Research Article

The Effect of Linear Discriminant Analysis and Quantum Feature Maps on QSVM Performance for Obesity Diagnosis

Zeynep Ozpolat, Ozal Yildirim and Murat Karabatak

Abstract— **Obesity, characterized by an excessive accumulation of body fat, is a significant health issue that predisposes individuals to numerous diseases. Therefore, early intervention and necessary measures in the diagnosis and treatment of obesity are of great importance. In medicine, classical machine learning algorithms are widely used to accelerate the prediction process. However, the increasing volume of data often renders these algorithms insufficient for accurate disease diagnosis. At this point, quantum computing-based algorithms offer more efficient and faster solutions by leveraging quantum physics, which operates contrary to the principles of classical physics. Dimensionality reduction techniques play a critical role in both classical and quantum classifiers. In this study, classical dimensionality reduction methods, namely Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA), were applied to an obesity dataset. The dataset was subsequently analyzed using Quantum Support Vector Machine (QSVM) and Support Vector Machine (SVM) algorithms. As part of the QSVM studies, three different quantum feature maps, which facilitate the quantum bit transformation of classical bit data, were also compared. The analysis revealed that the proposed LDA-QSVM method achieved 100% accuracy when used with the Z and Pauli X feature maps. This remarkable success, which is rarely seen in the literature on obesity data, underscores the potential of quantum-based algorithms in the diagnosis and treatment of obesity.**

Index Terms— **Obesity, Linear Discriminant Analysis, Quantum Support Vector Machine, Dimensionality Reduction, Quantum Machine Learning.**

I. INTRODUCTION

GLOBALY, OBESITY poses a significant public health concern. Examining the relationship between eating habits and physical condition is important for understanding and managing the obesity problem in detail [1]. Examining the relationship between eating habits and physical condition is important for understanding and managing the obesity problem in detail. Obesity not only has negative impacts on the health of individuals, but can also be a major burden on health systems and economies. Therefore, it is important to develop and implement effective strategies to combat obesity. Given that technological advances have raised living standards, it is inevitable that they will help experts in the field of medical diagnosis. Prediction systems, which aim to guide the diagnosis and treatment process of many diseases developed for this purpose, are actively used in obesity [2]. These systems play an important role in determining the obesity risk of individuals and making healthy lifestyle recommendations.

In recent years, when interdisciplinary studies have become popular, the approach between medicine and informatics has led to great advances. Machine learning applications have been widely used for diseases such as obesity that require complex and multifaceted investigations [3]. Thanks to these algorithms, large amounts of data can be analyzed and controls such as risk factors, treatment options and health status of patients can be easily monitored. Machine learning algorithms aim to find patterns and relationships to solve a problem [4]. However, growing data sizes and diversity have started to make this process difficult. For this reason, the concept of quantum computing and quantum machine learning, which has a different perspective of quantum physics, has gained its place today [5]. Thanks to the interesting perspective of quantum physics that allows us to consider every possibility, machine learning algorithms have also started to be actively used in the quantum world [6].

In diseases such as obesity, where many parameters are effective, the diversity in terms of attributes is very high. These attributes need to be reduced to enable more effective use of both classical and quantum algorithms [7]. However, since it is disease data, it would be more appropriate to reduce the number of attributes by using various mathematical operations instead of completely removing an existing attribute from the data set [8]. The most common dimensionality reduction algorithms are Principal Component Analysis (PCA) [9] and Linear Discriminant Analysis (LDA) [10].

Quantum computers are physically available in only a few locations worldwide and are typically accessible through cloud-based or simulation environments. These computers offer users a limited number of quantum bits (qubits) [11]. Unlike classical bits, qubits are fundamental units of quantum information that

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can represent multiple states simultaneously. Due to the limited number of qubits available, dimensionality reduction algorithms are crucial for effective data processing in quantum machine learning. Quantum machine learning algorithms utilize dimensionality reduction techniques not only for medical data but also across various other disciplines. Thus, applying dimensionality reduction methods is essential for optimizing the performance of quantum algorithms, just as it is for classical ones. After the relevant data is reduced to the number of qubits presented, it is converted into qubit form with the help of quantum feature maps [12]. Quantum feature maps are obtained using different combinations of quantum gates. Quantum feature maps with different properties are obtained with circuits built using Hilbert space and quantum gates. These feature maps make the datasets usable in quantum state space, facilitating the application of quantum machine learning algorithms.

Many studies have explored the potential of quantum machine learning algorithms in healthcare, and have shown significant progress in areas such as disease detection and classification. Some of these studies include: Kumar et al. [13] presented a QSVM quantum-based machine learning model for the detection of brain tumors. They showed that their proposed QSVM model provides 1.60% times better performance than classical SVM. Aksoy and Karabatak [14] analyzed the classification of EEG signals using QSVM. In their study, they classified EEG signals with QSVM with a performance of 99.47%. In another study [15], the authors achieved 100% success with Pauli X and Pauli Z feature maps for the detection of schizophrenia with EEG signals. Maouaki et al. [16] conducted a study comparing the classification performance of QSVM and classical SVM algorithms to improve prostate cancer detection methods. As a result of their analysis, they achieved 94% performance with ZZFeatureMap. Munşi et al. [17] evaluated the performance of QSVC and Variational Quantum Classifiers (VQC) for chronic heart disease prediction. They found that the results obtained with QSVC showed a better classification performance compared to VQC.

In this study, the data of patients with obesity were used for classification with QSVM, a quantum-based machine learning algorithm. In order to evaluate the performance of QSVM, comparative analyses were also performed with the classical SVM algorithm with the same standards. Before applying the classical and quantum classification algorithms, the dataset was subjected to dimensionality reduction with PCA and LDA separately. Classical SVM and QSVM algorithms were applied to the new data sets. During the studies, the dimensionally reduced data with LDA and PCA were converted into qubits with Z, ZZ and Pauli X feature maps and classified with QSVM. As a result of the analysis, it was determined that the proposed classification method as LDA-QSVM achieved successful results in predicting obesity disease. Considering the process of quantum-based algorithms, which are still under development, these results are very promising. These findings emphasize the potential of studies in the field of quantum computing for the development of new and effective methods for the treatment and prevention of obesity.

II. Materials and Methods

In this study, the classification performance of the QSVM algorithm is examined by testing various parameters on a dataset prepared to detect obesity based on eating habits and physical conditions. Quantum feature maps are used to transform a data set in classical form into qubit form. It has been observed that feature maps create performance differences in the QSVM algorithm used according to the transformations they make. Considering these changes, the performance of the QSVM algorithm is compared. A formal representation of the proposed method is given in Figure 1.

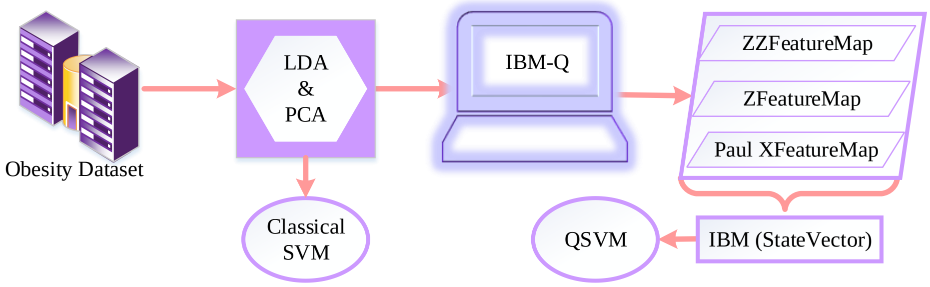

Fig.1. Schematic representation of the proposed method

A. *Obesity Dataset*

In this study, we use a dataset from the UC Irvine Machine Learning Repository, where obesity classes are created based on physical condition and eating habits [18]. This dataset contains 2111 records collected through questionnaires from patients and non-patients in Mexico, Peru and Colombia. In the dataset with 17 attributes, classification labels were obtained as Underweight, Normal Weight, Overweight Level I, Overweight Level II, Obesity Type I. Obesity Type II and Obesity Type III labels, which are not included in the data, were created synthetically with the SMOTE filter using Weka [18]. Another 23% of the data was obtained through a web platform. The main purpose of creating this dataset is to determine the obesity level of the person and to help create recommendation systems that can monitor these levels [19]. Information about the attributes of the dataset is given in Table 1 [20].

TABLE I
GENERAL INFORMATION ABOUT THE OBESITY DATASET

Features	Description	Data Type
Gender	Sex	Men-Women
Age	Age	Values between the ages of 14-61
Height	Height (Meters)	1.45-1.98
Weight	Weight (Kilograms)	39-143
Family History With Overweight	Family History of Overweight	Yes-No
FAVC	High Calorie Food Consumption	Yes-No
FCVC	Vegetable Consumption Frequency	FCVC > 2, positive vegetable intake at each meal FCVC≤2, zero vegetable intake in some meals
NCP	Number of Main Meals per Day	1-2-3-4
CAEC	Daily Snack Frequency	No, Sometimes, Often and Always
SMOKE	Smoking Status	Yes-No
CH2O	Daily Water Consumption Amount (Liters)	Between 1-3
SCC	Calorie Tracking	Yes-No
FAF	Physical Activity Frequency (Hours)	Between 0-3
TUE	Technological Tool Usage Time (Hours)	Between 0-2
CALC	Alcohol Consumption	Yes-No-Sometimes
MTRANS	Means of Transportation	Automobile, Motorcycle, Bicycle, Public Transportation, Walking
NObeyesdad	Obesity Level	Underweight, Normal Weight, Overweight Level I, Overweight Level II, Obesity Type I, Obesity Type II, Obesity Type III

When the data set was analyzed in general, it was observed that there was no missing data. It was determined that the data were homogeneously distributed according to the label groups.

B. Methods

In this paper, two different dimensionality reduction methods were applied to obesity data. The first one is the Principal Component Analysis (PCA) method, which is frequently used in quantum machine learning applications [21]. PCA is a statistical technique that reduces the dimensionality of data by identifying the principal components that capture the maximum variance in the data set. This method calculates the mean and variance of the data points and identifies the directions (principal components) along which the variance is maximized [14]. By projecting the data onto these components, PCA transforms the original data into a new set of uncorrelated variables (principal components), reducing the dimensionality while retaining as much variability as possible. The goal is to create a new data set of the desired size using eigenvalues and eigenvectors that correspond to the principal components. PCA is particularly effective in situations where the goal is to minimize information loss while reducing the complexity of the data.

The second method used is Linear Discriminant Analysis (LDA) [22]. LDA, like PCA, is a linear dimensionality reduction technique that also relies on eigenvalues and eigenvectors. However, LDA differs from PCA in its objective; while PCA focuses solely on maximizing variance within the data, LDA seeks to maximize the separation between different classes. It achieves this by finding the linear combinations of features that best separate the classes in the data. LDA thus takes into account not only the variance within classes but also the variance between classes. This makes LDA particularly useful for supervised learning tasks where the goal is to enhance class separability. As a result, LDA is often preferred in situations where class discrimination is critical, such as in classification tasks. In this study, the advantage of LDA's ability to enhance class separability is emphasized, highlighting its superiority over PCA in certain contexts.

Furthermore, it is important to note that both PCA and LDA assume that the underlying data distribution is linear. This assumption can sometimes limit their effectiveness, especially in cases where the data exhibits complex, nonlinear relationships. However, despite these limitations, PCA and LDA remain widely used due to their simplicity, computational efficiency, and ability to reduce data dimensionality in a way that preserves essential information. In quantum machine learning, where data often needs to be compressed to fit within the constraints of quantum computing resources, these techniques are particularly valuable.

The data set, which is freed from the curse of dimensionality by using dimension reduction methods, should be made processable in quantum-based algorithms. Quantum feature maps are used for this purpose. In this study, ZZ, Z and Pauli X are chosen as quantum feature maps . ZZFeatureMap aims to create a dataset that can be processed by quantum algorithms by using the Controlled Z gate to convert classical bits into qubits. It performs transformations by providing transitions between pairs of qubits [23]. ZFeatureMap is another feature map that uses the controlled Z gate as in ZZ. The most important difference from ZZFeatureMap is that it performs bit-to-qubit transformations using single-qubit transformations along the Z axis [24]. The underlying structure of the other two feature maps used is the Pauli feature map. PauliZ is known as ZFeatureMap and PauliZZ is known as ZZFeatureMap [25]. The feature map name is determined according to the gates used in the Pauli map. In this study, in addition to the Z and ZZ feature maps, the Pauli X map was used in the analysis. Quantum circuit models of ZZ, Z and Pauli X feature maps were drawn using the Qiskit library as shown in Figure 2. Here, the repetition values of all circuits drawn were chosen as reps=1.

The entanglement parameter, which indicates in which state the entanglement feature present in the ZZ and Pauli X feature maps is selected, was set to "full".

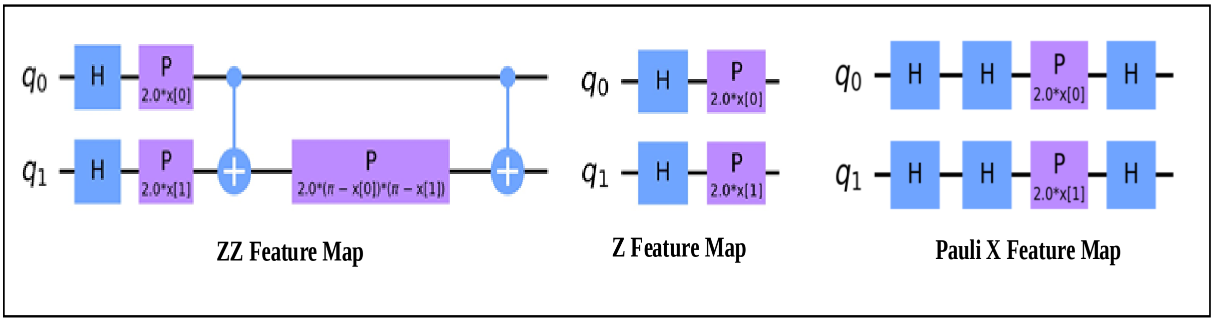

Fig. 2. Quantum circuits for ZZ, Z, and Pauli X feature maps, using Hadamard and Phase gates for data encoding.

Quantum feature maps are structures that transform classical data into qubits for processing in quantum environments. During the transformation process, the data is encoded in Hilbert space. While creating feature maps, circuit systems with different quantum gates are built. Thanks to these circuits, the data converted into qubits can be used in quantum machine learning algorithms [26]. The main factors used in feature map selection are; feature map circuit depth, data matching used in the encoding of classical data, quantum gates, and the processing order of binary qubit combinations [27].

The dataset transformed into qubit form using feature maps is now ready for use in a quantum machine learning application. The Quantum Support Vector Machine algorithm, which is frequently preferred in the literature in quantum machine learning, was preferred in this study [28]. The QSVM algorithm is a quantum-based classification algorithm based on the least squares method used in the classical SVM algorithm [29]. The classical SVM algorithm uses the least squares method to select the most appropriate hyperplane to classify the data into classes. QSVM first performs a coding step with vectors representing the quantum states of the data points. It then processes the data encoded into these quantum states with quantum circuits and performs classification as output. Thanks to the quantum circuit structures used in the QSVM algorithm, it can perform better in the classification of complex datasets [30].

III. Experimental Results

A dataset prepared for the diagnosis of obesity was used in the experimental studies. LDA and PCA algorithms were progressively applied to the obesity data and analyzed. The new datasets created for different dimensions were processed with feature maps to convert them into qubit form. The main objective of the study is to measure the change in the performance of the QSVM algorithm after applying different types of feature maps to the dataset. For this purpose, three different feature maps were used, namely ZZ Feature Map, Z Feature Map and Pauli X Feature Map. While using the Pauli feature map, several combinations were tried and all of the analyses were performed for the case with the highest performance. All of the analyzes are presented comparatively with tables and graphs.

In order to measure the performance of the QSVM algorithm against a classical classification algorithm, analyses were also performed with the SVM algorithm. The dataset was divided into training and test. The test size was set to 40% and random_state was set to 900. Since the feature map used will not have any effect on the classical SVM algorithm, the results related to SVM are given separately. The effect on SVM varies with the LDA and PCA algorithms used when reducing the size of the dataset. For this reason, Table 2 shows the performance and runtime obtained with SVM.

TABLE II
PERFORMANCE EVALUATION OF SVM ALGORITHM ACCORDING TO LDA AND PCA

		Features Number			
DR Methods	**SVM**	**3**	**4**	**5**	**6**
LDA	**ACC**	100.0	100.0	100.0	100.0
	Run Time (sec)	0.01	0.02	0.03	0.04
PCA	**ACC**	66.98	72.43	72.54	77.87
	Run Time (sec)	0.47	0.36	0.56	0.44

When Table 2 is examined, it is seen that the analysis results obtained with LDA show 100% success for each case in which the size is reduced. The results obtained with PCA fall behind LDA both in terms of runtime and performance.

Obesity data dimensionally reduced using PCA and LDA were converted into qubit form using ZZ, Z and Pauli X feature maps respectively. Then, the quantum classification algorithm QSVM was applied. When using ZZ and Pauli X feature maps, the parameters of the feature map were chosen as reps=2, entanglement=full, and reps=2 for Z since it has only circuit repetition parameter. The results of the analysis obtained by applying PCA and LDA for each feature map and classifying with QSVM are given in Table 3.

TABLE III
PERFORMANCE AND WORKING TIME OBTAINED IN ANALYZES

Feature Maps	DR Methods	QSVM	Qubit Numbers Q(3)	Q(4)	Q(5)	Q(6)
ZZ	LDA	ACC	60.71	60.71	29.23	29.23
		Run Time (sec)	10884	10989	15879	14967
	PCA	ACC	67.33	71.00	73.72	75.14
		Run Time (sec)	116.77	146.71	170.19	201.55
Z	LDA	ACC	100.0	100.0	100.0	100.0
		Run Time (sec)	97.67	100.97	99.87	107.25
	PCA	ACC	64.61	67.92	70.05	72.66
		Run Time (sec)	106.86	109.47	112.99	117.24
Pauli X	LDA	ACC	100.0	100.0	100.0	100.0
		Run Time (sec)	63.72	69.81	71.93	72.58
	PCA	ACC	62.84	67.57	68.52	71.36
		Run Time (sec)	70.83	75.42	74.28	76.19

The reason for the low performance and high running times in the ZZ feature map is that the dataset structure used is not suitable for processing in this feature map. ZZ feature maps are designed for use with more complex datasets. The circuits created by using the Z gate twice contribute to the solution of complex problems by actively providing the transition between qubits. The main reason for the low performance of the ZZ feature maps in this study is the lack of complex data. Except for the ZZ feature map, the results obtained with LDA in the other two feature maps show that the performance of the QSVM algorithm is much better than PCA. The performance improvement in dimensionality reduction due to LDA's good discrimination between classes, which has been proven in previous studies, is also evident in this study. In addition to the performance of LDA, the effect of the used feature maps on the performance of QSVM is clearly indicated in this study.

The performance comparison of the ZZ feature map, Z feature map and Pauli X feature map against the QSVM algorithm applied for dimensionally reduced datasets with LDA is given in Figure 3.

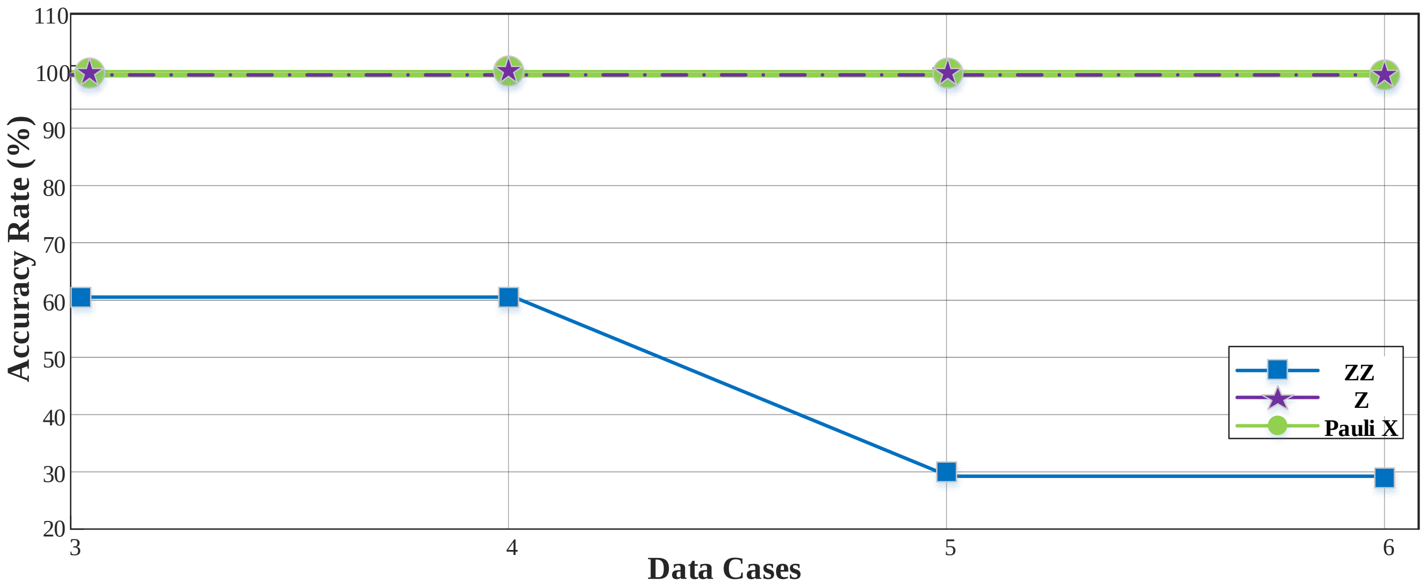

Fig.3. Performance comparisons of ZZ, Z and Pauli X feature maps

When Figure 3 is analyzed, Z and Pauli X feature maps showed 100% performance on the data reduced with the LDA algorithm on the obesity dataset. ZZ feature map caused a decrease in the performance of QSVM on the data generated by the reduction of LDA on this dataset. When the precision metric was calculated according to the 100% accuracy performances obtained for the Z and Pauli X feature maps, it was found to be 100% for each class. Since both accuracy and precision performances are 100% in obesity data, it is clear that it can help experts in the decision-making process in disease diagnosis.

IV. DISCUSSION

This study aims to apply a quantum machine learning algorithm to a dataset created for obesity detection. Among quantum machine learning algorithms, QSVM algorithm, which is a widely used algorithm in the literature, is selected. LDA and PCA, which are dimensionality reduction algorithms, were applied to reduce the data size in the obesity dataset, which has a high number of attributes. The new datasets obtained as a result of the application of these algorithms were passed through feature maps in order to apply quantum-based machine learning. The main purpose of this study is to measure the effect of the feature maps on the performance of the QSVM algorithm.

Experimental studies were carried out on the StateVector simulator made available by IBM Quantum Lab. Real computers could not be used due to the queue waiting time on real quantum computers. The StateVector simulator was preferred because it provides faster results compared to other simulators. By using ZZ, Z and Pauli X feature maps respectively, the data set in bit form was converted into qubit form to be used in quantum algorithms. Finally, the QSVM algorithm was applied to the new data sets obtained with different qubit numbers. In order to evaluate the performance of QSVM, dimensionally reduced data were also analyzed with SVM, a classical machine learning algorithm. Some of the studies in the literature using obesity dataset are given in Table 4.

TABLE IV
SOME STUDIES IN THE LITERATURE REGARDING THE OBESITY DATASET USED IN THE STUDY

	Studies with Obesity Data Set	
References	**Machine Learning Methods**	**Accuracy (%)**
Kaur vd. [31]	RF	95.5
	Bagging	95.03
	XGB	96.45
	GB	96.33
	SVM	87.34
	K-NN	81.42
Putzel ve Lee [32]	Multiclass Classification	73
Solomon vd. [33]	SVM	86.75
	Gaussian NB	88.17
	K-NN	78.23
	LR	86.91
	Decision Tree	94.95
	RF	91.95
	eXtreme Gradiyent Boosting	96.37
	Gradiyent Boost	96.06
	XGBoost	96.06
	MLP	93.38
	Solomon vd. Method	97.16
Nematzadeh vd. [34]	AvgPerseptron (Exhaustive Grid Search)	59.1
	FastForest(Grey Wolf Optimization)	96.9
	FastTree(Grey Wolf Optimization)	99.5
	LbfgsMxEn(Grey Wolf Optimization)	81.8
	LGBM(Grey Wolf Optimization)	99.2
	LineerSVM(Grey Wolf Optimization)	55.4
Mckensy-Sambola vd. [35]	Mckensy-Sambola vd. Method	87.0
Proposed Method	**LDA-QSVM** (Z Feature Map & Pauli X)	**100.0**
	PCA -QSVM (ZZ)	**71.36**

When the studies given in Table 4 are examined, it is seen that there are experiments with good performance in the analysis of the obesity dataset. However, the performance of none of these studies reached the performance of the proposed method. In this study prepared within the scope of this article, it was found that the QSVM algorithm reached maximum performance when LDA, one of the dimensionality reduction methods, was used. In the studies conducted with QSVM on different data sets, dimensionality reduction was generally performed with PCA technique. Compared to the PCA-QSVM method, the use of the LDA-QSVM method resulted in a 29% performance increase. The feature maps used in quantum classification techniques have many variations. Different quantum gates are used in each feature map. Among the feature maps used in this study, the ZZ feature map, each of which is set to two iterations, shows the lowest performance in the LDA-QSVM method compared to the other two maps. Due to the structural properties of LDA, it causes a decrease in performance when used with the ZZ feature map. The main reason for this is that the ZZ feature map increases the complexity by using double qubits. Since the PCA algorithm has a simpler structure compared to LDA, the feature map used has less impact on the performance of QSVM.

V. CONCLUSION

This study compares the performance of classical and quantum-based machine learning algorithms for the diagnosis of obesity. In order to improve the performance of QSVM, the effects of different combinations of classical dimensionality reduction methods and quantum feature maps on performance are investigated. LDA and PCA algorithms were selected as classical dimensionality reduction methods. With these algorithms, the data were reduced to 4 different dimensions and transformed into qubit form using quantum feature maps. Three different feature maps, ZZ, Z and Pauli X, were used. In order to compare QSVM with the classical SVM algorithm, SVM was applied to the data in bit form for 4 different dimensions. As a result of these analyses, it was determined that the proposed method as LDA-QSVM achieved 100% performance within the scope of Z and Pauli X feature maps. As a result of the literature review conducted by the authors, there is no study that has achieved this level of success with classical machine learning algorithms using the same obesity dataset. The success of a quantum machine learning algorithm in diagnosing obesity disease has an encouraging value for the use of quantum-based decision support systems in the medical field.

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