APPLICATION OF QUANTUM ARTIFICIAL INTELLIGENCE FOR AIRPORT POTENTIAL ANALYSIS AND AEROTROPOLIS DEVELOPMENT

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ABSTRACT

The development of aerotropolises—a strategic urban model where airports serve as economic hubs—requires analyzing multiple interdependent factors, including infrastructure, connectivity, regulations, investments, and regional economic dynamics. These datasets often contain hundreds of variables with nonlinear relationships that traditional methods struggle to capture, risking oversimplified feasibility assessments, especially for predictive modeling. Data Envelopment Analysis (DEA) remains essential for benchmarking efficiency, offering insights into current performance. In this study, DEA provided efficiency benchmarks; however, its static nature limits multidimensional evaluations, reinforcing the need for advanced approaches capable of handling high-dimensional data and uncovering complex patterns.

This research investigates Quantum Artificial Intelligence (QAI) as a disruptive method for aerotropolis potential assessment. By combining AI's pattern-recognition capabilities with quantum computing's parallelism, QAI can manage large-scale, multidimensional airport datasets. As a proof of concept, we implemented a Quantum Support Vector Machine (QSVM) and compared it to a classical SVM using DEA-based data from Brazilian airports. Although the dataset was intentionally small, results indicate that the quantum kernel offers a more discriminative representation, confirmed by structural metrics such as silhouette score and kernel alignment, despite similar accuracy.

The proposed framework demonstrates QAI's potential to enhance aerotropolis planning through robust analytical tools for multi-criteria decision-making and investment prioritization under uncertainty. Leveraging QAI allows stakeholders to simulate scenarios—such as infrastructure upgrades or regulatory incentives—and predict impacts on feasibility, improving strategic airport development and fostering competitiveness in air transport networks.

Keywords: Aerotropolis Planning, Airport Performance Analysis, High-Dimensional Data, Artificial Intelligence, Quantum Machine Learning.

GENERATIVE AI USAGE STATEMENT

The authors declare that the use of generative AI tools was limited to technical support activities, without compromising the originality, analysis, or conclusions presented in the work. All information obtained through these tools was carefully evaluated and integrated into the study, ensuring methodological rigor and academic integrity. The tool *ChatGPT by OpenAI* was used to assist in text review.

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1 INTRODUCTION

Air transport plays a pivotal role in global trade and economic integration, enabling rapid flows of goods, services, and people. Although air cargo represents less than 1% of trade by volume, it accounts for about 35% of trade value, underscoring its economic leverage Association (2023). Airports have evolved beyond transportation hubs into complex ecosystems that support logistics, technology, and governance frameworks, positioning them as anchors of regional competitiveness and integration into global supply chains Zhang e Graham (2020); Kasarda e Lindsay (2011); Freestone (2009). Their strategic importance now encompasses sustainability and resilience in modern transport networks Huo e Guo (2021); Chang e Hsu (2025).

This transformation aligns with forecasts projecting 10 billion annual passengers by 2050 and a tripling of air cargo volumes Organization (2024). Such growth pressures operators to adopt strategic planning beyond operational benchmarks, integrating socio-economic and environmental objectives. The aerotropolis concept, proposed by Kasarda Kasarda e Lindsay (2011), frames airports as nuclei for industrial clusters, logistics, and real estate development, creating multifunctional ecosystems Freestone (2009); Zhang e Graham (2020). Global examples include Incheon, Zhengzhou, and Taoyuan, which demonstrate adaptability across economic and regulatory contexts Yoo et al. (2022); Huo e Guo (2021); Chang e Hsu (2025). However, challenges remain regarding governance, sustainability, and equitable distribution of benefits Freestone (2009).

Evaluating aerotropolis feasibility requires multidimensional analysis of infrastructure, connectivity, land use, and governance Freestone (2009); Dožić (2019). Classical approaches such as Multi-Criteria Decision Analysis (MCDA) assist in balancing economic, social, and environmental factors but face scalability limits with high-dimensional datasets Dožić (2019). Data Envelopment Analysis (DEA), widely applied for benchmarking airport efficiency, offers valuable descriptive insights Banker et al. (1984); Cooper et al. (2007); Rocha et al. (2022). Yet, its static and deterministic assumptions limit scenario modeling and nonlinear interactions Organization (2009). Advanced computational frameworks are necessary to address these gaps.

AI techniques have improved decision support in transportation, with models such as Support Vector Machines (SVM) achieving robust performance in classification tasks Sadou e Njoya (2023); Cortes e Vapnik (1995). However, classical models struggle with the scalability and complexity of aerotropolis planning. Quantum Artificial Intelligence (QAI) leverages quantum feature maps to enhance data representation and discriminative power, offering promising solutions for high-dimensional problems Schuld e Killoran (2019); Havlíček et al. (2019). Quantum Support Vector Machines (QSVM) exemplify this approach.

This study explores the use of QAI to assess aerotropolis development potential through a proof-of-concept application of QSVM. Using DEA-based efficiency benchmarks from Rocha (2020), we compare QSVM to classical SVM via structural metrics, such as silhouette score, Fisher Discriminant Ratio, and Kernel Alignment, to evaluate whether quantum kernels provide superior feature separability and decision-making support for airport-driven regional planning.

2 METHODOLOGY

2.1 Dataset, Benchmarking, and Experimental Setup

The dataset originates from DEA-based efficiency evaluations of Brazilian airports described in Rocha (2020). Scenario 2 results—considering airport scale, passenger flow, and cargo throughput—provided the efficiency scores used as classification targets to distinguish airports with higher aerotropolis potential from those requiring improvement. DEA, widely applied in aerotropolis-related performance benchmarking, is a non-parametric method for assessing relative efficiency across multiple inputs and outputs Banker et al. (1984); Cooper et al. (2007). It defines a frontier of best practices and identifies performance gaps but lacks predictive capability and cannot capture nonlinear dependencies critical in complex systems influenced by infrastructure, regulations, and environmental constraints Dožić (2019).

To overcome these limitations, DEA-derived scores were integrated into a supervised learning pipeline for AI and Quantum AI models. Scores were converted into a binary target: airports with efficiency 90% labeled as *efficient* (Class 1) and others as *non-efficient* (Class 0), following standard DEA interpretations. Features were normalized to the $[0, 1]$ range using Min-Max scaling to ensure compatibility with kernel-based models. Data were split into training (70%) and testing (30%) sets using stratified sampling to preserve class balance.

Two models were implemented: a classical Support Vector Machine (SVM) with an RBF kernel—widely used for nonlinear classification due to its ability to project data into high-dimensional spaces Cortes e Vapnik (1995)—and a Quantum Support Vector Machine (QSVM), which embeds input data into a Hilbert space via quantum feature maps and entanglement-based transformations, leveraging Qiskit Machine Learning Schuld e Killoran (2019); Havlíček et al. (2019). QSVM employed the *ZZFeatureMap* with $n = 7$ qubits, `reps`=2, and linear entanglement.

Experiments were executed in Python, using `scikit-learn` for SVM and `Qiskit Machine Learning` for QSVM, running on the `AerSimulator` backend to ensure noise-free conditions. The environment included Python 3.10, scikit-learn 1.3.0, qiskit 0.45.0, and qiskit-machine-learning 0.5.0. Model performance was evaluated using accuracy and structural metrics, including Silhouette Score, Fisher Discriminant Ratio, and Kernel Alignment, to assess differences in feature space geometry.

2.2 Modeling Approach

Support Vector Machine (SVM) is a supervised algorithm for classification and regression that identifies an optimal separating hyperplane in feature space Cortes e Vapnik (1995). It maximizes the margin—the distance between the hyperplane and nearest class points (support vectors)—to improve generalization and reduce overfitting. Formally, it minimizes $|w|^2$ subject to $y_i(w \cdot x_i + b) \geq 1$, where w and b define the hyperplane.

Most datasets are not linearly separable in input space. To address this, SVM employs kernel functions through the *kernel trick*, mapping data into higher-dimensional spaces without explicit transformation. Among various kernels, the Radial Basis Function (RBF) is widely used for nonlinear classification, computing similarity based on Euclidean distance:

$$K(x_i, x_j) = \exp(-\gamma |x_i - x_j|^2), \quad (1)$$

where γ controls the influence of training examples Smola e Schölkopf (2004). The RBF kernel is effective for small and medium datasets with nonlinear boundaries, as in this study. While classical kernels model complex decision boundaries, their representational capacity is limited by classical computation, motivating quantum kernels for richer feature mappings, as discussed next.

Quantum Support Vector Machines (QSVM) extend the classical SVM by exploiting quantum computing principles to define kernels in exponentially large Hilbert spaces Havlíček et al. (2019). Rather than using a classical kernel function, QSVM evaluates the similarity between quantum states representing input samples. Each sample is embedded into a quantum state via a parameterized circuit called a *feature map*, which applies rotations and entanglement gates to create correlations that are classically intractable.

QSVM's main advantage lies in the richer feature representations enabled by quantum state spaces, which can capture complex correlations. Studies show QSVM can outperform classical SVM in scenarios involving structured, high-dimensional data, even on noisy intermediate-scale quantum (NISQ) devices Schuld e Killoran (2019).

This study adopted the *ZZFeatureMap*, a widely used embedding strategy for QSVM due to its ability to encode pairwise correlations through entanglement Havlíček et al. (2019). The map comprises: (i) Hadamard gates for initial superposition, (ii) $R_z(\phi)$ rotations encoding classical features as phase shifts, and (iii) a CNOT-based entanglement layer in linear topology. With $n = 7$ qubits (matching feature dimensionality) and $\texttt{reps} = 2$, the circuit introduces alternating encoding and entanglement layers, producing 21 rotation and 14 CNOT gates—balancing expressivity and computational feasibility for NISQ constraints.

The quantum kernel evaluates similarity as:

$$k(\mathbf{x}, \mathbf{x}') = |\langle \psi(\mathbf{x}) | \psi(\mathbf{x}') \rangle|^2, \tag{2}$$

where $|\psi(\mathbf{x})\rangle$ is the quantum state of input $\mathbf{x}$. This kernel substitutes classical functions (e.g., RBF) in the SVM dual formulation, while optimization remains classical. By leveraging quantum feature maps that induce complex geometries in feature space, QSVM aims to enhance class separability when classical kernels fail to generalize.

3 RESULTS AND ANALYSIS

3.1 Classical SVM Performance

The classical SVM achieved 100% accuracy on the test set, mainly due to the dataset's small size and clear class separation after normalization. The binary classes, derived from DEA scores using a 90% threshold, created well-distinguished groups in feature space. Such results are typical in controlled scenarios with high inter-class variability and limited complexity, reinforcing that this experiment serves as a proof of concept rather than a test of generalization. In real-world conditions with noise, overlapping distributions, and higher dimensionality, performance would likely decline, requiring more advanced kernels and tuning.

To visualize decision boundaries, the dataset was projected into two dimensions using Principal Component Analysis (PCA), which preserves maximum variance in orthogonal components without influencing model training. Figure 1 displays the decision regions and sample distribution induced by the RBF kernel.

The two-dimensional visualization presented in Figure 1 was generated using Principal Component Analysis (PCA), which projects the original feature space — composed of seven variables related to airport operational and economic metrics (*Num_ Companies*, *Area_ m2*,

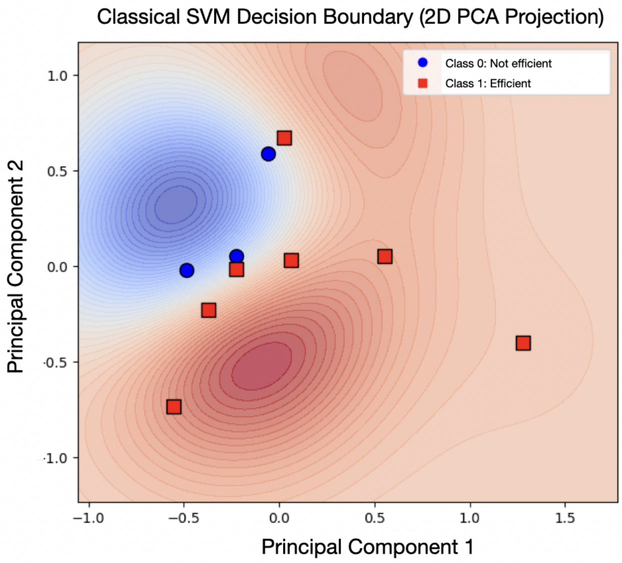

Figure 1: Decision regions of the classical SVM with RBF kernel after PCA projection. The axes indicate the two principal components and their explained variance.

Passengers, *Revenue_NA*, *Horizon*, *Port_Distance_km*, and *Urban_Index*) — onto two orthogonal components that capture the highest variance in the dataset.

This projection does not correspond to individual variables but rather to linear combinations of all original features, ensuring maximum information retention in a reduced-dimensional space. Specifically, the first principal component (PC1) accounts for the greatest share of total variance, while the second principal component (PC2) captures the second-highest variance contribution, maintaining orthogonality to PC1.

The resulting plane facilitates graphical representation of the classifier's decision regions and class distribution, which would otherwise be unfeasible in the original seven-dimensional space. It is important to emphasize that PCA was employed solely for visualization purposes and had no influence on model training or prediction processes.

3.2 QSVM Performance and Kernel Analysis

The QSVM, implemented with 7 qubits and a two-repetition *ZZFeatureMap*, achieved 100% accuracy, matching the classical SVM. While this reflects the dataset's simplicity, accuracy alone does not capture differences in feature representation. Kernel analysis (Figures 2 and 3) reveals clear structural contrasts between the RBF and quantum kernels.

The classical RBF kernel shows smooth similarity gradients, typical of distance-based mappings, resulting in moderate overlap between classes. Conversely, the quantum kernel exhibits strong polarization, concentrating similarities near 0 or 1. This behavior, induced by nonlinear embeddings with entanglement and R_z rotations, expands the Hilbert-space dimensionality, reducing inter-class correlations and enhancing separability.

Structural metrics confirm these patterns: Silhouette score, Fisher Discriminant Ratio, and Kernel Alignment were consistently higher for the quantum kernel, indicating superior discriminative geometry despite equal accuracy. These properties are critical for high-dimensional, multi-criteria datasets—common in aerotropolis planning—where classical kernels struggle to capture nonlinear dependencies.

Figure 2 presents Gram matrices for both kernels, while Figure 3 shows the distribution of pairwise similarities. The RBF kernel maintains values mostly between 0.3–0.8, whereas the quantum kernel concentrates near zero, pushing samples from different classes toward quasi-orthogonal states. Such decorrelation without additional feature engineering is a strategic advantage for robust decision-making under uncertainty.

Although QSVM incurs higher computational cost under classical simulation, these geometric benefits suggest strong potential for future scenario modeling and sensitivity analysis as quantum hardware matures.

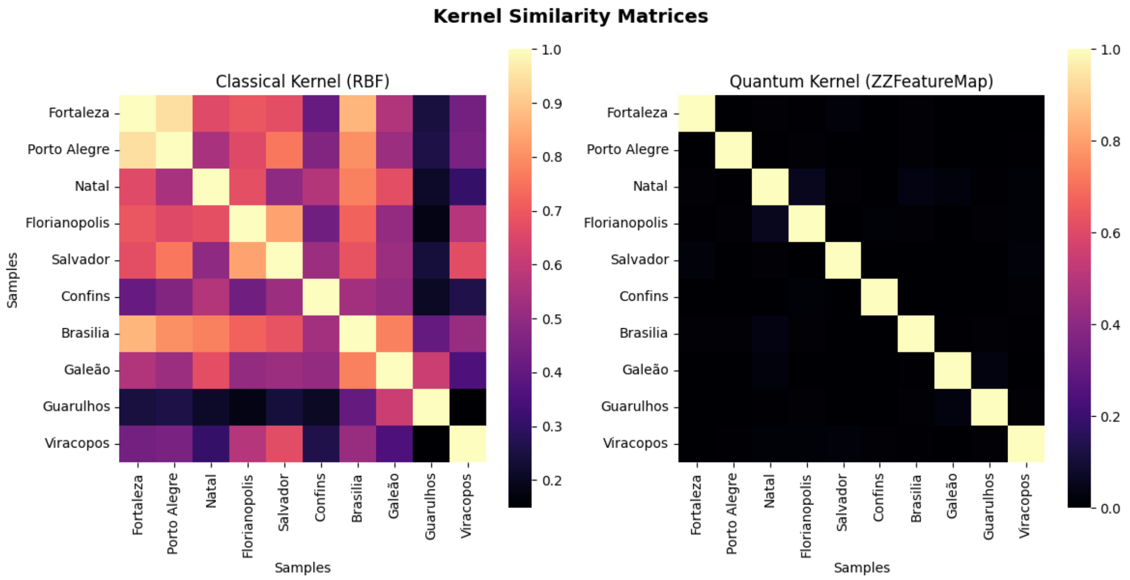

Figure 2: Kernel similarity matrices: (a) Classical RBF kernel; (b) Quantum kernel with ZZFeatureMap (2 repetitions, linear entanglement).

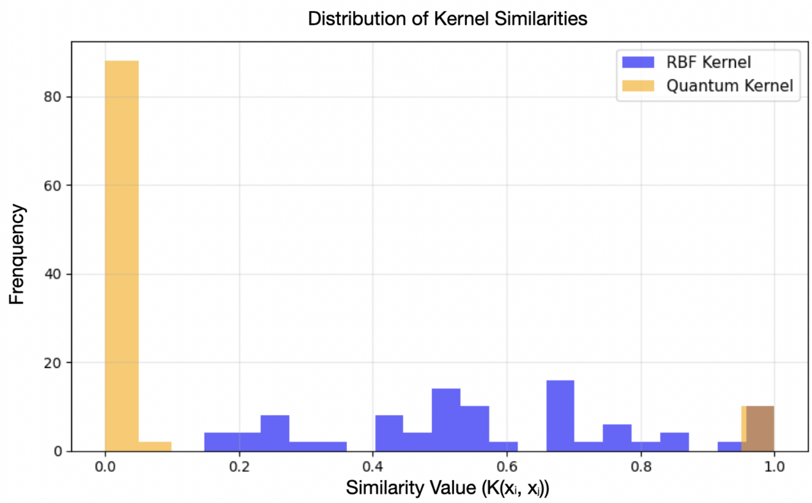

Figure 3: Distribution of pairwise similarities: RBF vs. quantum kernel. The quantum kernel shows stronger polarization, concentrating most values near zero, indicating higher inter-class separability.

3.3 Metric Analysis

Table 1 presents the key metrics for both models: Accuracy, runtime (Training and Inference), and structural indicators (Silhouette Score, Fisher Discriminant Ratio—FDR, and Kernel Alignment—KA). All executions used a CPU backend for both classical and simulated quantum approaches.

Table 1: Comparison of SVM and QSVM: Accuracy, Runtime, and Structural Metrics

Metric	**SVM (RBF)**	**QSVM (ZZFeatureMap)**
Accuracy (%)	100.00	100.00
Training Time (s)	0.0023	0.4540
Inference Time (s)	0.0004	0.7217
Silhouette	-0.0703	0.1949
FDR	0.1524	0.2701
Kernel Alignment	0.1806	0.3164

Both models achieved perfect accuracy, which reflects the dataset's simplicity rather than algorithmic superiority. In real-world contexts with higher dimensionality, noise, and overlapping distributions, differences are expected, likely favoring quantum kernels for their ability to encode nonlinear correlations.

Regarding computational cost, classical SVM was far faster, while QSVM incurred higher overhead due to repeated quantum kernel evaluations and circuit simulation. This gap is expected under current NISQ-era constraints but should decrease with future quantum hardware, enabling QSVM to outperform classical models on large-scale, highly correlated datasets.

Beyond accuracy, structural metrics reveal critical distinctions in feature space geometry. Silhouette score was negative for the RBF kernel (-0.0703), indicating class overlap, while the quantum kernel achieved a positive value (0.1949), suggesting better separability. Likewise, FDR and Kernel Alignment were substantially higher for QSVM, reflecting superior discriminative structure.

These findings confirm that, even under identical accuracy, the quantum kernel organizes data more effectively in high-dimensional Hilbert space. This structural advantage supports its applicability for complex planning tasks such as aerotropolis feasibility analysis, where interactions among multiple criteria dominate.

3.4 Discussion

The results highlight three main contrasts between classical SVM and its quantum-enhanced variant. First, both models reached 100% accuracy on the test set, an outcome explained by the dataset's small size and clear class separation due to the DEA threshold. However, such parity does not generalize to real-world problems, where feature spaces are more complex and interdependent.

Second, the QSVM incurred substantially higher computational cost, with training and inference times nearly two orders of magnitude greater. This overhead stems from repeated quantum kernel evaluations and circuit simulations on classical hardware—a limitation typical of the current NISQ era rather than an inherent drawback of quantum approaches.

Third, structural metrics (Silhouette, FDR, and Kernel Alignment) and similarity distribution analyses revealed a key advantage of quantum kernels: superior feature space separability. The quasi-orthogonality observed in quantum embeddings suggests enhanced robustness for scenarios involving nonlinear interactions, noise, and multi-criteria decision boundaries—conditions common in high-dimensional datasets where classical kernels often struggle.

A limitation of the current proof-of-concept is the reliance on a single train-test split without hyperparameter optimization. Future work should include systematic cross-validation and parameter tuning to ensure robustness of the observed structural gains, especially when extending the framework to larger datasets.

Overall, these findings confirm that the value of quantum-enhanced models lies not in short-term accuracy gains but in reshaping the geometry of decision spaces for complex tasks. While runtime inefficiency persists under simulation, the theoretical benefits demonstrated here position QSVM as a promising tool for future decision-support systems. The next section connects these insights to aerotropolis feasibility analysis and discusses practical directions for applying quantum machine learning in planning.

4 CONCLUSION

This study presented a proof-of-concept evaluation of Quantum Support Vector Machines (QSVM) for airport performance analysis using DEA-based efficiency data. Both QSVM and classical SVM achieved perfect accuracy due to the dataset's simplicity, but structural metrics revealed that quantum kernels provide superior class separability, suggesting benefits for complex, high-dimensional scenarios.

Implications for Aerotropolis Planning: Aerotropolis development involves multiple interdependent variables that traditional tools like DEA handle only statically. Quantum kernels, by embedding data into large Hilbert spaces, offer enhanced modeling of nonlinear dependencies and uncertainty. The observed geometric advantages indicate QSVM's potential to support scenario analysis and multi-criteria decision-making in airport planning.

Practical Outlook: Current QSVM runtimes are high under classical simulation, reflecting NISQ-era limitations rather than fundamental scalability issues. With advancing quantum hardware, such methods could enable real-time evaluation of intricate planning scenarios, improving strategic decision-making for infrastructure development.

Future Research: Scaling experiments to larger datasets, integrating temporal dimensions, and testing on real quantum hardware are crucial next steps. Hybrid strategies combining QSVM with multi-criteria frameworks should also be explored to operationalize quantum models in aerotropolis feasibility assessments.

In short, while immediate gains over classical models are not evident for small datasets, this study demonstrates that quantum kernels introduce structural properties that could reshape analytical frameworks for complex airport planning challenges.

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Carta de Resposta aos Revisores

Título do artigo: *Quantum Support Vector Machines for Aerotropolis Analysis: A Proof-of-Concept Study*

1. Dataset size and lack of cross-validation

Comentário do revisor:
A análise é limitada pelo pequeno tamanho da amostra e pelo uso de apenas uma divisão treino/teste, sem validação cruzada nem ajuste sistemático de hiperparâmetros, dificultando confirmar a robustez dos resultados.

Resposta:
Concordamos com essa observação. O caráter de *proof-of-concept* (PoC) do estudo de fato se baseia em um conjunto reduzido, derivado de escores de eficiência DEA de publicação anterior. E a PoC aqui abordada trata de fase atual das nossas pesquisas que ainda continuam avançando para um espectro maior de dados e discussões em um futuro próximo, exigindo no momento esta prova de conceito que já provê discussões densas e comprovativas como expomos aqui. Contudo, essa limitação foi explicitamente reconhecida no manuscrito:

- **Section 3.1 — Classical SVM Performance**:

"The classical SVM achieved 100% accuracy on the test set, mainly due to the dataset's small size and clear class separation after normalization. The binary classes, derived from DEA scores using a 90% threshold, created well-distinguished groups in feature space. Such results are typical in controlled scenarios with high inter-class variability and limited complexity, reinforcing that this experiment serves as a proof of concept rather than a test of generalization."

- **Section 3.4 — Discussion**:

"First, both models reached 100% accuracy on the test set, an outcome explained by the dataset's small size and clear class separation due to the DEA threshold."

Na versão revisada do manuscrito acrescentamos ao final da *Discussion* uma frase esclarecendo que futuros trabalhos incluirão validação cruzada sistemática e ajuste de hiperparâmetros para testar robustez em bases maiores, que inclusive é fase conseguinte do projeto de nosso time.

2. Computational cost of QSVM

Comentário do revisor:
O QSVM apresenta custo computacional significativamente maior sob as restrições de simulação.

Resposta:
Esse ponto já foi enfatizado no texto:

- **Section 3.4 — Discussion**:

"Second, the QSVM incurred substantially higher computational cost, with training and inference times nearly two orders of magnitude greater. This overhead stems from repeated quantum kernel evaluations and circuit simulations on classical hardware—a limitation typical of the current NISQ era rather than an inherent drawback of quantum approaches."

Portanto, acreditamos que o manuscrito aborda diretamente a crítica, ao enquadrar o custo elevado como uma limitação dos simuladores atuais e não do paradigma quântico em si, tratando-se apenas de fase contemporânea da tecnologia, mas que não invalida a prova de conceito discutida aqui.

3. Evidence of nonlinearities and kernel justification

Comentário do revisor:
Seria valioso mostrar, por meio de análise exploratória ou testes de separabilidade, que as variáveis de fato apresentam não linearidades que justifiquem o uso de kernels quânticos.

Resposta:
Esse ponto foi parcialmente contemplado em:

- **Section 3.2 — QSVM Performance and Quantum Kernel Behavior**:

"The quantum kernel matrix reveals a more polarized distribution of similarities, with clusters of values concentrated near 0 and 1. This effect results from the nonlinear feature embedding performed by the quantum feature map, which leverages entanglement and parameterized rotations to encode pairwise correlations."

Na versão revisada incluímos uma frase adicional explicitando que esses padrões refletem a presença de interações não lineares entre as variáveis, reforçando a justificativa para o uso de kernels (e especialmente kernels quânticos). Também indicamos como trabalho futuro a realização de testes formais de separabilidade e análises exploratórias mais detalhadas.

4. Formatting and template adherence

Comentário do revisor:
Alguns ajustes de formatação são necessários para alinhamento completo com o template do evento.

Resposta:
Revisamos cuidadosamente o manuscrito para garantir conformidade com o template SITRAER, incluindo:

- Melhoria dos textos e legendas das figuras, tornando-as mais descritivas;
- Conferência e padronização das referências de acordo com o estilo requerido.

Considerações finais

Agradecemos aos revisores pelos comentários criteriosos. Com as revisões realizadas, acreditamos que o manuscrito agora apresenta com maior clareza as limitações e direções futuras, mantendo o foco na contribuição principal: demonstrar, de forma inovadora, o potencial do aprendizado de máquina quântico para análise de aeroportos e planejamento de aerotrópoles, que posteriormente pode ser mais profundamente explorado inaugurando uma nova era de aplicação nessa área do conceito de inteligência artificial aperfeiçoada por computação quântica.