are trained and tested on identically prepared subsets.
- Final models (from the 320-sample set) are saved using `joblib`, including the scaler and PCA pipeline for QSVM.

5.2.5 Prediction on New RGB Images

- Trained models can be reloaded to perform inference on unseen RGB-only images.
- **NIR Estimation:** For RGB-only inputs, the NIR channel is estimated as:

$$\mathrm{NIR}_{\mathrm{estimated}} = 0.85 \times R + 0.12 \times G + 0.03 \times B$$

- Superpixel segmentation and feature extraction are applied to these new images.
- The extracted features are passed to the trained model for prediction.
- Predicted cloud probabilities are thresholded (default: 0.7) to generate a cloud mask.

5.3 Weather Classification Task

5.3.1 Objective

The objective is to classify weather or scene images into five categories (e.g., *cloudy*, *sunny*) using Classical SVMs and QSVM. The aim is to assess the viability of quantum kernel methods for multiclass image classification.

5.3.2 Data Preprocessing

- **Data:** A dataset of weather and scene images is employed, featuring up to 500 images for each category. Each image is resized to 64×64 pixels, with pixel values normalized to fall within the [0, 1] range.
- **Splitting:** The dataset is split into 80% for training and 20% for testing, using stratified sampling to preserve the proportions of each class.
- **Balancing & Scaling:** The training set addresses class imbalance by utilizing SMOTE. Following this, features are standardized with `StandardScaler`. It is assumed that scaling occurs after an initial feature extraction phase, such as using a CNN like `ResNet50`, in line with the original programming context.

5.3.3 Feature handling

- Classical SVM: Trained using scaled feature vectors, derived before any PCA reduction.
- QSVM: Trained on the features derived after applying PCA to the scaled vectors, preserving 95% of the variance, which usually leads to approximately 12 dimensions appropriate for the quantum circuit.

5.3.4 Model Architectures

Classical SVMs:

- **Framework:** Utilized `sklearn.SVC` for implementation.
- **Kernels:** Both standard `linear` and `RBF` kernels have been evaluated.

- **Tuning:** Hyperparameters (`C` for both and `gamma` for the RBF) are fine-tuned using `GridSearchCV` on the training dataset.

Quantum SVM (QSVM):

- **Framework:** Developed using `Pennylane` to create a custom quantum kernel.
- **Circuit:** Utilizes an `AngleEmbedding` feature map followed by a `StronglyEntanglingLayers` variational circuit, implemented on 12 qubits.
- **Kernel Method:** The kernel matrix is calculated in advance based on the outputs of the quantum circuit and is subsequently employed in `sklearn.SVC` with `kernel='precomputed'`.
- **Multiclass:** Managed using the `OneVsRestClassifier` wrapper around the QSVM.
- **Constraint:** The training for QSVM is restricted to a maximum of 100 samples due to the high computational cost associated with calculating the quantum kernel matrix.

5.3.5 Experiment Design

- Sample sizes: 50, 100, 200, and 300 images (from training set).
- Evaluation metrics:
  - Accuracy
  - F1-score (macro average)
  - Training and prediction time
- Best models (on largest set) are used for sample test image predictions.

A Cloud Detection Code

In this appendix, we provide the code PDF used in this research.

Click here to view the Code PDF

B weather classification code

Click here to view the Code PDF

7 Results

7.1 Cloud Data

The effectiveness of various models (Linear SVM, RBF SVM, and Quantum SVM) was assessed at different sample sizes. Table X provides a summary of the accuracy achieved by each model across these sample sizes. It is clear from the table that the RBF SVM consistently surpasses both the Linear SVM and Quantum SVM, particularly at larger sample sizes. The RBF SVM model achieved its highest accuracy of 92.81% with a sample size of 160.

On the other hand, the Quantum SVM exhibited lower accuracy, showing a significant drop as the sample size increased. This decline may be attributed to the complexities involved in simulating quantum kernels.

Table 2: Accuracy Comparison of Linear SVM, RBF SVM, and QSVM(12 Qubits) at Different Sample Sizes of cloud data

Sample Size	**Linear SVM Accuracy**	**RBF SVM Accuracy**	**QSVM Accuracy**
20	0.875000	0.925000	0.925000
40	0.912500	0.912500	0.912500
60	0.916667	0.925000	0.883333
80	0.918750	0.925000	0.887500
160	0.918750	0.928125	0.875000
320	0.917188	0.923438	0.859375

Figure 3: Predicted cloud classification using RBF SVM. The predicted cloud coverage is 86.6%, exceeding the threshold of 0.7, and the image is classified as cloudy.

Figure 4 displays a comparison of the performance accuracy of various models (Linear SVM, RBF SVM, and QSVM) at different sample sizes. As illustrated in the graph, the RBF SVM consistently achieves better results than both Linear SVM and QSVM, especially with larger sample sizes.

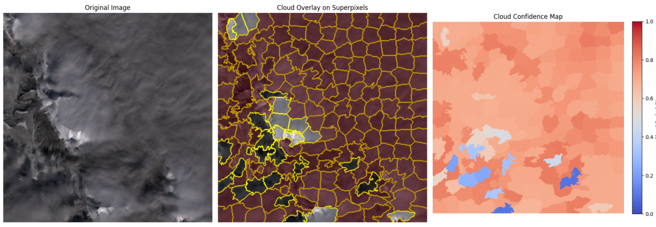

Figure 3: shows an example prediction using the RBF SVM model for detecting cloud.

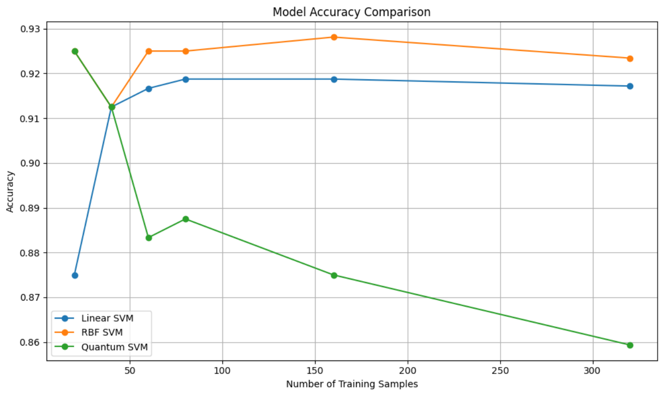

Figure 4: Accuracy comparison between RBF, Linear and Quantum svm for cloud data

7.2 Weatherdata

In the weather classification task, the RBF SVM proved to be the most effective model. It reached an accuracy of 61.6% with a sample size of 100. This indicates that the RBF kernel is adept at managing the variability and intricacies of weather image data, surpassing both Linear SVM and Quantum SVM in this area as well.

Table 3: Accuracy Comparison of Linear SVM, RBF SVM, and QSVM(12 Qubits) at Different Sample Sizes of weather data

Sample Size	Linear SVM Accuracy	RBF SVM Accuracy	QSVM Accuracy
50	0.574	0.606	0.184
100	0.588	0.616	0.190
200	0.568	0.604	0.20
300	0.58	0.59	0.19

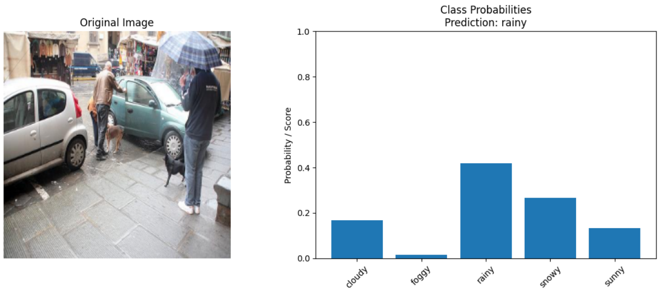

Figure 5: shows an example prediction using the RBF SVM model for classifying weather.

Although its accuracy is somewhat lower than that of cloud data, the model successfully differentiated weather conditions to a satisfactory degree, as indicated by the classification results presented below.
Figure 6 shows a comparison of the performance accuracy among the various models (Linear SVM, RBF SVM, and QSVM) at different sample sizes.The graph shows that the RBF SVM routinely outperforms the QSVM and Linear SVM.

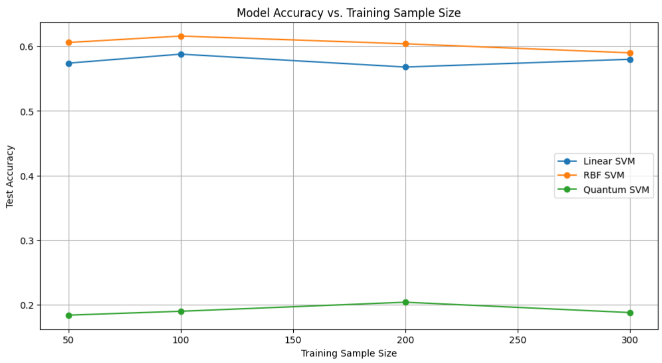

Figure 6: Accuracy comparison between RBF, Linear and Quantum svm

Conclusion

The following are the conclusions for each section:

Cloud Classification with SVM and QSVM

The significance of precisely identifying cloud patterns from satellite imagery has been underlined in this work because it is essential for climate research, environmental monitoring, and weather forecasting. Several machine learning techniques, including **Linear SVM**, **RBF SVM**, and **Quantum SVM (QSVM with 12 qubits)**, were used to complete the classification task. The **RBF SVM** continuously produced the best results, reaching a maximum accuracy of **92.81%**, on a cloud dataset with varying sample sizes. Visualising the model's performance was also made easier by the anticipated cloud coverage image. Despite its promise, QSVM's performance declined with larger datasets, suggesting that more optimisation is required.

Weather Classification with SVM and QSVM

As precise weather forecasting is essential for daily planning, disaster relief, and agriculture, this section of the study sought to categorise weather types using satellite imagery. A weather image dataset was utilized with sample sizes ranging from 50 to 300. Models like **Linear SVM**, **RBF SVM**, and **QSVM** were applied, where again, **RBF SVM** outperformed others, achieving an accuracy of **61.6%** at a sample size of 100. The QSVM model struggled in this task with lower accuracy, showing that classical models are currently more effective for such classification tasks.

I hope that my thesis work can contribute to future research in satellite image analysis, particularly in cloud and weather classification using both classical and quantum machine learning methods. The results and visuals presented can aid in developing more accurate and efficient models in this domain.

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