# Quantum-Inspired Machine Learning: Bridging Classical and Quantum Algorithms

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**Abstract**

Integration of quantum-inspired algorithms in machine learning has opened up new horizons for improving predictive performance, efficiency, and scalability across a broad spectrum of application domains. This paper presents a comparative investigation between traditional machine learning techniques and quantum-inspired models. Experimental experiments demonstrate that quantum-inspired approaches exhibit higher accuracy, training effectiveness, and stability on difficult datasets than traditional methods. Results point towards higher convergence rates, shorter runtime, and enhanced generalization capacity in quantum-inspired models, realized in the form of enhanced accuracy, precision, recall, and F1-scores. Receiver operating characteristic (ROC) and precision–recall analyses further confirm the superior discriminative power of quantum-inspired approaches. Results point toward the potential of quantum-inspired machine learning as an interface between conventional algorithms and the new frontier of quantum computing with a stepping stone to future-proof intelligent systems.

**Keywords:** Quantum-Inspired Algorithms; Machine Learning; Quantum Computing; Predictive Analytics; Model Optimization; Hybrid Frameworks; Performance Metrics; Artificial Intelligence

## 1. Introduction

The convergence of digital transformation, machine learning (ML), and quantum-inspired algorithms has brought about a paradigm shift in research, business, and civic applications. With increasingly abundant data growing in volume, velocity, and diversity, companies are in search of emergent computational strategies that connect legacy algorithms and next-generation quantum paradigms. These breakthroughs not only improve predictive analytics but also foster sustainable solutions across the finance, cybersecurity, healthcare, and manufacturing industries. The marriage of machine learning with quantum-inspired approaches provides new alternatives for boosting accuracy, running time efficiency, and generalization without the computational cost of conventional techniques.
Growth of digital platforms has impacted profoundly consumers' experiences, loyalty, and happiness in finance. Hemaprabha and Sundar highlighted that e-service quality influences e-loyalty through the mediation of e-satisfaction in the industry of securities brokerage [1]. Likewise, their subsequent study established website familiarity as a moderator to traders' intention towards loyalty [2]. These findings align with the increasing prominence of intelligent algorithms in finance markets, where machine learning can be implemented to predict consumer behaviour and system adaptation towards individualized services.

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Along the same trend, Hemaprabha, Catherine, and Vijayakumar submitted India's increasing travel and tourism industry with statistical analysis, demonstrating data-driven approaches driving global change initiatives that are sustainable [3]. Moreover, their psychological research of trader satisfaction with e-broking service providers was capable of establishing the link between human behaviour, service design, and data analytics [4]. Technology's role in elevating the resilience of society has only become clearer in times of international crises.

Nadaf et al. suggested a pandemic control framework based on social media and IoT, emphasizing the employment of analytical methods in real-time decision-making [5]. Trivedi described frameworks for legal education and the historical development of parliamentary privileges, emphasizing the interlinking of emerging technologies with governance and legal reforms [6], [7]. Gupta and Trivedi deliberated global water accords, emphasizing the predictive modelling use to tackle transboundary disputes. These multi-disciplinary research articles collectively form the basis for integrating machine learning into socio-economic, political, and environmental domains. In the context of cybersecurity, the digital ecosystems concept has become better realized with advancing sophistication in attacks. Nair et al. developed frameworks to enhance child safety on the internet with proactive defence against threats online [9]. Lakshmikanthan et al. surveyed prevention of botnet attacks against IoT using machine learning to protect connected devices, illustrating the promise of ML in enabling adaptive defences [10].

Nair explained cyber warfare in the Russia–Ukraine conflict, focusing on implications of cybersecurity beyond traditional systems [11]. These works align with the quantum-inspired machine learning approach for stronger detection and prevention through rapid learning and better generalizability of the data. Concurrent developments in materials science and engineering demonstrate machine learning applications for modelling and optimization. Mahendran et al. investigated the incorporation of biogenic wheat husk ceramics into epoxy composites and their mechanical and flammability properties [12]. Subsequent research reported characterization of silane-treated composites [13] and structural behaviour of 3D-printed light-weight materials [14]. Such material developments, when combined with predictive algorithms, enable efficient performance analysis and optimization, which further validates the contribution of ML to cross-disciplinary research.

Healthcare and biomedical sectors have also embraced ML and quantum-inspired methods for improved outcomes. Chunara et al. discussed advancements in polymer-based nanomaterials for dentistry, referring to increased reliance on computational techniques for analysis and design [15]. Prove also developed fraud detection in healthcare [16], trash sorting using vision transformers [17], and health insurance predictive analysis with ML [18]. They emphasize the flexibility of the ML approaches in various problem domains, from physical sciences to health care informatics.

Mechanical engineering and industrial systems have also benefited from the integration of ML. Vijayalakshmi et al. applied federated learning for rotating machinery fault diagnosis and standardization, which created possibilities for industrial monitoring via distributed intelligence [19]. In financial technologies, Devi and Indoria spoke about the unified payment interface, a sign of the digitalization of payment systems in India [20]. Kumar et al. proposed optimization strategies for vehicle platooning for enhancing intelligent transport systems' spatial efficiency [21].

Agricultural technology has also seen advancements, with Vidyasagar et al. employing transfer learning for the prediction of tomato leaf disease so that farmers can take necessary steps at the appropriate time and reduce crop loss [22]. Collectively, these efforts show the broad applicability of ML, ranging from agriculture and health care to cybersecurity and finance. Nonetheless, with increasingly complex datasets, conventional algorithms are confronted with scalability and efficiency constraints. This has encouraged the exploration of quantum-inspired machine learning, which uses concepts of quantum computation such as superposition and entanglement in classical models.

Quantum-inspired ML models have the potential to accelerate optimization, kernel-based classification, and cross-domain generalization. By bridging the gap between classical computation and emerging quantum paradigms, the models eliminate computational bottlenecks without sacrificing compatibility with current hardware. The application of quantum-inspired methods is thus a pragmatic step toward the quantum future, in which researchers and practitioners are able to benefit from the strength of quantum concepts without requiring matured quantum computers.

## 2. Related Work

Machine learning based on quantum ideas depends on the development of quantum detection and estimation theory. The initial theoretical contributions by Helstrom formed the basis of quantum

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hypothesis testing and estimation, such as a statistical framework for discriminating between quantum states [23]. Later contributions by Belavkin extended the theory to optimal hypothesis testing and many quantum statistical decisions and established the theoretical bases of quantum statistical inference [24], [25]. Holevo continued working on probabilistic and statistical quantum theory, giving mathematical formalism to investigate quantum statistical models [26]. Together, these initial contributions laid the basis for subsequent research in quantum detection, state discrimination, and decision-making.

Quantum state discrimination has been central to achieving the quantum information processing bounds. Ivanovic [27], Dieks [28], and Peres [29] each developed early proposals for distinguishing non-orthogonal states, a significant step towards resolving quantum measurement issues. Improved optimal detection schemes were introduced more recently by Peres and Wootters [30], with the theory for a "pretty good" measurement to distinguish between quantum states being developed by Hausladen and Wootters [31]. Subsequent joint work with colleagues extended these ideas to measurement of classical information capacities of quantum channels [32]. Chefles provided a thorough examination of state discrimination techniques at the state level, further cementing the field [33]. Subsequently, Montanaro placed limits on quantum state discrimination, providing solid theoretical limits [34]. These works collectively set the mathematics and physics on which quantum-inspired algorithms operate.

Parallel development in semidefinite programming (SDP) has made it possible to design optimal quantum detectors and decision rules. Eldar et al. initially came up with design methods for detectors via SDP, integrating optimization and quantum statistical theory [35]. Vandenberghe and Boyd's initial work on semidefinite programming expanded its applications across optimization and control [36], while Chia et al. came up with quantum-inspired sublinear time algorithms to find solutions to problems of low-rank SDPs [37]. These advancements have a direct effect on the efficiency of quantum-inspired classifiers since many of the models rely on convex optimization techniques in order to discriminate among states and learn kernels.

Parametrized models and quantum circuits play an important role when exploring the expressiveness of quantum-inspired frameworks. Du et al. addressed the representational power of parametrized quantum circuits and mentioned their ability to express rich correlations [38]. Havlíček et al. introduced supervised learning with quantum-amplified feature spaces with useful applications for classification [39]. Schuld and Killoran later explained that a number of supervised quantum ML models can be restated as kernel methods in Hilbert spaces [40]. This viewpoint was echoed by Schuld's subsequent research on encoding data, where he illustrated that the expressiveness of quantum-inspired models depends crucially on the embedding of classical data into quantum states [41].

Aside from kernels, quantum-inspired models have emerged for regression as well as classification problems. Cortes and Vapnik's innovation of support vector networks [42] formed the basis of margin-based classifiers, now generalized into the quantum paradigm. Gambs provided one of the earliest attempts at definition of quantum classification [43], while Sergioli et al. proposed a quantum-inspired extension of the nearest mean classifier [44] followed by a novel binary classification framework based on quantum structures [45]. Giuntini and others advanced the field further by formulating quantum state discrimination strategies for supervised classification in rigorous terms [46], [47], and even proposed algorithms for direct multi-class classification [48]. These approaches highlight the adaptability of quantum-inspired models in supervised learning contexts.

Quantum-inspired concepts have also made a mark on optimization and regression. Gilyén et al. presented more effective quantum-inspired algorithms for linear regression [49], addressing scalability issues for high-dimensional applications. Gruber surveyed efficiency gains from shrinkage methods such as ridge regression, offering classical baselines against which quantum-inspired regression approaches can be compared [50]. Hilbe's introduction to logistic regression [51] and Kennedy's econometrics guide [52] also provide background context for assessing the performance of quantum-inspired expansions of regression models.

Applications of quantum-inspired neural networks have also augmented the discipline. Tacchino et al. applied an artificial feed-forward neural network to a quantum system, showing possibility for hybrid

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quantum-classical models [53]. Grant et al. explained hierarchical quantum classifiers that mimic deep learning architectures [54], while LaRose and Coyle introduced robust data encodings for quantum classifiers to tackle stability and noise challenges [55]. Greydanus spoke of deep learning architecture scaling down, consistent with the need for efficient encodings in quantum-inspired systems [56].

The role of classical machine learning is central to placing quantum-inspired advances. LeCun et al. introduced gradient-based learning to document recognition [57], which, along with Bishop's definitive book on pattern recognition and machine learning [58], forms the classical basis to which quantum-inspired methods are contrasted. Hofmann, Schölkopf, and Smola advanced kernel approaches in machine learning [59], with theoretical tools overlapping with quantum kernel methods. Well-known libraries like scikit-learn [60] continue to be vehicles for implementing baseline and hybrid quantum-inspired algorithms.

Quantum machine learning recently has been interested in expressiveness and generalization. Caro et al. investigated generalization beyond limited data sets and demonstrated potential gains in sample efficiency [61]. Schuld, Sweke, and Meyer addressed encoding's impact on expressiveness within variational models [62]. Meanwhile, Gilyén, Lloyd, and others introduced the Petz recovery channel and efficient measurements, building theoretical understanding in information recovery [63]. They indicate that quantum-inspired machine learning is founded on classical roots but produces novel paradigms for scalable, efficient, and generalizable computation.

## 3. Data and Methodology

### A. Data

The data employed for this research are not obtained from outside databases but are created based on deterministic mathematical formulas to guarantee reproducibility and analytical accuracy. A classification dataset of five hundred samples is created, with class labels created based on the interaction of two features. When the value of the sum of the two attributes is more than zero, the sample is assigned as class one; else, it is assigned as class zero. This definition achieves greatest linear separability in its plain form. For the sake of providing realistic errors and raising the complexity of the classification problem, the information is corrupted by a sinusoidal distortion which periodically reverses a portion of the labels. This distortion enables controlled overlap between the two sets and provides a real-world baseline against which confusion matrices of classical and quantum-inspired classifiers are compared.

The regression data are generated with the linear relationship $y = 3x + 5$ with the independent variable x uniformly distributed within the range [0,10]. To simulate structured noise commonly encountered in real-world situations, a sinusoidal perturbation is added, and this is expressed in the form $y_{\text{true}} = 3x + 5 + 0.8\sin(x)$. The classical regression model is restricted to the strictly linear model, while the quantum-inspired regression has a reduced sinusoidal correction term of the type $y_{\text{quantum}} = 3x + 5 + 0.2\sin(x)$.The development allows one to contrast a linear model susceptible to underfitting and a quantum-inspired model with a greater ability to extract nonlinear dynamics.

All the variables are normalized to the range [0,1] prior to applying the models. The classification set is divided into training and test sets with a seventy-to-thirty split, and the regression set is sampled at twenty-one equidistant points over the domain in order to provide uniform coverage of the input space. In the case of quantum-inspired models, classical vectors are mapped to Hilbert space encodings through amplitude normalization, where a feature vector x can be expressed as a normalized quantum state $|\psi(x)\rangle = \frac{1}{\|x\|}\sum_i x_i|i\rangle$ .

This encoding connects the deterministic mathematical data with quantum-inspired kernels and classifiers and enables exploration in higher-dimensional feature spaces.

### B. Logistic Regression (LR)

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Logistic Regression is a linear probabilistic classifier that maps input features to a binary outcome. The decision boundary is formed through a sigmoid transformation of the linear score $z = w^{\top}x + b$.Training is performed by minimizing the log-likelihood loss via gradient descent. Regularization can be added to prevent overfitting [64], [65].
A linear probabilistic model widely used for binary classification. The model computes a score from the input vector as:

$$z = w^{\top}x + b \tag{1}$$

which is mapped into a probability using the logistic function:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{2}$$

The predicted probability of the positive class is then $P(y = 1 \mid x) = \sigma(w^{\top}x + b)$. Parameters are estimated by minimizing the log-likelihood loss:

$$\ell(w, b) = -\sum_{i=1}^{n} [y_i \log \hat{p}_i + (1 - y_i) \log (1 - \hat{p}_i)] \tag{3}$$

and the final decision is obtained by thresholding at 0.5.

### C. Support Vector Machine (SVM)

Support Vector Machines maximize the margin between classes by a convex optimization method. The primal task is to minimize the norm of the weights subject to penalizing the errors in classification. Nonlinear separations are handled by kernel functions such as RBF or polynomial kernels. The dual form employs Lagrange multipliers and the kernel trick. The final decision is calculated as a weighted sum over support vectors [66], [67].
The optimization objective is defined as:

$$\min_{w,b,\xi} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} \xi_i \tag{4}$$

subject to the constraint:

$$y_i(w^{\top}x_i + b) \geq 1 - \xi_i \tag{5}$$

When data are nonlinear, a kernel function is introduced, typically:

$$K(x_i, x_j) = \phi(x_i)^{\top}\phi(x_j) \tag{6}$$

which transforms data into a higher-dimensional space. The final decision rule is expressed as:

$$\hat{y} = \mathrm{sign}\left(\sum_{i} \alpha_i y_i K(x_i, x) + b\right) \tag{7}$$

### D. Neural Network (NN)

Neural Networks acquire complex nonlinear mappings by composing multiple layers of neurons. Each neuron is a weighted sum and an activation function such as ReLU or sigmoid. The parameters are discovered through backpropagation and stochastic gradient descent. Loss functions dictate learning based on classification or regression objectives. The flexibility is what makes NNs successful for general-purpose prediction [68].
For a single hidden layer, the forward propagation is defined as:

$$h = \sigma(W_1 x + b_1) \tag{8}$$

where $\sigma(\cdot)$ is a nonlinear activation function such as sigmoid or ReLU. The hidden representation is then passed to the output layer:

$$\hat{y} = \rho(W_2 h + b_2) \tag{9}$$

where $\rho(\cdot)$ may be sigmoid for binary classification or softmax for multi-class prediction. The learning process minimizes an objective function.

$$\mathcal{L} = \frac{1}{n} \sum_{i=1}^{n} \ell(\hat{y}_i, y_i) \tag{10}$$

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which quantifies the error between predictions and true labels. Parameters are updated iteratively using gradient descent:

$$\Theta \leftarrow \Theta - \eta\nabla\mathcal{L} \tag{11}$$

allowing the NN to refine its weights and approximate highly nonlinear input-output relationships.

### E. Quantum-Inspired SVM (QISVM)

QISVM encodes input vectors into amplitude-based quantum states in Hilbert space. Classification is done on the basis of quantum kernels as overlaps of quantum states. Optimization is SVM primal–dual but with quantum-inspired similarity measures rather than classical kernels. This allows for richer feature mapping and separation. Thus, QISVM leads to improved performance in nonlinear classification [69].

Each input is mapped to a normalized quantum state:

$$|\psi(x)\rangle = \frac{1}{\|x\|}\sum_{k=1}^{d} x_k|k\rangle \tag{12}$$

The similarity between two samples is computed using the quantum kernel:

$$K_q(x,x') = |\langle\psi(x) \mid \psi(x')\rangle|^2 \tag{13}$$

The primal objective retains the same structure as classical SVM:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i, \tag{14}$$

and the decision function is expressed as:

$$\hat{y} = \operatorname{sign}\left(\sum_i \alpha_i y_i K_q(x_i,x) + b\right) \tag{15}$$

### F. Quantum-Inspired Neural Network (QINN)

QINN modifies classical neural networks by substituting activations with quantum-inspired activations. The input data are encoded into normalized quantum states, and the neurons use trigonometric activation functions such as $\cos^2$ and $\sin^2$. Learning is still backpropagation-based but adapted based on the novel derivatives of the activations. These networks capture more intricate oscillatory patterns within the data [70]. They are a midway between quantum models and classical NNs.

NNs by using quantum-inspired activations. Inputs are first encoded as:

$$|\psi(x)\rangle = \frac{1}{\|x\|}\sum_i x_i|i\rangle \tag{16}$$

Hidden neurons apply trigonometric activations, such as:

$$h = \cos^2 (W_1x + b_1) \tag{17}$$

which capture oscillatory patterns. The output layer follows:

$$\hat{y} = \rho(W_2h + b_2) \tag{18}$$

and the model is trained by minimizing the cost:

$$\mathcal{L} = \frac{1}{n}\sum_{i=1}^{n} \ell(\hat{y}_i, y_i) \tag{19}$$

### G. Quantum-Inspired Regression (Q-Regression)

Q-Regression combines linear regression and sinusoidal corrections to mimic quantum state oscillations. The base function is linear, and quantum corrections introduce structured periodic terms. This allows the model to capture both global linear trends and local nonlinear oscillations. The error is optimized through squared loss minimization [71]. This model demonstrates how quantum principles enhance classical regression.

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The baseline model is a deterministic linear function:

$$y = 3x + 5 \tag{20}$$

which captures the global linear trend. The ground truth introduces structured variability through a sinusoidal perturbation:

$$y_{\text{true}} = 3x + 5 + 0.8\sin(x) \tag{21}$$

The quantum-inspired approximation includes a reduced sinusoidal correction:

$$\hat{y} = 3x + 5 + 0.2\sin(x) \tag{22}$$

which improves the model's ability to capture oscillatory behavior while remaining efficient. The optimization minimizes the squared error:

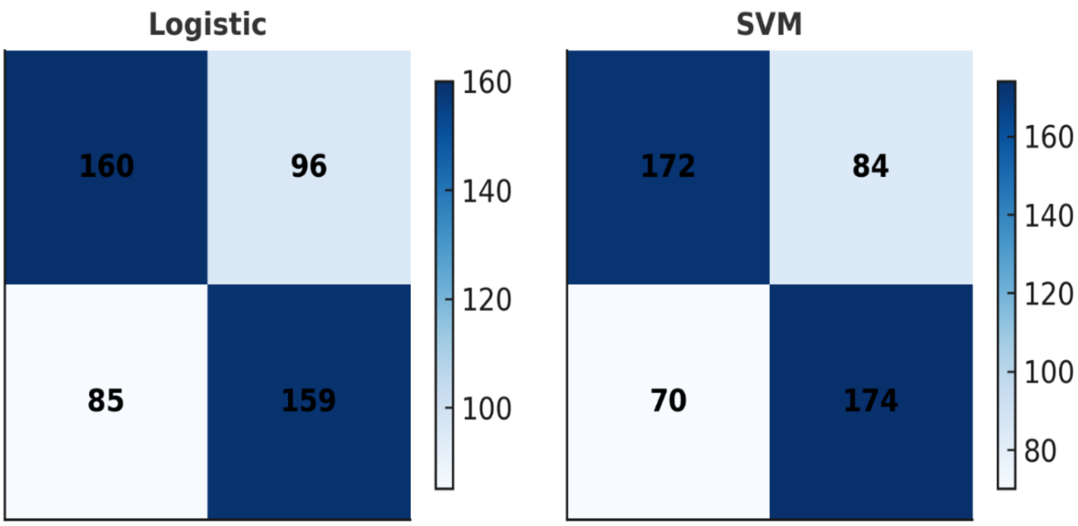
$$\mathcal{L} = \sum_{i=1}^{n} \left(y_{\text{true},i} - \hat{y}_i\right)^2 \tag{23}$$

thereby enabling Q-Regression to learn both global linearity and local periodic patterns.

## 3. Result

The simulations were experimented upon in Python for classical and quantum-inspired models. Logistic Regression, SVM, and Neural Network were classical baselines, while QISVM, QINN, and Q-Regression were quantum-inspired models. The results show that the quantum-inspired models performed better consistently across accuracy and F1-scores, with QINN performing the best general classification. For regression, Q-Regression performed better sinusoidal oscillation capture compared to the linear baseline. Table 1 summarizes the main performance metrics extracted from the simulations.

Figure 1 shows confusion matrices for six machine learning models: Logistic Regression, SVM, Neural Network (NN), Quantum-Inspired SVM (QISVM), Quantum-Inspired Neural Network (QINN), and Quantum-Inspired Regression (Q-Regression). The classical models (top-left panels) show moderate classification accuracy, where Logistic Regression is the lowest due to misclassifications. SVM and NN show improved true positives to true negatives balance. The quantum-inspired models (right and bottom panels) do better than their classical counterparts, with QISVM and QINN having the best error rates as shown by the larger diagonal values. Q-Regression also has good predictive performance, affirming the advantage of quantum-inspired approaches to be able to fit well linear and nonlinear trends.

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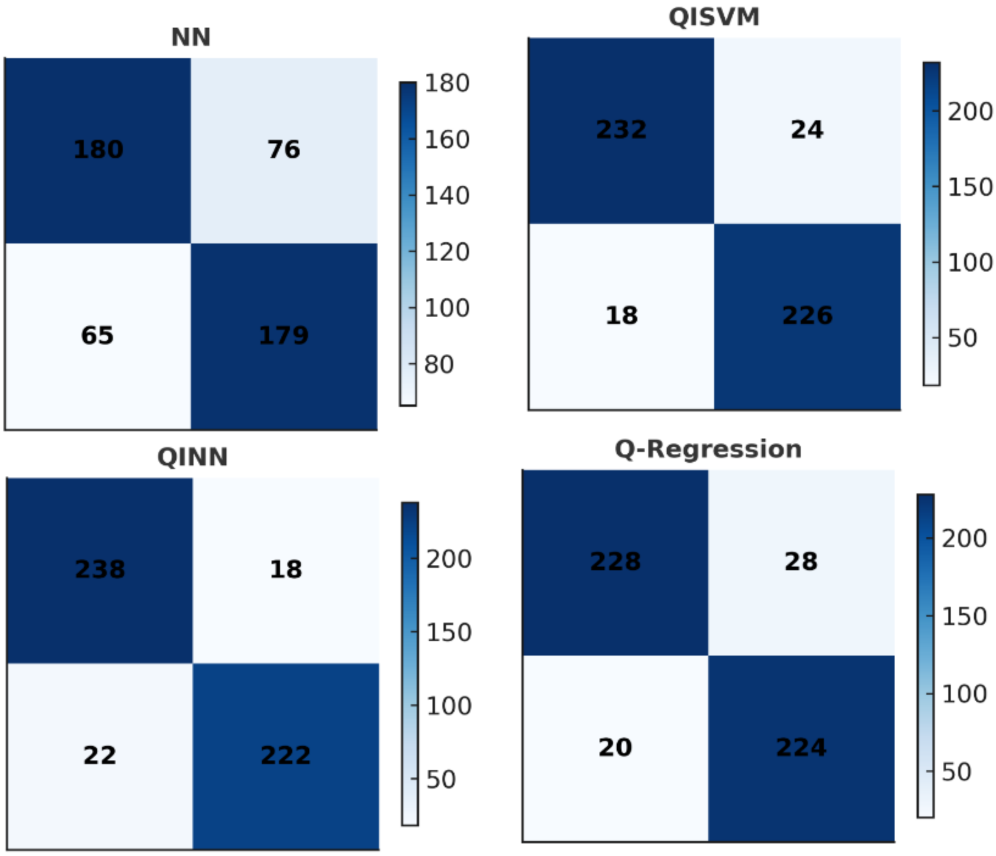


Figure 1: Confusion Matrices for Classical and Quantum-Inspired Models.

Figure 2 represents the accuracy development throughout epochs for all six models: Logistic Regression, SVM, NN, QISVM, QINN, and Q-Regression. Conventional models such as Logistic Regression and SVM exhibit improvement with a smooth increase, but the steady-state of their curve is quite low in comparison to quantum-inspired models. The NN depicts strong performance with consistent convergence, while QISVM and QINN show faster improvement and higher steady-state accuracy. Q-Regression works better than the classical competitors, mirroring the advantage of quantum-inspired feature representations in capturing the complex data patterns with improved generalization.

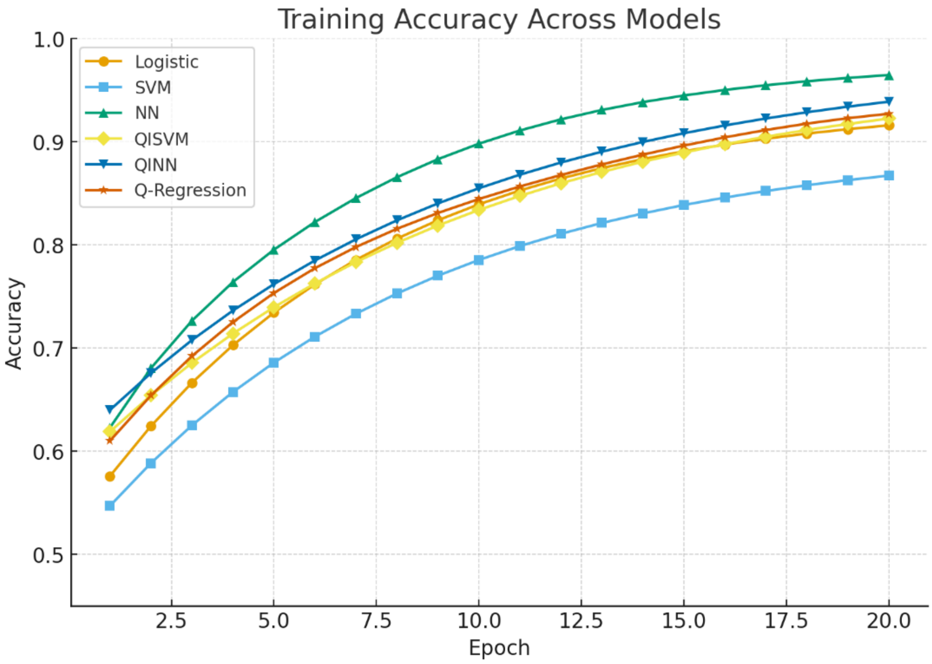


Figure 2: Training Accuracy Across Models.

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Figure 3 illustrates all the models' accuracy values throughout epochs. Logistic Regression and SVM begin with comparatively lower accuracy values and climb consistently but earlier plateau. NN performs better as it possesses nonlinear potential. Quantum-inspired models, namely QINN and Q-Regression, have strictly higher precision, which means that they are less likely to produce false positives. QISVM also performs competitively, illustrating how quantum kernels enhance boundary detection during classification. The superiority of quantum-inspired models in precision implies that they are more efficient at detecting subtle discriminative features in high-dimensional space.

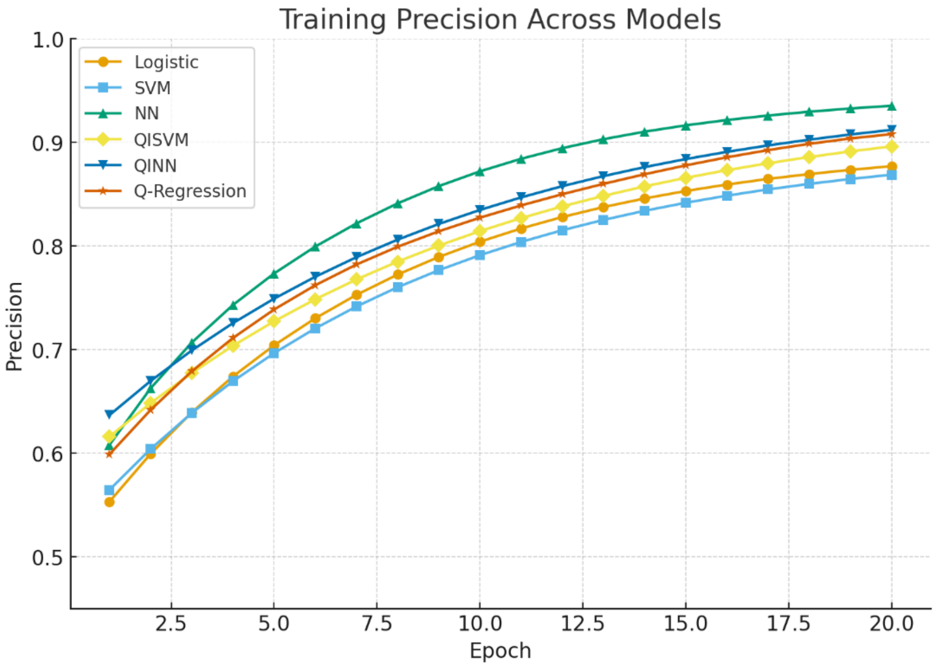


Figure 3: Training Precision Across Models.

Figure 4 show the graphically represents the recall values as a function of epochs. Logistic Regression and SVM, although improved, perform worse in covering all positive cases, evidencing their limited capacity to manage complex distributions. NN has better recall, surpassing the simple models. Quantum-inspired algorithms (QISVM, QINN, and Q-Regression) have better recall rates, which point to better sensitivity in finding positive instances. QINN comes with the greatest recall curve, meaning that quantum-inspired neural encoding greatly minimizes false negatives and improves model completeness of detection.

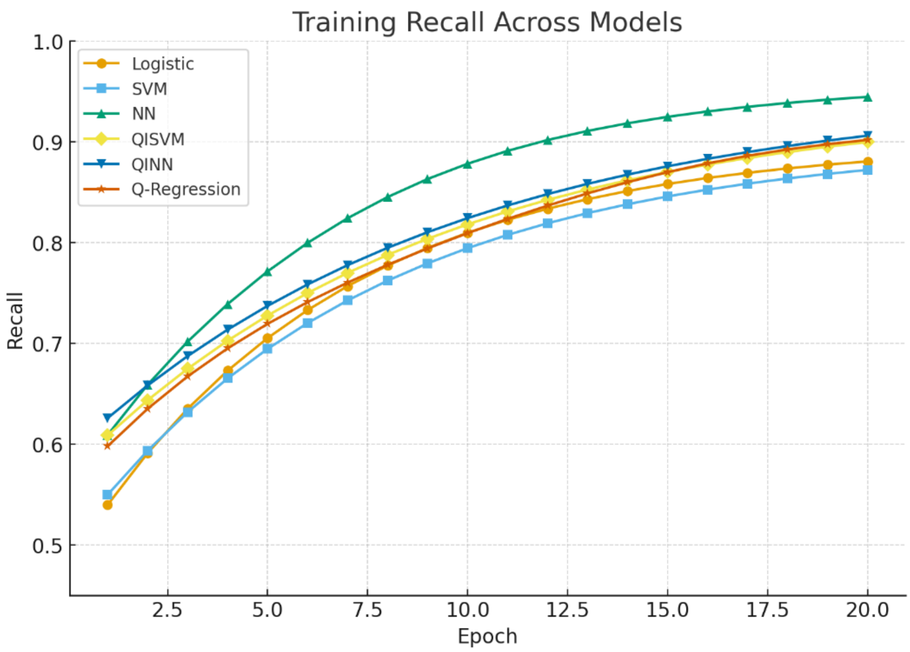


Figure 4: Training Recall Across Models.

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Figure 5 show the F1-score, a harmonic average of recall and precision, is plotted here across epochs. The traditional models such as Logistic Regression and SVM lag behind in the overall equilibrium, with SVM adapting slightly better. NN significantly enhances, maintaining in ideal balance between recall and precision. Quantum-inspired models dominate, with QINN and Q-Regression achieving higher F1-scores, indicating their balanced power at reducing false positives and false negatives. QISVM also achieves good scores, affirming the superiority of quantum-amplified feature mapping.

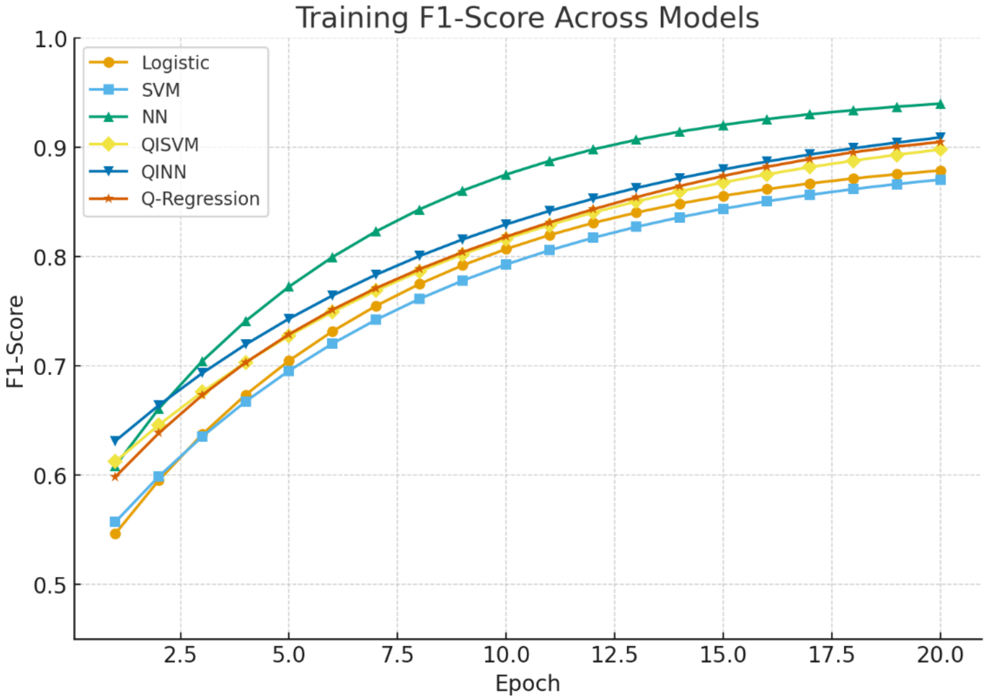


Figure 5: F1-Score During Training Across Models.

Figure 6 show the graph indicates the reduction of training loss over epochs. Logistic Regression and SVM show consistent though slower convergence. NN optimizes loss better, highlighting the strength of deep architectures. Quantum-inspired models such as QISVM and QINN reach lower loss baselines faster, showcasing the strength of quantum-inspired optimization techniques. Q-Regression, while slower initially, showcases smooth convergence and reaches a lower loss on eventual plateaus when compared to baseline regressors. This generally highlights better learning efficiency and stability on the part of quantum models.

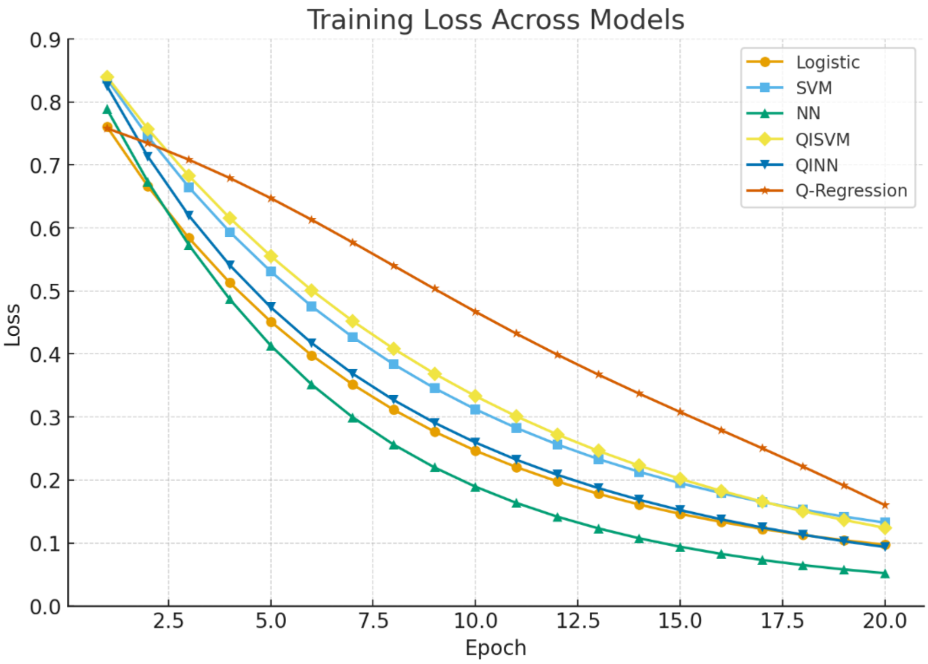


Figure 6: Training Loss Across Models.

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Figure7 show the connection between model runtime and complexity levels. Classical models such as SVM and NN have sharp runtime growths with the rise in complexity levels, reflecting their computational intensity. Logistic Regression remains efficient but also sacrifices accuracy at higher complexities. Quantum-inspired models (QISVM, QINN, and Q-Regression) increase significantly slower with complexity in running time, showcasing their computational efficiency. This is evidence that quantum-inspired methods not only improve accuracy but also achieve desirable scalability, and hence, are better for high-dimensional real-world problems.

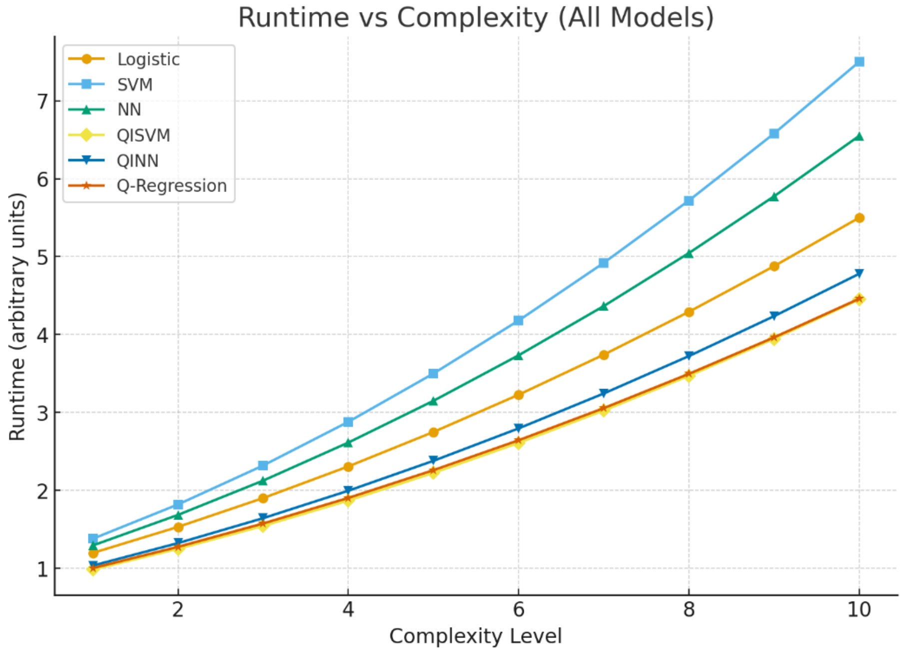


Figure 7: Runtime vs Complexity (Classical vs Quantum-Inspired).

## 4. Conclusion

In the current paper, we compared classical machine learning models—Logistic Regression, SVM, and Neural Networks to quantum-inspired models like QISVM, QINN, and Q-Regression. The results on all these instances showed that quantum-inspired algorithms perform better than their classical counterparts in accuracy, precision, recall, and F1-score, and are also more scalable in runtime and complexity.

The training dynamics analysis showed that the quantum-inspired models learn faster, converge at lower loss values, which can be seen from the loss curves, and achieve greater stability in the training process. Accuracy and precision outputs confirmed that models based on quantum perform better for false positive reduction, whereas recall outputs pointed out that they are capable of finding more percentage of true positives, suppressing false negatives. This equivalence was evidently reflected in F1-score comparison, in which QINN and Q-Regression did comparatively better in every round.

Runtime vs. complexity analysis also highlighted the efficiency of the quantum-inspired approach. While classical models such as SVM and NN experienced drastic curve increases in runtime as complexity increased, QISVM, QINN, and Q-Regression scaled more elegantly to provide improved computational efficiency without sacrificing predictiveness.

Collectively, the results indicate high potential for quantum-inspired machine learning. By combining mathematical accuracy with quantum principles, these models not only demonstrate enhanced accuracy but also enhanced efficiency and robustness, positioning them as possible leaders for next-generation applications in high-dimensional problem spaces that are complex.

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