A Comparative Study of Classical and Quantum Machine Learning Models for Sentimental Analysis

Diksha Sharma¹, Parvinder Singh², Atul Kumar³

¹Indian Institute of Technology Jodhpur, Rajasthan-342037, India
²Central university of Punjab Bathinda, Punjab-151001, India

(Dated: September 13, 2022)

We analyse and classify the sentiments of a text data constructed from movie reviews. For this, we use the kernel based approach from quantum machine learning algorithms. In order to compose a quantum kernel, we use a circuit constructed using a combination of different Pauli rotational gates where the rotational parameter is a classical non-linear function of data points obtained from the text data. For analysing the performance of the proposed model, we analyse the quantum model using decision tree, gradient boosting classifier, and classical and quantum support vector machines. Our results show that quantum kernel model or quantum support vector machine outperforms all other algorithms used for analysis in terms of all evaluation metrics. In comparison to a classical support vector machine, the quantum support vector machine leads to significantly better results even with increased number of features or dimensions. The results clearly demonstrate increase in precision score by 9.4% using a quantum support vector machine as against a classical support vector machine if the number of features are 15.

Keywords: Quantum Entanglement, SVM, Supremacy, QSVM, Quantum Computing;

I. INTRODUCTION

Machine learning is a branch of artificial intelligence which efficiently uses the underlying data to generate insightful classifications and predictions with the help of algorithms- while gradually improving the accuracy using historical data or information [1]. Machine learning algorithms evolve from mathematical models reinforcing the prognosis associated with the dataset which in-turn further facilitates the informed decision process. Such algorithms help a machine to work efficiently even for analysing massive quantity of data. With the impact of machine learning algorithms on science and technology, it is imperative to develop and analyse new machine learning algorithms. In fact, the last two decades have witnessed an enormous transformation in terms of algorithms and the area has become a leading research area across academia and industry. Another area that has impacted academic and industrial progress is quantum information and computation. Quantum algorithms- based on the fundamental laws of quantum mechanics- have shown optimal assurance to offer efficient applications to material science [2, 3], computational chemistry [4], cryptography [5, 6], traffic navigation [7, 8], security [9, 10], finance [11], biology [12] and machine learning [13]. Both, machine learning and quantum computing, deal with large-scale networks to effectively address critical problems, therefore, a natural question is to analyse the potentials of quantum computing in the realms of machine learning, i.e., quantum machine learning. Quantum computing, in comparison to classical computation, is believed to assist machine learning algorithms in enumerating distance or similarity between data-points with an adequate speedup, if not exponential [14, 15]. The advantage can be translated in terms of time and space complexity or can be obtained using adiabatic quantum computing for attaining optimum results [16]. Moreover, with the role of entanglement and non-classical correlations being established as the reasons for several potential applications in quantum information and computation [17, 18], quantum machine learning algorithms are conceived to be much more powerful and effective as compared to their classical counterparts.

In addition to the quantum machine learning algorithms, data is also an important factor to achieve the desired accuracy. In general, data can be classified as quantitative or qualitative. Among various types of data, text data plays a key role in daily life, e.g., placing an online order, booking tickets or buying food online, reviews of movies or stores etc. With the advent of e-commerce, one of the most desirable requirements is the availability of reviews or compact surveys for every product before placing an order. Of course, there is a large amount of data available for different products but at the same time analysing the available data as positive or negative for a common man, without any error of biasedness, is also extremely challenging. The classification or analysis of textual data is therefore known as sentiment analysis or opinion mining. Sentiment analysis not only helps customers to fulfill their need and expectation, but also the industry to improve their products as per the market requirements. Machine learning algorithms are historically considered to be effective in analysing the text data as positive or negative statement in the analysis of different cases. Recently, quantum machine learning algorithms have also been developed for classification of data but a very few algorithms are comprehensively analyzed in comparison to classical algorithms [19]. In this paper, we study the use of quantum as well as classical machine learning algorithms for sentimental analysis and further compare the classical and quantum machine learning algorithms in term of different evaluation matrices. In this work, we apply different quantum machine learning algorithms with multiple feature maps to increase the overall accuracy. Further, we find that quantum machine learning algorithms predict the sentiments more precisely with higher accuracy than the classical machine learning algorithms.

* atulk@iitj.ac.in  parvinder.singh@cup.edu.in
A. Sentimental Analysis

Sentiments are opinions, thoughts or feelings of an author towards an object, an entity, or an event. Natural language processing (NLP) provides techniques to identify the emotion from the text, named as sentimental analysis. Therefore, extracting the subjective information contained in an opinion is known as sentiment analysis or opinion mining [20]. Sentiment analysis or document-level sentiment classification, classifies a sentence by considering that sentence as a single information unit which includes positive, negative or neutral statements [21]; implicates the use of data mining and machine learning to mine the text. Sentiment analysis is used in social media monitoring, recommendation system, customer service, brand monitoring, stock market prediction, product analysis to name a few [22–25].

B. Machine Learning

In artificial intelligence, machine learning is typically referred as the process of training a model to make predictions from inter-linkages of the previously seen data, i.e., machine learning algorithms improve their performance with the experience. Depending on the application, machine learning algorithms are classified into three major categories, namely supervised, unsupervised and reinforcement machine learning algorithms. Supervised learning algorithms predict the label or class of unknown data objects using the prior information related to the label of similar objects. Therefore, supervised learning algorithms take a labeled data as an input in the training phase, where labels are corresponding outcomes of features. Whereas in the testing phase, the trained model acts on the unlabeled data and predict the label. Moreover, based upon the data, supervised machine learning algorithms are further divided into classification and regression techniques. For example, if supervised machine learning algorithms are used to predict the label or class of an unknown data object then it represent classification techniques; and if supervised machine learning algorithms are used to predict the future value of real-valued variable then it represent regression techniques [20]. As opposed to the supervised learning, in unsupervised learning, the models deal with an unlabeled training data. These models or algorithms get insights from the data without explicit interventions. Therefore, unsupervised learning algorithms analyse data to get a pattern directly from the input data objects. This process is known as pattern/knowledge discovery or clustering. Depending on the data, another variant of unsupervised learning is anomaly detection or association analysis [27]. Moreover, reinforcement learning algorithms are widely used in a game-like environment where a model or an agent performs a set of action in order to maximize rewards without the training to solve a given problem. The agent gets a reward or punishment for each performed action, and the goal is a cumulative maximum reward with an optimal solution to the problem [28]. Reinforcement learning is used in robotics and automobiles where a machine performs some actions to complete a task and receives a degree of achievement as positive reward and risk of an action as negative reward.

The machine learning models have the potential to learn and to discover patterns to exceptionally predict the class for unknown data objects. For example, the text data contains reviews or opinions that can be seen as inter-related words. Therefore, machine learning algorithms are attractive tools to classify the textual data into positive or negative sentiments. It can extract the essence of statements and improve the accuracy by getting trained from a large set of sample data. Further, quantum machine learning algorithms can also be used to improve the performance measures for sentimental analysis, as quantum computing offers an exponential speed-up over the classical computing, due to the existence of long-range of nonlocal correlations between qubits.

II. PRELIMINARY AND FUNDAMENTALS

A. Classical Machine Learning Algorithms

There are number of algorithms which can be classified as supervised learning algorithms. Sentiment analysis, also known as text classification, uses supervised learning models to classify a dataset as positive or negative. In this paper, we redress supervised learning using different classical machine learning algorithms such as support vector machine, decision tree, and gradient boosting. For demonstrating the sentiment classification, Ye et al. used support vector machine and naïve bayes, and demonstrated the support vector machine to be more efficient for accurate classification [29]. Similarly, Pang et al. also classified a dataset using naïve bayes, maximum entropy classification and support vector machine algorithms and deduced that support vector machine performs as the best algorithm in comparison to other algorithms [30]. There are other instances to support the efficiency of support vector machine algorithms in outperforming other classical algorithms in terms of accuracy [31, 32]. Gradient boosting classifier is also used to perform sentiment analysis for achieving significant better results [33]. Moreover, decision tree and naïve bayes algorithm used by Zuo for sentiment classification of the review dataset [34] leading to decision tree algorithms outperforming the naïve bayes algorithms. The classical machine learning algorithms used in this article for sentiment analysis are the well established algorithms known for their best performance in the literature.

In this section, we briefly describe different classical supervised machine learning algorithms. For our purpose, we will mainly explore the support vector machine, decision tree, and gradient boosting algorithms.

1. Decision Tree

Decision tree-influenced by the human classificational method- is based on divide and conquer approach. It classifies the data by recursively molding the features into a tree structure. A decision tree is built upside down with the top
node representing the root of tree, inductively splits into several branches connecting the internal nodes and ends up in the leaf node. Each leaf node is a decision node representing a particular class.

The emplacement of features at a root or internal node highly impacts the algorithm’s classification performance. Therefore, attribute selection measures select the splitting criterion or attribute that optimally divides the data into smaller chunks until an individual class-label is attained. Decision tree primarily uses three attribute selection measures—information gain, gain ratio and gini index. Information gain works in a greedy manner by selecting a feature that yields highest information. Information gain for a dataset $Y$ for any feature $X$ is the reduction of Shannon’s entropy of $Y$ given $X$ from the uncertainty of $Y$, i.e.,

$$ID(Y; X) = H(Y) - H(Y|X)$$

Clearly, information gain also represents the mutual information between $Y$ and $X$. Gain ratio is the successor of information gain as it further removes the restriction of using only categorical values. It penalizes each attribute by dividing the information gain with entropy of that attribute; known as split-information. Further, gini index is a CART algorithm (Classification And Regression Tree) that splits the dataset based on the feature with minimum impurity such that

$$Gini(Y) = 1 - \sum_{i=1}^{n} p_i^2$$

where $p_i$ is the probability of a feature in dataset belonging to a class. The main objective of designing a decision tree is to provide a set of decision rules to ambiguously classify features to get a robust classification model.

2. Support Vector Machine (SVM)

Support Vector Machine (SVM) is one of the robust classification algorithms based on the statistical methods introduced by Vapnik [35]. SVM classifies data points to different classes by finding a hyperplane also known as the decision surface. The decision surface is chosen in a way that classifies data points with maximum margin in between the support vectors where support vectors are nearest points to the hyperplane. Hyperplane further creates a boundary among data objects in a multi-dimensional feature space. The position and orientation of the decision surface is clearly influenced by support vectors. SVM further classifies non-separable input data points by mapping those to the higher dimensional space to ensure distinct classifications using the decision surface. One can use the linear SVM for sentiment classification, because it shows significant performance [36]. The decision boundary equations are represented as

$$\vec{W} \cdot \vec{x}_i + b \geq 1 \quad \text{when } \ y_i = +1$$
$$\vec{W} \cdot \vec{x}_i + b \leq -1 \quad \text{when } \ y_i = -1$$

where $x_i$ is the support vector, $W$ is normal to hyperplane, $b$ is offset and classification of support vector $y_i \in \{-1, 1\}$. The optimization problem of maximizing the margin therefore turns out to be minimizing the value $||W||^2/2$ while satisfying the constraint $y_i(\vec{W} \cdot \vec{x}_i + b) \geq 1$.

3. Gradient Boosting

Ensemble learning uses multiple machine learning models that are strategically combined to solve a computational problem more efficiently, i.e., ensemble learning increase the overall performance of classification or prediction model. In ensemble learning, many weak learners are combined to create a model with high performance measures. Boosting is an ensemble learning technique that boosts the weak learner into a stronger one. Gradient Boosting algorithm is also known as gradient boosting machines where a number of weak learners are trained over the training data and compositely form a strong learner with greater accuracy. Weak learners are models that can predict the test data slightly better than random guessing. For this, gradient boosting optimizes the loss function using gradient decent by collaborating multiple weak learners. Here, the gradient is the derivative of a function with input parameters that needs to be optimized. The loss function can be mathematically written as

$$F = \arg \min_{\alpha} \sum_{i=1}^{n} L(y_i, \alpha)$$

where $\alpha$ is the predicted value, $y$ is the actual value, and $L$ is a loss function chosen for the classification.

B. Evaluation Metrics

Evaluating a classification model is an essential step to measure its performance over the unknown data objects. As machine learning algorithms are applied to diverse academic domains including the very sensitive ones such as the medical domain where a misclassification or an incorrect prediction can have severe implications, performance evaluation is one of the most important ingredients in machine learning. Hence, modeling evaluation matrices are critical parameters for the success of machine learning algorithms where evaluation matrices quantify the model by providing different measures like accuracy, precision, recall etc. In order to evaluate the performance of a classification model, instances of correct prediction or classification are recorded. For instance, confusion matrix is an example of a evaluation matrix and can be used to record the classification and misclassification records. The confusion matrix is constructed based on the test data results of a model. Figure 4 demonstrates a format of a confusion matrix showing that the confusion matrix contains correct classifications and misclassifications records in the form of four important values, i.e., TP - True Positive, FP - False Positive, FN - False Negative and TN - True Negative. A brief description of these values are enumerated below as
1. True Positive (TP) contains number of data points that are actual positive and also predicted as positive, i.e., correctly classified by the algorithm as the class of concern;

2. False Positive (FP) represent data points that are actual negative but predicted as positive, i.e., data points are misclassified as the class of concern;

3. False Negative (FN) contains number of data points that are actual positive but computed as negative i.e., data points are misclassified as not the class of concern; and

4. True Negative (TN) represents the value for the data points that are actual negative and also predicted as negative, i.e, correctly classified by the algorithm as not the class of concern.

Further, the performance of classification model in term of accuracy, precision, recall and F1-score is evaluated using all these values, namely

![Confusion Matrix](image)

**FIG. 1.** Confusion matrix for performance evaluation for a problem involving two classes

- **Accuracy:** Accuracy is evaluated as the ratio of total number of data instances which are classified accurately to the total number of classification done.

\[
Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}
\]

- **Precision:** Precision evaluates the total number of truly predicted positives for the positive class or concerned class. Precision and false positive are inversely proportional, therefore, as the value for precision increases, number of instances with false positive decreases. In the similar way, precision can be defined for the negative class as well. In the nutshell, precision measures the exactness or reliability of a model.

\[
Precision(P) = \frac{TP}{TP + FP} \quad Precision(N) = \frac{TN}{TN + FN} \tag{2}
\]

- **Recall:** Recall determines the predicted positive class which was actually positive. In other words, recall measures the sensitivity of the model. Higher the recall, lesser will be the number of predicted false negative or false positive instances.

\[
Recall(P) = \frac{TP}{TP + FN} \quad Recall(N) = \frac{TN}{TN + FP} \tag{3}
\]

- **F1-Score:** F1-Score combines precision and recall values to yield a single measure for the performance of the model. F1-score measures the testing accuracy of the model, defined as the harmonic mean of the precision and the recall.

\[
F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}
\]

- **Receiver Operating Characteristics (ROC) Curve:** In order to visualize the performance of classification model, receiver operating characteristics (ROC) curve is a useful tool. The ROC curve primarily measures the efficacy of the model in the prediction of true positive while neglecting the incidence of false positive. In ROC curve, the false positive rate is plotted with respect to true positive rate.

\[
TruePositiveRate(TPR) = \frac{TP}{TP + FN} \quad FalsePositiveRate(FPR) = \frac{FP}{TN + FP} \tag{5}
\]

C. **Quantum Computing and Quantum Machine Learning Algorithms**

The statistical nature of quantum theory puzzled many physicist including Einstein which further prompted him and couple of his colleagues to raise questions on foundations of quantum mechanics, now known as Einstein-Podolsky-Rosen (EPR) paradox [37]. However, J. S. Bell proposed another thought experiment by designing an inequality whose violation - the Bell inequality- confirms the presence of correlations between subsystems of a composite system contradicting the very assumptions of locality and realism as advocated by EPR [38]. The fundamental debate has now translated to the practical implementation of fault tolerant quantum computer which can utilize the nonlocal aspects of quantum theory to perform efficient tasks which are either not possible using classical resources or may require exponential time and memory even with the use of best of classical resources. Of course, there may be several instances of NP-hard problems which would also be quantumly hard but then one do not expect quantum computers to provide solutions to all problems. Nevertheless, a quantum computer can efficiently solve many instances of classically hard problems. The technological developments have ensured a rapid advancements towards realization of a quantum computer, at least with more than 100 qubits. Even
with the intricate challenges of controlling, measuring, and accessing the quantum information, the future of quantum computation to address large-scale computational issues is highly promising. Quantum computing has the capability to embrace machine learning by strengthening the analysis through quantum machine learning algorithms. In this section, we briefly discuss foundational aspects of quantum computing and quantum machine learning algorithms that we use for sentiment analysis.

1. Fundamentals of Quantum Computing

Quantum computation uses the fundamental aspects of quantum theory for the paradigm shift in computing from classical to quantum regime \cite{39, 40}. For a two-level system, the fundamental unit is termed as a qubit with can be represented as an arbitrary linear superposition of the two orthogonal basis vectors. To be precise, a qubit - using computational basis states \(|0\rangle\) and \(|1\rangle\) - can be described as \(|\psi\rangle = \alpha|0\rangle + \beta|1\rangle\) where \(\alpha, \beta \in \mathbb{C}\) and \(|\alpha|^2 + |\beta|^2 = 1\). For multiple qubits, the inherent nature of superposition leads to another interesting quantum mechanical phenomena known as entanglement \cite{41}. For two qubit pure entangled systems, the four maximally entangled Bell states are extensively used for optimal communication and computational tasks \cite{42, 43}. For more than two qubit systems, there exist multiple classes of entanglement due to the complex nature of multiqubit entanglement \cite{44}. The entangled systems violating the Bell or Bell-type inequalities exhibit nonlocal correlations with no classical analogues. The nonclassical correlations are not limited to entangled systems only, but can be extended to separable ones as well \cite{45, 46}. It has been well established now that entanglement and nonclassical correlations offer efficient advantages to quantum computation over classical resources.

Analogous to the classical circuits, quantum circuits also comprise of wires and quantum gates. However, the only constraint quantum gates need to satisfy is that the operator representing the gate must be a unitary operator - unlike classical gates quantum gates are reversible \cite{47}. For example, the single qubit quantum gates are X-gate, Y-gate and Z-gate; commonly known as Pauli gates. One of the most valuable single qubit quantum gate is the Hadamard gate or H-gate which evolves a single qubit state into a superposition state.

2. Quantum Support Vector Machine (QSVM)

Supervised quantum models are summarised as a kernel method where analysis or classification of the data is performed in a high dimensional Hilbert space accessible through inner products \cite{48}. Quantum support vector machine represents a quantum-classical hybrid approach where kernel value is computed using a quantum computer and the classification process is performed on a classical machine. For computing the kernel values, classical data must be converted into quantum states. Therefore, first the classical data points are transformed to quantum states using feature mapping techniques, and then the kernel values are estimated. In fact, the kernel is analogous to calculating inner products between quantum states \cite{49} such that

\[
K(x_i, x_j) = \left| \langle \psi_{x_i} | \psi_{x_j} \rangle \right|^2
\]

(6)

where \(x_i, x_j \in \text{dataset}\) and \(\left| \langle \psi_{x_i} | \psi_{x_j} \rangle \right|^2\) can be further defined as

\[
\left| \langle \psi_{x_i} | \psi_{x_j} \rangle \right|^2 = \left| \langle 0^n | U(x_i) | 0^n \rangle \right|^2
\]

(7)

From Eq. (7), one clearly see that kernel values can be practically computed using quantum circuits by evolving the initial state \(|0\rangle\) under the influence of a unitary operator \(U_{\psi(x)}\) and then finally measuring the state in computational basis. Eventually, the computed kernel value is passed to the classical SVM for classification, i.e.,

\[
\text{class} = \text{sign} \left( \sum_{i=1}^{d} y_i \alpha_i K(x_i, z) + b \right)
\]

(8)

where \(b\) represents offset. Here, if the sign of classical SVM is positive then the state belongs to a positive class and if the sign of classical SVM is negative then the state belongs to a negative class \cite{35}.

III. RELATED WORK

The fusion of machine learning with quantum computing projects a promise to develop several new and exciting algorithms - including the variational algorithms - for optimal speed-up to large-scale data driven tasks \cite{13, 50, 51}. In this section, we briefly discuss some of the algorithms developed in the field of quantum machine learning.

Quantum computing benefits classical supervised and unsupervised machine learning algorithms. Rebentrost et al. have shown the implementation of quantum version of the support vector machine using phase estimation and quantum matrix inversion algorithm for maximizing the speed \cite{52}. Another significant quantum support vector machine was proposed by Havelick et al. which was also implemented on IBMQ open-source software \cite{49}. The proposal was based on evaluating the kernel of classical support vector machine quantum mechanically analogous to computing the inner product of the quantum states. Lu et al. \cite{53} demonstrated the construction of a quantum decision tree where the von-Neumann entropy determines the split over the node and fidelity measures the distance between two quantum states. On the experimental front, the efficient use of quantum computing in classifying high-dimensional vectors and mathematical routines was further established using an entanglement based classification \cite{54}. Schuld et al. introduced a quantum pattern classification algorithm based on k-nearest neighbours where the distance between states is measured using the Hamming distance \cite{55}. Moreover, they also utilized the proposed algorithm for classifying Modified National Institute of Standards and Technology (MNIST) dataset \cite{55}. The results facilitated Ruan et al.
to design a quantum k-nearest neighbour algorithm for calculating the Hamming distance between training inputs and testing state \[56\]. On similar lines, Wiebe \textit{et al.} also presented a quantum algorithm for nearest neighbour and k-means clustering algorithm, evolving quantum computing into the realms of unsupervised machine learning \[57\]. For this, they have proposed two methods for calculating the distance between vectors using a quantum computer, namely inner product method and euclidean method. Another hybrid k-means clustering algorithm was proposed by Sarma \textit{et al.} for finding k-subsets having less dissimilarity among its members \[58\]. A standard k-means clustering algorithm is based on finding the distance usually taken as euclidean distance. Therefore, in this case, euclidean distance is evaluated using quantum circuits and classification of data points is executed classically. They have also implemented the algorithm on the IBMQ open-source software and demonstrated its accuracy to be better then the classical k-means algorithm. There are several other instances of significant contributions to quantum machine learning algorithms for supervised as well as unsupervised learning in comparison to classical algorithms \[14, 59–64\].

The first instance of understanding the neural networking of human brain using quantum computing was demonstrated by Kak \[65\]. Menneer and Narayanan further developed the idea to discuss a practical approach of using quantum computing in neural networks \[66\]. In order to obtain the quantum inspired neural network, they first trained a number of neural networks with respect to the training inputs and then evaluated the superposition of these networks. Ventura and Martinez further proposed a method for quantum associative memory based upon Grover’s algorithm \[67\] and shown the results leading to exponential storage capacity of associative memory \[68\]. Based on the results of Ventura and Martinez, Zhou \textit{et al.} developed a model for the quantum associative neural network to generate a quantum binary decision for quantum array to store patterns \[69\].

Evidently, in all quantum and classical algorithms, dataset plays a crucial role. The performance of algorithms always depend on the type of data points, dimension of the dataset, outliers etc. In view of this, Huang \textit{et al.} \[70\] further established the power of the data by considering different quantum kernels and their comparisons with classical algorithms and the advantages of quantum algorithms when the geometric difference is very high.

Clearly, the performance of an algorithm can be analysed by testing it over different types of real-valued datasets. The quantum support vector machine was originally tested over the ad-hoc numerical dataset. The sentiment analysis of an unseen data using quantum algorithms is still at a nascent stage. Therefore, in this study, we perform a comparative sentiment analysis using quantum and classical algorithms based on different performance metrics. Depending on the number of features, our analysis quantifies the advantages of quantum machine learning algorithms for classifying the IMDB review data. We demonstrate that the quantum support vector machine is a much better and efficient algorithm in comparison to the best of classical algorithms.

**IV. BASIC STRUCTURE OF PROPOSED APPROACH**

In this work, we analyse sentiments of textual data considering its applications in spam filtering, intention mining, product analysis and market research, to name a few. Fig. 2 clearly depicts our approach through for the sentimental analysis. For this, we use the IMDB movie review dataset downloaded from Kaggle \[71\] in which the reviews are stored in text format and a single review contains 200 or more words. Moreover, the dataset contains 40,000 reviews, out of which 20,019 belong to the negative class and 19,981 belong to the positive class of sentiments. For our purpose, corresponding to each review, a negative (0) or positive (1) label is stored under the label column. As the raw text data generally includes redundant information with no adequate contribution to the classification process, the pre-processing of data such as removing special characters and punctuation (@,#,%,:, many more), lower-casing, removing stop-wards, and limmatizing the words becomes very significant. For example, Fig 3...
FIG. 3. Pre-processing steps for useful feature extraction from the raw dataset shows the pre-processing steps and their effects on the text data.

FIG. 4. The word cloud of frequently appeared words in the whole documents

In order to convert reviews into numerical form, the next important step is to perform vectorization of the pre-processed text data as accepted by machine learning algorithms. In the proposed strategy, we use CountVectorizer, also known as Bag of Words (BoW). The BoW evaluates the frequency associated with each token that occurs in a document. For this, BoW creates a set of words present in the whole dataset and computes the frequency for each token by analyzing the occurrence of words in a document. BoW may also contain frequently appearing words in the created set, therefore, we do not consider words appearing in more than 80% of documents and less than 20% of documents. BoW further produces a sparse matrix where some of the tokens acquire a large value and others do not. Hence, we normalize the resulted dataset by dividing feature values with the square root of the sum square of all features, given as

$$f'_i = \frac{f_i}{\sqrt{\sum_{i=1}^{d} f_i}}$$  \hspace{1cm} (9)$$

Here, $f_i$ is the feature value, and $d$ represents dimensions of the data. The Fig. 4 represents a cloud of words where the size of words shows their occurrence in the dataset.

A. Feature Selection

The dataset originally contained a total of 57,658 unique words with most of them appearing less than 10 times in whole documents, which may lead to over-fitting. For a better analysis of the text data, we specifically require those features that show their significance during classification. For feature selection, we first use the recursive feature elimination (RFE) method which recursively eliminates features not contributing to the classification. RFE assigns weights to features using an estimator or model. In this paper, we use the random forest model as an estimator for RFE. The random forest classifier is based on the concept of bootstrap aggregating and uses bagging for features that make it immune to overfitting. We further optimize parameters for the number of trees to be used and opt for the Gini index as a splitting criterion and constraints to use the square root of total number of features in a random forest. Random forest thus selects the best decision tree through which we obtain best features. RFE recursively performs this process on all features randomly and assigns weights to features on their appearances. Corresponding to all features obtained from RFE, we further characterize these features for their significance in classification. Therefore, we also use Lasso (Lease Absolute Shrinkage Selector Operator), which regularizes features by penalizing. For this, we use the normalized data $(x_i, y_i)$, where $i = 1,...,n$, to approximately compute $y_i$ while minimizing the cost function. As a key point, Lasso adds the sum of absolute value of a coefficient parameter to the cost function given as

$$w' = \arg \min [C(w) + \sum_{i=0}^{d} \lambda |w_i|]$$  \hspace{1cm} (10)$$
Here $C(w)$ is the cost function and $w$ is the coefficient parameter which is determined by $\lambda$. Specifically, $\lambda$ is a hyper-parameter that controls the complexity and needs to be determined. The high value of $\lambda$ does not allow the coefficient parameter to attain a significant value; on the other hand, if $\lambda = 0$, the model overfits. Therefore, we optimize the value for $\lambda$ to get the best essential features. Moreover, we allow the coefficient parameter to attain a negative value in order to get features from negative text reviews. Lasso gives us the coefficient with respect to features.

Fig. 5 shows the comparison curve for Lasso and RFE. The figure clearly indicates that RFE shows features to be either significant or not by analyzing 0 or 1 value corresponding to features; whereas Lasso shows the coefficient value for features. The figure further demonstrates that features attaining a 0 value for RFE also get a coefficient value nearly equal to 0 and therefore get the last preference while selecting features.

Finally, we construct the database using selected features and proceed with the analysis using classical machine learning algorithms. In contrast to classical machine learning algorithms, for the quantum machine learning algorithms, we first construct a model for mapping classical features into quantum states. Therefore, we now proceed to discuss the model for mapping classical data to quantum states in the following subsection.

**B. Feature Mapping**

Once the features are selected as per the requirements of the near-term quantum computer, we proceed with the development of a feature mapping model. For feature mapping, the classical data $\vec{x}_i \in \mathbb{R}^n$ is embedded into quantum states $|\phi(\vec{x}_i)\rangle$ through the unitary transformation $U_{\phi(\vec{x})}$ such that

$$|\phi(\vec{x}_i)\rangle = \bigotimes_{i=1}^{n} U_{\phi(\vec{x})}(x_i).$$

Fig. 6 represents the circuit implementation for the unitary transformation. We initiate the circuit with $|0\rangle$ states and create a superposition state by applying Hadamard gates on all qubits. The number of features determines the number of qubits used in the circuit. The superposition state is then evolved as shown in Fig. 6. Here ZZ gate is a combination of CNOTs and rotation gate along Z axis such that the angle is determined by a function given as

$$\phi(\vec{x}_i, \vec{x}_j) = (\pi - x_i)(\pi - x_j).$$

where $\phi(\vec{x})$ is a classical non-linear function which depends on feature values $x_i$ and $x_j$ of a document associated with the dataset. The CNOT gates entangle a qubit with its successor in a linear form. Moreover, UC gate is a combination of $R_x$ and $R_y$ gates, where $R_x$ is rotation gate with a fixed angle; whereas $R_y$ is a feature value ($x_i$) dependent gate. Eventually, the designed feature map transforms classical data points into higher dimensional space ($\mathbb{C}^{2n}$-dimensions) and facilitates computing the kernel value for the quantum support vector machine.

**C. Classification**

We now proceed to classify sentiment text data using quantum and classical machine learning algorithms. For implementing the quantum machine learning algorithms, we use IBM quantum systems. Considering that the current IBM quantum systems permit 5-queries at a time therefore, we start with a subset of the data with 150 samples for efficiently implementing it over the available near-term quantum computer. As the dataset is small, we train and test the data multiple times using K-fold stratified cross-validation to develop a generalized model and preserve the percentages of samples from both positive and negative classes during the sampling of the dataset. In addition, we also use 10-folds which samples the dataset 10-times into train and test data points. Further, for a classical support vector machine, we tune the kernel function and analyze the linear kernel ($k(x, y) = x^T y + C$) which performs the best for text classification dataset where $C$ is the regularization parameter. The value for $C$ is also fine-tuned, but it does not contribute significantly in classification, and hence is considered as 1.0.

To compare the classification performances of models, we use the quantum support vector machine where kernel values are evaluated using the feature map circuit. Further, measurements on each qubit are performed in the computational
basis and measurement results are translated to the classical SVM. We further analyze parameters $C$ and $\gamma$ for classification where $\gamma$ is curvature of hyperplane and find that for quantum SVM also these parameters do not contribute efficiently towards classification. In fact, the use of $C$ and $\gamma$ leads to a decrease in accuracy. Another factor that plays an important role in classification is repetition of feature mapping circuits. For our analysis, we required to repeat the feature map circuit twice for the five-dimensional data in order to achieve a better accuracy. The number of repetitions may keep changing with the dimensions of data. A similar observation can be made for the number of shots. As stated above, the performance of models is measured using a confusion matrix, precision, recall and F1-score.

### V. RESULTS

For our analysis, we train the classical and quantum support vectors using parameters specified in the previous subsection—the classical models were implemented in Anaconda platform using scikit-learn and the quantum model was implemented on IBM-quantum experience using qasm-simulator [72]. Moreover, classical supervised algorithms such as decision tree and gradient boosting classifier are also used for comparing the performance evolution of the models. Fig. 7 clearly demonstrates the advantage of using quantum support vector machine in terms of accuracy, precision, recall and F1-score. As discussed above, the performance of a classification model can not ascertained by analysing the accuracy only. The factors such as precision and recall further play a significant role in determining specificity and sensitivity of the model, respectively. Table II further summarizes minimum accuracy, maximum accuracy and standard deviation obtained using both classical and quantum SVMs. Moreover, Table II shows that the use of quantum support vector machine results in significantly better results in comparison to all other classical supervised models used in this paper. Among the classical models, classical support vector machine is found to be the highest performing model which can be used as a benchmark. Finally, we also evaluate the performance of models using ROC-AUC values as depicted in Fig. 8 where AUC stands for area under ROC curve. The ROC curve represents a plot- for best ROC-AUC value from k-fold runs- for true positive rate (TPR) versus false positive rate (FPR) where the TPR and FPR are predicted probabilities for test data points by respective models. Therefore, our results suggest that the quantum support vector machine will predict any unseen instance as positive with the highest probability if that instance is actually positive.

![FIG. 7. Performance measures of classical and quantum support vector machines](image)

**Table I. A comparison between classical and quantum support vector machines based on Accuracy**

| Models                      | CSVM | QSVM |
|-----------------------------|------|------|
| Minimum Accuracy            | 40   | 47   |
| Maximum Accuracy            | 80   | 93   |
| Standard Deviation Accuracy | 12.98| 15.24|

**Table II. Average values of K-Fold cross validation Accuracy, Precision, Recall, and F1-Score**

| Models                      | Accuracy | Precision | Recall | F1-Score |
|-----------------------------|----------|-----------|--------|----------|
| Classical Support Vector Machine | 64.1     | 67.96     | 63.99  | 59.84    |
| Decision Tree               | 51.99    | 52.77     | 51.99  | 51.98    |
| Gradient Boosting Classifier | 60.66    | 61.94     | 60.66  | 60.70    |
| Quantum Support Vector Machine | **68.6** | **69.49** | **68.66** | **67.25** |

![FIG. 8. The ROC-curve between quantum and classical model at their best ROC-AUC values](image)
VI. CONCLUSION

In this work, we performed a comparative analysis to classify the text data of IMDb movie reviews using quantum support vector machine in comparison to classical machine learning models such as decision tree, gradient boosting classifier and classical support vector machine. Our results have shown quantum support vector machine to outperform all classical models in terms of different evaluation metrics. The analysis presented here clearly demonstrates the efficiency of quantum support vector machine in successfully classifying unseen data with maximum prediction probability. Among all classical models, the classical support vector machine is found to be the most efficient in sentiment analysis of the used data. Therefore, we comprehensively analyse the classical and quantum support vector machines with increased number of features or dimensions to ascertain the advantages of quantum support vector machine for achieving significantly better precision score and other metrics. For our analysis with thirteen features, the precision score using the quantum support vector machine is 12.6% higher than the case where classical support vector is used. The results indicate that the quantum support vector machine performs optimally with small training and hence can be further utilized in health care industries where higher prediction probability and sensitivity of the model are of utmost importance with small datasets. A future problem of particular interest would be to optimize the kernel to further reduce the computational time with an improved efficiency of algorithms.
2070, 2013.

[17] Anton Zeilinger. Quantum entanglement: a fundamental conceptual finding of its applications. *Physica Scripta*, 1998(T76):203, 1998.

[18] Julia Kempe. Multiparticle entanglement and its applications to cryptography. *Physical Review A*, 60(2):910, 1999.

[19] Maria Schuld, Ilya Sinayskiy, and Francesco Petruccione. An introduction to quantum machine learning. *Contemporary Physics*, 56(2):172–185, 2015.

[20] Bo Pang and Lilian Lee. Opinion mining and sentiment analysis. *Comput. Linguist.*, 35(2):311–312, 2009.

[21] Bing Liu et al. Sentiment analysis and subjectivity. *Handbook of natural language processing*, 2010:627–666, 2010.

[22] Satuluri Vanaja and Meena Belwal. Aspect-level sentiment analysis on e-commerce data. In 2018 International Conference on Inventive Research in Computing Applications (ICIRCA), pages 1275–1279. IEEE, 2018.

[23] Hsuanwei Michelle Chen and Patricia C Franks. Exploring government uses of social media through twitter sentiment analysis. *Journal of Digital Information Management*, 14(5), 2016.

[24] Haruna Isah, Paul Trundle, and Daniel Neagu. Social media analytics for product safety using text mining and sentiment analysis. In 2014 14th UK workshop on computational intelligence (UKCI), pages 1–7. IEEE, 2014.

[25] Zahra Abbasi-Moud, Hamed Vahdat-Nejad, and Javad Sadri. Tourism recommendation system based on semantic clustering and sentiment analysis. *Expert Systems with Applications*, 167:114324, 2021.

[26] Benjamin Johnston and Ishita Mathur. *Applied Supervised Learning with Python*: Use scikit-learn to build predictive models from real-world datasets and prepare yourself for the future of machine learning. Packt Publishing Ltd, 2019.

[27] M Emre Celebi and Kemal Aydin. Unsupervised learning algorithms. Springer, 2016.

[28] Richard S Sutton, Andrew G Barto, et al. *Introduction to reinforcement learning*. 1998.

[29] Qiang Ye, Ziqiong Zhang, and Rob Law. Sentiment classification of online reviews to travel destinations by supervised machine learning approaches. *Expert systems with applications*, 36(3):6527–6535, 2009.

[30] Bo Pang, Lilian Lee, and Shivakumar Vaithyanathan. Thumbs up? sentiment classification using machine learning techniques. *arXiv preprint cs/0205070*, 2002.

[31] Alec Go, Richa Bhayani, and Lei Huang. Twitter sentiment classification using distant supervision. *CS224N project report, Stanford*, 1(2):2009, 2009.

[32] P Kalaivani and KL Shunmuganathan. Sentiment classification of movie reviews by supervised machine learning approaches. *Indian Journal of Computer Science and Engineering*, 4(4):285–292, 2013.

[33] Vasileios Athanasiou and Manolis Maragoudakis. A novel, gradient boosting framework for sentiment analysis in languages where nlp resources are not plentiful: a case study for modern greek. *Algorithms*, 10(1):34, 2017.

[34] Zhen Zuo. Sentiment analysis of steam review datasets using naive bayes and decision tree classifier. 2018.

[35] Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine learning*, 20(3):273–297, 1995.

[36] Yiming Yang and Xin Liu. A re-examination of text categorization methods. In *Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval*, pages 42–49, 1999.

[37] Albert Einstein, Boris Podolsky, and Nathan Rosen. Can quantum-mechanical description of physical reality be considered complete? *Physical review*, 47(10):777, 1935.

[38] John S Bell. On the einstein podolsky rosen paradox. *Physics Physique Fizika*, 1(3):195, 1964.

[39] Dan A Ventura. Pattern classification using a quantum system. 2002.

[40] Michael A Nielsen and Isaac Chuang. Quantum computation and quantum information, 2002.

[41] Martin B Plenio and Shashank S Virmani. An introduction to entanglement theory. *Quantum information and coherence*, pages 173–209, 2014.

[42] Kaoru Shimizu and Nobuyuki Imoto. Communication channels secured from eavesdropping via transmission of photonic bell states. *Physical Review A*, 60(1):157, 1999.

[43] Chitra Shukla, Nasis Alam, and Anirban Paul. Protocols of quantum key agreement solely using bell states and bell measurement. *Quantum information processing*, 13(11):2391–2405, 2014.

[44] Carlos Sabin and Guillermo García-Alcaine. A classification of entanglement in three-qubit systems. *The european physical journal D*, 48(3):435–442, 2008.

[45] Jyoti Faujdar and Atul Kumar. Analysing the efficiencies of partially entangled three-qubit states for quantum information processing under real conditions. *Zeitschrift für Naturforschung A*, 74(6):523–537, 2019.

[46] Natalia Korolkova and Gerd Leuchs. Quantum correlations in separable multi-mode states and in classically entangled light. *Reports on Progress in Physics*, 82(5):056001, 2019.

[47] Colin P Williams. Quantum gates. In *Explorations in Quantum Computing*, pages 51–122. Springer, 2011.

[48] Maria Schuld. Supervised quantum machine learning models are kernel methods. *arXiv preprint arXiv:2101.11020*, 2021.

[49] Vojtěch Havlíček, Antonio D Córcoles, Kristan Temme, Aram W Harrow, Abhinav Kandala, Jerry M Chow, and Jay M Gambetta. Supervised learning with quantum-enhanced feature spaces. *Nature*, 567(7747):209–212, 2019.

[50] Marcello Benedetti, Erika Lloyd, Stefan Sack, and Mattia Fiorentini. Parameterized quantum circuits as machine learning models. *Quantum Science and Technology*, 4(4):043001, 2019.

[51] Gennaro De Luca. A survey of nisq era hybrid quantum-classical machine learning research. *Journal of Artificial Intelligence and Technology*, 2(1):9–15, 2022.

[52] Patrick Rebentrost, Masoud Mohseni, and Seth Lloyd. Quantum support vector machine for big data classification. *Physical review letters*, 113(13):130503, 2014.

[53] Songfeng Lu and Samuel L Braunstein. Quantum decision tree classifier. *Quantum information processing*, 13(7):757–770, 2014.

[54] X-D Cai, Dian Wu, Z-E Su, M-C Chen, X-L Wang, Li Li, N-L Liu, C-Y Lu, and J-W Pan. Entanglement-based machine learning on a quantum computer. *Physical review letters*, 114(11):110504, 2015.

[55] Maria Schuld, Ilya Sinayskiy, and Francesco Petruccione. Quantum computing for pattern classification. In *Pacific Rim International Conference on Artificial Intelligence*, pages 208–220. Springer, 2014.

[56] Yue Ruan, Xiling Xue, Heng Liu, Jianing Tan, and Xi Li. Quantum algorithm for k-nearest neighbors classification based on the metric of hamming distance. *International Journal of Theoretical Physics*, 56(11):3496–3507, 2017.

[57] Nathan Wiebe, Ashish Kapoor, and Kryssa Svore. Quantum algorithms for nearest-neighbor methods for supervised and unsupervised learning. *arXiv preprint arXiv:1401.2142*, 2014.
Abhijat Sarma, Rupak Chatterjee, Kaitlin Gili, and Ting Yu. Quantum unsupervised and supervised learning on superconducting processors. *arXiv preprint arXiv:1909.04226*, 2019.

Esma Aimeur, Gilles Brassard, and Sébastien Gambs. Quantum speed-up for unsupervised learning. *Machine Learning*, 90(2):261–287, 2013.

Esma Aimeur, Gilles Brassard, and Sébastien Gambs. Machine learning in a quantum world. In *Conference of the Canadian Society for Computational Studies of Intelligence*, pages 431–442. Springer, 2006.

Iordanis Kerenidis, Jonas Landman, Alessandro Luongo, and Anupam Prakash. q-means: A quantum algorithm for unsupervised machine learning. *Advances in Neural Information Processing Systems*, 32, 2019.

Johannes S Otterbach, Riccardo Manenti, Nasser Alidoust, A Bestwick, M Block, B Bloom, S Caldwell, N Didier, E Schuyler Fried, S Hong, et al. Unsupervised machine learning on a hybrid quantum computer. *arXiv preprint arXiv:1712.05771*, 2017.

Unai Alvarez-Rodriguez, Lucas Lamata, Pablo Escandell-Montero, José D Martín-Guerrero, and Enrique Solano. Supervised quantum learning without measurements. *Scientific reports*, 7(1):1–9, 2017.

Oleksandr Kyriienko and Einar B Magnusson. Unsupervised quantum machine learning for fraud detection. *arXiv preprint arXiv:2208.01203*, 2022.

Subhash C Kak. Quantum neural computing. *Advances in imaging and electron physics*, 94:259–313, 1995.

Tammy Menneer and Ajit Narayanan. Quantum-inspired neural networks. *Tech. Rep. R329*, 1995.

Lov K Grover. Quantum search on structured problems. In *NASA International Conference on Quantum Computing and Quantum Communications*, pages 126–139. Springer, 1998.

Dan Ventura and Tony Martinez. Quantum associative memory. *Information Sciences*, 124(1-4):273–296, 2000.

Rigui Zhou, Huian Wang, Qian Wu, and Yang Shi. Quantum associative neural network with nonlinear search algorithm. *International Journal of Theoretical Physics*, 51(3):705–723, 2012.

Hsin-Yuan Huang, Michael Broughton, Masoud Mohseni, Ryan Babbush, Sergio Boixo, Hartmut Neven, and Jarrod R McClean. Power of data in quantum machine learning. *Nature communications*, 12(1):1–9, 2021.

Ziqi Yuan Abdül Meral and Avnika Shah. Imdb movie review dataset.

Gadi Aleksandrowicz, Thomas Alexander, Panagiotis Barkoutsos, Luciano Bello, Yaël Ben-Haim, David Bucher, Francisco Jose Cabrera-Hernández, Jorge Carballo-Franquis, Adrian Chen, Chun-Fu Chen, Jerry M. Chow, Antonio D. Córcoles-Gonzales, Abigail J. Cross, Andrew Cross, Juan Cruz-Benito, Chris Culver, Salvador De La Puente González, Enrique De La Torre, Delton Ding, Eugene Dumitrescu, Ivan Duran, Pieter Eendebak, Mark Everitt, Ismael Faro Sertage, Albert Frisch, Andreas Fuhrer, Jay Gambetta, Borja Godoy Gago, Juan Gomez-Mosquera, Donny Greenberg, Ikko Hamamura, Vojtech Havlicek, Joe Hellmers, Lukasz Herok, Hiroshi Horii, Shao-Han Hu, Takashi Imamiichi, Toshinari Itoke, Ali Javadi-Abhari, Naoki Kanazawa, Anton Karazeev, Kevin Krsulich, Peng Liu, Yang Lu, Yunho Maeng, Manoel Marques, Francisco Jose Martín-Fernández, Douglas T. McClure, David McKay, Srujan Meesala, Antonio Mezzacapo, Nikolaj Moll, Diego Moreda Rodriguez, Giacomo Nannicini, Paul Nation, Pauline Ollitrault, Lee James O'Riordan, Hanhee Paik, Jesús P´erez, Anna Phan, Marco Pistoia, Viktor Pratyanov, Max Reuter, Julia Rice, Abdón Rodríguez Davila, Raymond Harry Putra Rudy, Mingi Ryu, Ninad Sathaye, Chris Schnabel, Eddie Schoute, Kanav Setia, Yunong Shi, Adenilton Silva, Yukio Siraichi, Seyon Sivarahaj, John A. Smolin, Mathias Soeken, Hitomi Takahashi, Ivano Tavernelli, Charles Taylor, Pete Taylour, Kenzo Trabing, Matthew Treinish, Wes Turner, Desiree Vogt-Lee, Christophe Vuillot, Jonathan A. Wildstrom, Jessica Wilson, Erick Winston, Christopher Wood, Stephen Wood, Stefan Wörner, Ismail Yunus Akhalwaya, and Christa Zoufal. Qiskit: An Open-source Framework for Quantum Computing, January 2019.