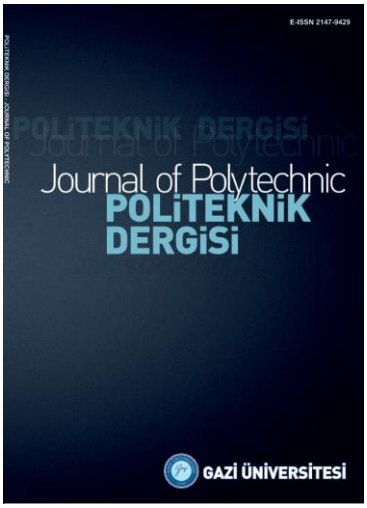

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Development a hybrid model based on harris hawks optimization (HHO) algorithm and quantum learning to diagnosis of prostate cancer

Prostat kanserinin teşhisinde harris hawks optimizasyon (HHO) algoritması ve kuantum öğrenmeye dayalı hibrit bir model geliştirilmesi

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Development A Hybrid Model Based on Harris Hawks Optimization (HHO) Algorithm and Quantum Learning to Diagnosis of Prostate Cancer

Highlights

- *A novel hybrid model combining Harris Hawks Optimization (HHO) and Quantum Learning (QL) is proposed.*
- *Achieved 97.84% diagnostic accuracy on a clinical prostate cancer dataset.*
- *Reduces computational complexity through intelligent feature selection.*

Graphical Abstract

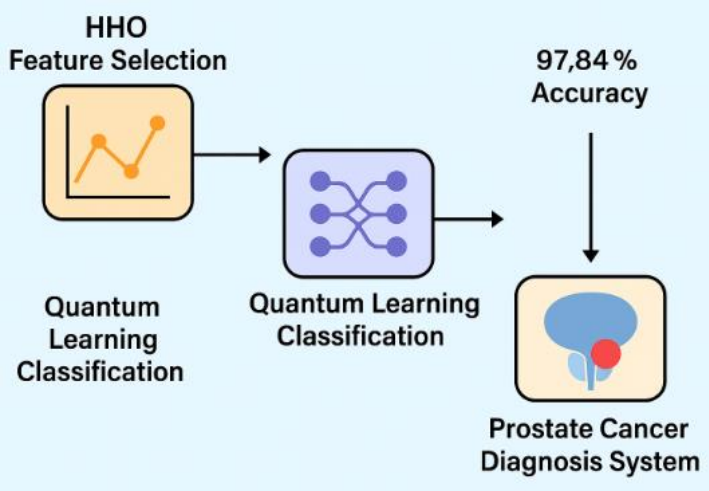

Figure. Graphical Abstract

Aim

To develop an accurate and efficient hybrid model using Harris Hawks Optimization (HHO) and Quantum Learning (QL) for early and non-invasive diagnosis of prostate cancer using clinical data.

Design & Methodology

- ***Dataset:*** *100 clinical samples (38% cancer, 62% healthy) from Kaggle.*
- ***Feature Selection:*** *HHO algorithm selected 6 optimal features out of 8.*
- ***Classification:*** *Quantum Learning model trained with selected features.*

Originality

*This study introduces a **novel hybrid approach (HHO + QL)** to tackle prostate cancer diagnosis. Unlike conventional models, it reduces unnecessary biopsies and improves classification accuracy by combining **metaheuristic optimization** with **quantum-inspired computation**.*

Findings

- *Achieved **97.84% accuracy** in classification.*
- *Outperformed existing methods such as MLP (91.36%), SVM (84.16%), and CIWO+DL (97.19%).*

Conclusion

The proposed HHO-QL hybrid model proves to be an effective, accurate, and efficient method for prostate cancer diagnosis. Its performance surpasses traditional machine learning models and presents a promising solution for clinical application.

Declaration of Ethical Standards

The authors declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Development A Hybrid Model Based on Harris Hawks Optimization (HHO) Algorithm and Quantum Learning to Diagnosis of Prostate Cancer

Araştırma Makalesi / Research Article

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ABSTRACT

Prostate cancer (PC) represents a significant health problem and stands among the primary mortality causes in men, partly due to the drawbacks of the diagnostic techniques currently used. Annually, these current diagnosis techniques cause many men to lose their lives simply because they cannot get an accurate diagnosis on time. A potentially practical and cost-effective approach for diagnosing PC is applying artificial intelligence, particularly machine learning. This work is aimed at developing a machine learning (ML) model for the diagnosis of prostate cancer on clinical data of 100 men, among whom 38% were suffering and 62% were healthy. The proposed model combines the Harris Hawk Optimization (HHO) and Quantum Learning (QL) methods. The results reveal that this new approach provides better accuracy, 97.84%, than other ML approaches.

Keywords: Prostate cancer detection, Machine Learning, Cancer detection, Quantum learning, Harris Hawk Optimization (HHO)

Prostat Kanserinin Teşhisinde Harris Hawks Optimizasyon (HHO) Algoritması ve Kuantum Öğrenmeye Dayalı Hibrit Bir Model Geliştirilmesi

ÖZ

Prostat kanseri (PK) önemli bir sağlık sorunudur ve kısmen kullanılan tanı tekniklerinin dezavantajları nedeniyle erkeklerde başlıca ölüm nedenleri arasında yer almaktadır. Her yıl, bu mevcut teşhis teknikleri, sadece zamanında doğru bir teşhis alamadıkları için birçok erkeğin hayatını kaybetmesine neden olmaktadır. PK teşhisi için potansiyel olarak pratik ve uygun maliyetli bir yaklaşım, yapay zeka, özellikle de makine öğrenimi uygulamaktır. Bu çalışma, %38'i hasta ve %62'si sağlıklı olan 100 erkeğin klinik verileri üzerinde prostat kanseri teşhisi için bir makine öğrenimi (ML) modeli geliştirmeyi amaçlamaktadır. Önerilen model Harris Hawk Optimizasyonu (HHO) ve Kuantum Öğrenme (QL) yöntemlerini birleştirmektedir. Sonuçlar, bu yeni yaklaşımın diğer ML yaklaşımlarına göre %97,84 oranında daha iyi doğruluk sağladığını ortaya koymaktadır.

Anahtar Kelimeler: Prostat kanseri tespiti, Makine Öğrenmesi, Kanser tespiti, Kuantum öğrenme, Harris Hawk Optimizasyonu (HHO).

1. INTRODUCTION

Even after so much advancement in medical science, cancer continues to be a significant health problem of our times. It forms the second most common cause of death after heart and lung diseases[1], [2]. Cancer is a deadly disease and is often caused by an accumulation of genetic disorders and several pathological changes[3]. Cancerous cells are abnormal growths that may occur in any part of the body and pose a severe threat to life [4]. Also known as tumors, cancers require early detection to determine the most effective treatment options[5]. Inadequate diagnosis, complicated medical history, and challenges of treatment usually are the main drivers of mortality [6]. According to the World Health Organization(WHO), over 10 million people across the globe are diagnosed with various types of cancer each year, with this number expected to rise to 15 million by 2030 [7]. Prostate cancer is a type of cancer that starts in the prostate gland, one of the small organs of men that produce seminal fluid [8]. Prostate cancer is the second most common type of cancer worldwide in men. Its incidence rate increases drastically after the age of 50 years [8]. Prostate cancer comes out to be at the top of the list of the most frequently diagnosed cancers[9], and, at the moment, represents an increasingly important public health challenge with population aging [10], [11]. This risk of developing prostate cancer is increased by several factors, which include advancing age, family history of the disease, and genetic mutations, such as BRCA1 and BRCA2 [12], [13]. Additionally, African American men have higher incidence rates of prostate cancer compared to other racial groups [14]. Lifestyle factors, such as a high intake of red meat and dairy products and obesity, are also associated with an increased risk [14]. In its early stages, prostate cancer may not present any symptoms [15]. The prostate is an integral part of the male reproductive system, located in the pelvic region beneath the urinary bladder and anterior to the rectum, as shown

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in Figure 1. It encircles a portion of the urethra and typically measures about 3 cm in length and weighs around 20 grams in an adult male. The prostate is known for its ability to accumulate zinc and produce citrate, playing a role in the creation and storage of seminal fluid. Prostate glands contribute to about 20% of seminal fluid production. When affected by disease, they can impact urination, ejaculation, and bowel movements[16]. The symptoms of prostate cancer can closely resemble those of other conditions, especially in the early stages. Common indicators include urinary difficulties, pelvic discomfort, hematuria (blood in urine), and fatigue from anemia. Risk factors for prostate cancer include advanced age, genetic predisposition, and ethnicity, with having a close relative with prostate cancer increasing one's risk due to its hereditary nature [16].

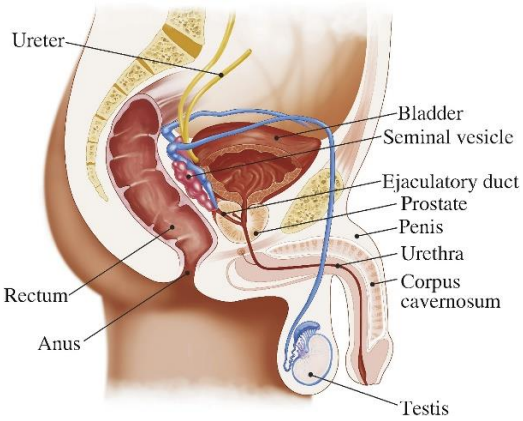

Figure 1. Prostate physiology [16]

The practice of prostate cancer screening has been controversial since the Medicare Benefits Schedule (MBS) commenced subsidizing PC testing in 1989. While PC testing and DRE represent an essential assessment of risk and making an initial diagnosis, concerns about over-diagnosis and overtreatment have driven improvements in diagnostic pathways [17]. Although PC screening may have some utility in defining risk assessment to decide who will need further evaluation in specific individuals, it is not recommended in asymptomatic individuals, and decisions should be individualized based on such factors as age, life expectancy, and risk factors, including family history, as well as consideration of informed choices. It may lead to excessive interventions due to the misuse of PC screening because of the possibility of high PSA levels in nonmalignant conditions like benign prostatic hyperplasia, prostatitis, or even after prostate manipulation, thereby leading to unnecessary biopsies. Moreover, unnecessary and excessive treatment may be followed in managing all cancers [18]. Given the importance of prostate cancer and the high incidence of cases in men, interest has long been expressed in developing new modalities for the early detection of PC[17]. Table 1 illustrates the progress in the diagnostic front of prostate cancer from 1995 to 2022.

The table shows the progress that started with the prostate cancer diagnostic methods at their most essential in 1995 and changed into sophisticated approaches by 2022.

Table 1. Evolution trend of prostate cancer diagnosis methods

1995	DRE/raised PSA	6 core TRUS biopsy	Treatment /AS		
2005	DRE/raised PSA	10 core TRUS biopsy	Treatment /AS		
2015	DRE/raised PSA	mpMRI	18-30 core transperineal biopsy	CT + Bone scan	AS/ Treatment
2022	DRE/raised PSA	mpMRI	18-30 core transperineal biopsy	PSMA PET	AS/ Treatment/ focal therapy

Hint: AS = active surveillance; CT = computed tomography; DRE = digital rectal examination; mpMRI = multiparametric magnetic resonance imaging; PET = positron emission tomography; PSA = prostate-specific antigen; PSMA = prostate-specific membrane antigen; TRUS = transrectal ultrasound

Advanced imaging modalities, such as multiparametric magnetic resonance imaging and prostate-specific membrane antigen positron emission tomography, have revolutionized the accuracy of diagnosis after the standardization and refinement of biopsy techniques. More accurate diagnostic capability has added treatment options for more precise treatment strategies like focal therapy, in addition to the traditional methods and active surveillance of prostate cancer.

These numerous improvements show that technology continues to evolve and brings further understanding of prostate cancer. These improvements strive to progress early detection, refine diagnostic processes, and lead to better patient outcomes at the very end.

Early detection of prostate cancer is crucial for improving patient outcomes. Given the variety of available treatment options, understanding the specific characteristics of different tumor types is essential for developing effective treatment strategies. Currently, histopathology and immunohistochemistry are the primary diagnostic techniques. However, these methods can be complex and may not always provide accurate results for every patient. Consequently, there is a pressing need for a rapid, non-invasive, and highly sensitive method to differentiate between various tumor forms[19]. Economic valuations of health and illness [20], [21], and disease management programs, including the following types of costs, are borne by individuals and society. These are:

- Direct costs: These are capital and operational costs for health interventions.
- Intangible, direct costs: These are costs for support of the program or other sundry types of payments.
- Indirect costs: These are patients' and their families' time and opportunity costs.
- Intangible costs: This is the cost in terms of pain, anxiety, and stress that people suffer.
- Indirect costs: The productivity and efficiency lost from falling ill.

Maintaining a healthy lifestyle with a balanced diet and regular physical can help reduce the risk of prostate cancer [22]. Early detection through routine screenings makes the disease more manageable [23]. The introduction of advanced computer-based technologies, particularly artificial intelligence(AI) [24], and machine learning[25], has enabled more precise and cost-effective early diagnosis of PC [26]. AI improves diagnostic sensitivity by analyzing complex data from various sources, such as PSA levels, MRI-guided biopsies, and genomic biomarkers, thereby enhancing efficiency and accuracy in diagnosing and managing prostate cancer [27]. AI significantly advances prostate cancer care by improving diagnosis, treatment, and management, promising faster, personalized care and reduced costs. However, overcoming challenges in data exchange and building strong clinical evidence is essential for its continued integration into standard clinical practice [28]. Quantum learning, which implements quantum algorithms into machine learning processes, uses the parallel computational power of quantum systems to accelerate processes and make them more effective[29]. For example, quantum classifiers reached 86% accuracy for Progressive Supranuclear Palsy diagnosis, outperforming classic methods [30]. Hybrid approaches mixing quantum and classical algorithms have also been probed to improve data science, in a demonstration of how versatile QML can be [31].

This study developed a hybrid quantum deep convolutional neural network to provide the best accuracy for the diagnosis of CKD, 99.98%, and efficiency, 0.0641 seconds per image. However, accessing and generalizing this model can be challenging due to its complex nature and computational resource demand[32]. Reference [33] aims to detect prostate cancer by enhancing the Quantum Support Vector Machine and high-power quantum feature mapping. QSVM has higher sensitivity and a high F1-Score of 93.33%, though it is more complex and resource-intensive than classical methods. The study aimed to develop a quantum-inspired deep learning model with ordinal regression, which may give higher performance for medical image diagnosis related to prostate cancer and diabetic retinopathy. While it attained better performance and interpretability by exploiting ordinal information and quantifying prediction uncertainty, there is a trade-off related to multi-class accuracy and complexity [34]. The research was focused on proposing and validating a Quantum Squirrel-inspired Feature Selection algorithm that would facilitate high-accuracy gene selection in prostate cancer. Accordingly, QSFS achieved 100% accuracy with the least features and identified relevant biomarkers, although careful hyper-parameter tuning is required, with local search efficiency varying [35].

1.1. Contribution

This study focuses on developing a hybrid model for the early diagnosis of prostate cancer using clinical data to enhance diagnostic accuracy and speed. The main contributions of this paper include:

- Developing a quantum learning approach using Harris Hawks Optimization (HHO).
- Reduction of the computational complexity associated with the quantum learning approach.
- Improvement of medical systems for prostate cancer diagnosis.

1.2. Originality

The research focused on some of the most critical challenges in the diagnosis of prostate cancer, such as the case of high numbers of unnecessary biopsies due to low specificity and the scarcity of standard diagnostic data. It proposed selecting optimal features using the HHO optimization algorithm to solve unnecessary biopsies. It highlighted the use of standard data sets from reputed scientific sources for the challenge of limited data availability.

2. RELATED WORKS

This Prostate cancer was initially described by Adams in 1853. At that time, the disease was considered to be a rare one and not well understood, with only limited methods for its detection available. An evolutionary process underlying cancer progression, formulated by Darwin, leads to many subclones within a single primary tumor[36]. This is an essential evolutionary mechanism in the process of metastasis formation, which is one of the main causes of morbidity and complications in cancer patients. Metastasis is a process through which cancer cells spread from their primary site to different body parts. In PC, cancer arises as a result of genetic mutations in cells of the prostate gland. As expected, primary androgen deprivation therapy is usually given to men with metastatic PC; however, resistance against this treatment develops over time[37]. Research has identified recurrent somatic mutations, changes in DNA copy number, and oncogenic structural rearrangements in primary PC[38], [39]. The possibility of totally revolutionizing the field of medicine in terms of diagnostic accuracy finally got a much-needed boost through the integration of AI-based technologies. Some very novel methods offering promising results have been developed in the highly imaging techniques-dependent prostate cancer diagnosis. For instance, a study [40], For example, a study proposed several machine learning techniques like Bayesian techniques, Support Vector Machines (SVM) with several types of kernels (like polynomial, RBF, and Gaussian), and Decision Trees for the diagnosis of prostate cancer. It used texture analysis techniques, morphological features, Scale-Invariant Feature Transform (SIFT), and Elliptic Fourier Descriptors for feature extraction. The SVM with Gaussian Kernel showed a maximum accuracy of 98.34%, and the SVM model based on Gaussian Kernel generated an AUC of 0.999. When the texture and morphological feature extractions were integrated with either SVM with Gaussian Kernel or the EFDs, the performance in terms of accuracy reached 99.71%, and

in terms of AUC, reached 1.00. Another research [41] developed an ensemble model by implementing intelligence analysis to increase the accuracy of classification, diagnosis, and treatment of prostate cancer. This study showed 92.45% accuracy. The results underscore the effectiveness of various algorithms. Since high-dimensional datasets related to prostate conditions are primarily redundant and anomalous, dimensionality reduction and isolating only very relevant features have to be taken into consideration to improve classification precision and diminish operational costs. Identifying the best feature subset from a vast search space is a challenging problem. The central feature selection issue is identifying the most informative features that explain the system best. Feature selection lends several advantages: reduced processing time, ease of data interpretation, avoiding dimensionality problems, and less risk of overfitting. Extraneous, irrelevant, and redundant features are removed after the identification of the most relevant features, hence shrinking the computational size and increasing the speed of data analysis. Of the meta-heuristic algorithms, HHO is outstanding because of its wide range of searches within the computing space. On this basis, the HHO algorithm is a meta-heuristic technique capable of simulating Harris's hawk-hunting process, wherein different vectors update their positions toward choosing the best solutions for selecting relevant features from among the best values attained.

Although extensive research has focused on single metaheuristic algorithms and quantum machine learning techniques, the lack of effective integration between nature-inspired optimization strategies and quantum learning in the field of prostate cancer diagnosis remains a major challenge. Existing diagnostic models mainly utilize traditional optimization methods or standard learning approaches, which may show limitations in the face of medical data complexity and the need for high accuracy. In this paper, a novel hybrid framework, HHO-QL, is proposed, which uniquely combines the powerful global search capabilities of Harris Hawks Optimization (HHO) with the computational advantages of Quantum Learning (QL) principles. This innovative combination not only significantly improves the diagnostic performance of the model, but also reduces its computational complexity. The proposed hybrid model, by improving the process of selecting relevant features and accelerating the convergence of the learning process, effectively addresses the fundamental limitations of previous studies and takes an important step towards developing more accurate and efficient prostate cancer detection systems.

3. MATERIAL AND METHOD

3.1. Material

This study used the prostate cancer dataset, available from Kaggle, as a high-quality benchmark in diagnosing diseases. The data retrieved from Kaggle.com contains 100 individual samples, each described by eight features: - "radius," "texture," "perimeter," "area," "smoothness," "compactness," "symmetry," and "fractal dimension." Of those 100 patients, 38 have been diagnosed with prostate cancer, and the rest are healthy (https://www.kaggle.com/datasets/sajidsaifi/prostate-cancer.). Table 2 below presents a smaller subset of these samples for closer inspection. Each row concerns a particular case and details various measurements related to tumors. The table has the following fields:

1- ID: An identifier that identifies most cases uniquely.
2- Radius: The size of the radius of the tumor. Typically, in millimeters
3- Texture: A value denoting the roughness or smoothness of the tumor.
4- Perimeter: The parameter of the tumor.
6- Perimeter: Representing the perimeter of the tumor, expressed in square millimeters.
6- Smoothness: Describing tumor surface smoothness or roughness.
7- Compactness: Similar to the area in a way, except it applies to compactness.
8- Symmetry: This is defined by the degree to which the tumor shape is identical.
9- Fractal Dimension: the complexity of the shape, which includes any irregularities of the tumor.
10- Diagnosis: Final diagnosis, '1' being a malign tumor, and '0' a benign one.

Table 2. Part of the prostate cancer dataset

id	radius	texture	perimeter	area	smoothness	compactness	symmetry	Fractal dimension	Diagnosis result
1	23	12	151	954	0.143	0.278	0.242	0.079	0
2	9	13	133	1326	0.143	0.079	0.181	0.057	1
3	21	27	130	1203	0.125	0.16	0.207	0.06	0
4	14	16	78	386	0.07	0.284	0.26	0.097	0
5	9	19	135	1297	0.141	0.133	0.181	0.059	0
6	25	25	83	477	0.128	0.17	0.209	0.076	1
7	16	26	120	1040	0.095	0.109	0.179	0.057	0
8	15	18	90	578	0.119	0.165	0.22	0.075	0
9	19	24	88	520	0.127	0.193	0.235	0.074	0
10	25	11	84	476	0.119	0.24	0.203	0.082	0

* Note: "1" in Diagnosis result means "Big tumor (i.e., cancer)" and "0" means "most common (i.e., healthy)"
Table 2 illustrates the variability of tumor measures and characteristics case by case, with "Diagnosis Result" being the final classification based on the malignancy of the tumor.

3.2. Proposed method

This research is based on a new quantum learning approach combining quantum algorithms with machine learning systems to establish a compelling computational paradigm. Quantum learning exploits these peculiar properties of quantum computing, namely, superposition and entanglement, which empower it to treat information in ways that no classical computer can rival. It provides complex data set analysis and fast execution of machine learning algorithms at speeds way above the conventional methods. Such possible applications of quantum learning are immense because it really can revolutionize areas like cryptography, pharmaceutical research, and optimization by providing both more efficient and accurate solutions than those concocted by traditional computing techniques [41]. In this regard, the Harris Hawk Optimization method has been utilized to fine-tune the proposed quantum learning algorithm, especially in hyperparameter tuning and optimization of the training process for the involved data. The HHO represents a gradient-free, population-based optimization technique inspired by the natural strategy of Harris hawks' hunt. This method can be applied to any optimization problem with an appropriate formulation. The hunting behavior of the Harris hawk is a prime example of nature's ingenuity and adaptability. This bird is known for its ability to imitate some hunting actions and calls in order to further blend in with an environment. This flexibility opens an effective form of hunting, which conserves energy for attaining maximum results while hunting, yet being less eager while chasing to protect from some dangers, which shows a balance of aggression and caution [50].

The hawks, as predators, determine their fellow members' distances and the position of the prey, which is the hare. If q < 0.5, the hawks randomly perch on top of high trees, as detailed in Equation 1. Otherwise, if q ≥ 0.5, the Hawks will use another mechanism in search of the optimal way of hunting.

$$X(t+1) = \begin{cases} X_{rabit}(t) - r_1 |X_{rand}(t) - 2r_2 X(t)| & q \geq 0.5 \\ \left(X_{rabit}(t) - X_m(t)\right) - r_3\left(LB + r_4(UB - LB)\right) & q < 0.5 \end{cases} \quad (1)$$

The following will be considered the parameters for the model:

- (X(t+1)): The hawks are located at the following location.
- ($X_{rabit}(t)$): The location of the rabbit at time (t).
- (X(t)): The actual location of the hawks at the time (t).
- (r_1, r_2, r_3, r_4, q): Random numbers between 0 and 1 are used for random selection.
- LB and UB: The lower and upper bound for the variables.
- ($X_{rand}(t)$): Hawks were randomly selected from the active hawks population.
- (X_m): Mean of location of active hawks.

The model is meant to generate random locations over the confined area of group space (LB, UB). The first law is algebraic and dependent on a random location and location of hawks. The best location is searched in the second law, so that group is much a source of entropy by itself. A parameter (r3) is a scaling factor for enlarging randomness and one more (r4) is a proximity factor to 1, allowing the production of similar groups. In the case above, randomness comes from the randomness in the distance of displacement, which is summed up in the value of LB. Another factor of randomness is summed for being checked to obtain greater diversity in the output, that is, to discover other districts of the area. Throughout the presentation of the results, it is possible to devise various laws by this process. But still, we have chosen the most straightforward law that could only drive the hawks' behavior according to Eq. (2).

$$X_m(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t) \quad (2)$$

In this respect, ($X_i(t)$) is the position of each hawk in the *t-th* iteration, and (N) is the overall hawk population. Even if the central position of the hawks can be figured out by simple techniques, we use the simplest rule approach to make the hawks' movements defined in Equation (2).

The optimization algorithm of the Harris hawks is designed to transfer the explorative phase to the exploitative phase by varying the variance in hunting tactics once the prey has escaped. During the escape behavior, the energy level of the prey diminishes to an extent that is significant enough to be included in the model, and the prey energy has been characterized as follows [50]:

$$E = 2E_0\left(1 - \frac{t}{T}\right) \quad (3)$$

The parameter (E) indicates the prey's energy level, which has just fled. The parameter (T) refers to the maximum number of iterations, while (E0) is the initial energy level of the prey. When the algorithm is running, E0 randomly changes in each iteration. (E0) is always between 0 and 1, showing a decrease in the physical strength of the prey. When the value of (E0) drops from 0 to 1, it implies that the hare is physically exhausted. On the other hand, when the value of (E0) rises from 0 to 1, the hare is physically strengthening[50]

The pseudo-code of the HHO proposed is reported in the following algorithm [50]

1. Algorithm 1 Pseudo-code of HHO algorithm
2. Inputs: The population size N and maximum number of iterations T

3. Outputs: The location of rabbit and its fitness value
4. Initialize the random population Xi (i = 1, 2... N)
5. While (stopping condition is not met) do
6. Calculate the fitness values of hawks
7. Set Xrabbit as the location of rabbit (best location)
8. for (each hawk (Xi)) do
9. Update the initial energy E0 and jump strength J▷ E0=2rand () 1, J=2(1-rand ())
10. Update the E using Eq. (3)
11. if (E1) then ▷ Exploration phase
12. Update the location vector using Eq. (1)
13. if (E < 1) then > Exploitation phase
14. if (r ≥0.5 and E≥ 0.5) then ▷ Soft besiege
15. Update the location vector
16. else if (r ≥0.5 and |E| <0.5) then ▷ Hard besiege
17. Update the location vector
18. else if (r <0.5 and |E|≥ 0.5) then ▷ Soft besiege with progressive rapid dives
19. Update the location vector
20. else if (r <0.5 and |E| < 0.5) then ▷ Hard besiege with progressive rapid dives
21. Update the location vector
22. Return Xrabbit

This flowchart represents a structured process for developing and implementing a diagnostic model to avoid unnecessary biopsies in clinical practice. It is the systematized approach toward improving the diagnosis of prostate cancer by using sophisticated algorithms with machine learning techniques to decrease unnecessary medical procedures and enhance the specificity of diagnostic methods. The proposed method is detailed in Figure. 2.

The process begins with reading the dataset, which consists of clinical information for PC patients, after which data preprocessing is conducted. HHO has been used to select the optimal features. In the context of HHO, N denotes the number of Hawks, and D is the number of dimensions of the optimization problem or decision variables. Thus, the HHO is represented by an (N*D) matrix where every row represents a possible solution to the optimization problem. Herein, N is the size of the dataset entries, while D refers to the number of features. Their position of Hawks is calculated according to Equation 4 as follows:

$$Hawks\ position = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{12} \\ x_{22} & x_{22} & \dots & x_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nd} \end{bmatrix} \quad (4)$$

In the set $x_i = (x_{i1}, x_{i2}, \dots, x_{id}), i = 1,2, \dots, n,$ each x_i represents a possible solution in the solution space. The fitness of Hawks is computed based on the objective function according to Eq. (5):

$$fit_i = 1 - \frac{Obj_i - worst(Obj)}{best(Obj) - worst(Obj)} \quad (5)$$

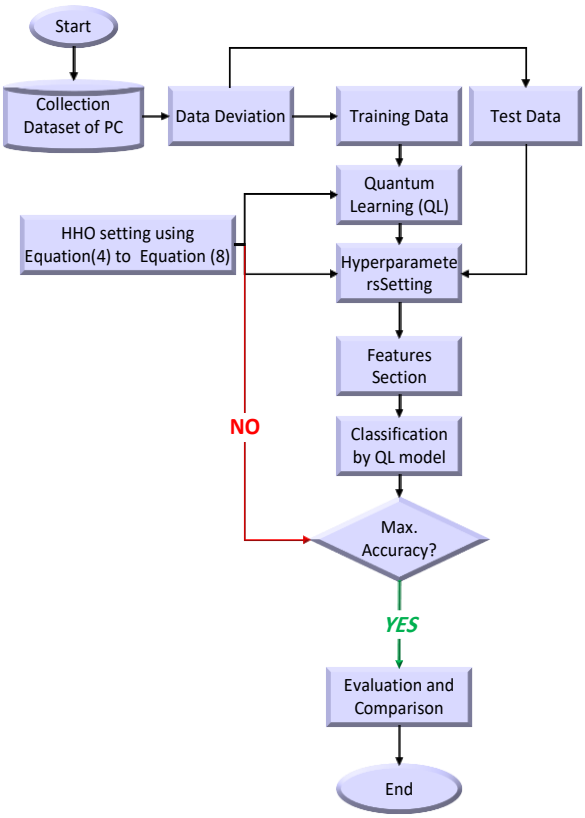

Figure 2. The Systematic Path to Improving Prostate Cancer Diagnosis Accuracy

In Eq. (5), fit_i is the fitness of the Hawk. The parameter Obj_i is the value of the objective function for the *i-th* Hawk. The worst and best parameters are the worst and the best position of rabbits. Initiating also, in the developed model, for the same reason mentioned above in the initialization section, the HHO should be discrete, not continuous. The following equation is used to convert the numbers into binary, and this equation accepts two solutions found by the V-shaped hyperbolic tangent function.

According to the following equation (6), because in the proposed method, it has continuous values, then it should be converted into binary because it's due to the random stepping.

$$y^k = |tanh x^k| \quad (6)$$

$$x_{ij} = \begin{cases} 0, & if\ rand < y^k \\ 1, & otherwise \end{cases} \quad (7)$$

The HHO algorithm is applied to select potential feature subsets for the best performance in the proposed model. The fitness function used in feature selection by HHO is formulated according to Equation (8). In this equation, |n| is the total features, and |S| is the number of selected features. The term 'accuracy parameter' indicates the accuracy rate, and the parameters δ and ρ are constants and are driven to the values 1 and 99, respectively.

$$Fitness = \delta . Accuracy + \rho . \frac{|n| - |S|}{|n|} \quad (8)$$

In the next stage, the QL algorithm is used to classify the features. Finally, in the performance analysis of the model, in the utilization of the following equations, the respective confusion matrix is applied to it:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

$$Specificity = \frac{TN}{TN+FP} \quad (11)$$

$$Recall = \frac{TP}{TP+FN} \quad (12)$$

$$F1 - Score = 2 \times (Precision \times Recall)/(Precision + Recall) \quad (13)$$

4. RESULTS AND DISCUSSION

4.1. Feature Selection Using Harris Hawks Optimization Algorithm

The first stage utilized an HHO algorithm to select the most appropriate features in this dataset. For this purpose, 80% of the data was used for training, and the rest, 20%, for testing. Eight hawks were used with 150 iterations. Figure 3 illustrates the steep convergence curve at the beginning, thus proving that the algorithm quickly converges to a near-optimal solution—a characteristic very important in feature selection, as it decreases computational time. Then, it levels off at the bottom, thus indicating that the algorithm has converted into a local or global optimum with no further significant improvement. In this respect, smoothness or little bumps on the curve reflect a stable optimization process that might improve the reliability of the feature selection.

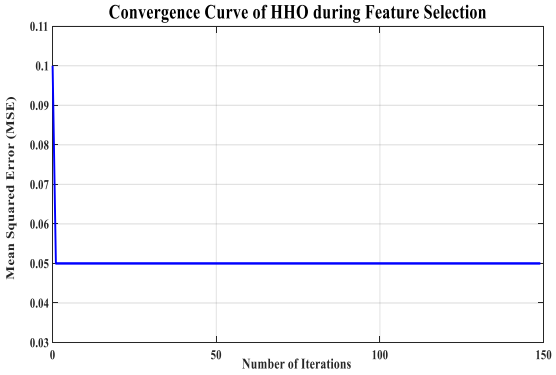

Figure 3. The convergence curve of HHO in feature selection

4.2. Advanced Prostate Cancer Detection Using Harris Hawks Optimization And Quantum Learning Techniques

The HHO algorithm becomes very promising in feature selection, particularly within large datasets. The HHO selects only the relevant features and increases the performance of a machine-learning model by reducing noise and increasing generalization. In addition, the fast convergence rate of HHO saves computational time, becoming vital in applications sensitive to time. This algorithm can still improve parameters tuning, such as population size and balance between exploration and exploitation. Table 3 also presents the results regarding mean squared error, number of selected features, and total features for feature selection. In the feature selection process, the HHO algorithm succeeded in identifying and selecting the top six features, which were selected based on their ability to improve classification accuracy and reduce overlap (redundancy) between features. The algorithm evaluated different feature subsets using a fitness function directly related to classification performance. The results of this evaluation showed that these six selected features have the highest discriminatory power for prostate cancer diagnosis. Inclusion of this optimal set of features in the diagnostic model significantly improved its performance. This is due to This was achieved by reducing the noise in the data and also reducing the computational complexity of the model, while preserving the vital diagnostic information necessary to distinguish healthy samples from those with prostate cancer. The intelligent selection of these features has played a significant role in increasing the efficiency and reliability of the proposed model.

Table 3. Result of feature selection

No. of original features	No. of features selected	MSE Error
8	6	0.05

Table 3 shows that out of the eight original features, six were selected to give the minimum error of MSE, which was only 0.05.

Table 4 encapsulates the original features with the selected ones using the HHO algorithm. In the next step, the chosen features will act as input to the quantum learning model.

Table 4. Original and Selected Features of the Prostate Cancer Dataset

Orig.	id	radius	texture	perimeter	area	smoothness	Compact.	Symm.	Fractal dimension
S. F	radius	perimeter	area	Compact.	Symm.	Fractal dimension	-	-	-

In this work, the HHO algorithm has been used to adjust the hyper-parameters of the quantum learning model. While classic computers work with bits that carry either 0 or 1, Quantum Computation (QC) works with a qubit—a quantum bit, which may simultaneously involve the state of 0 and 1. The fundamental unit of quantum information is a qubit, and it exists in a superposition of two states: |0> and |1>. The Hilbert space in Quantum Computation (QC) provides an abstract vector space allowing quantum superposition, whereby the system occupies many states simultaneously.

Deep learning and quantum computing have developed massively in the last few years. An explosion in the amount of data has ultimately led to researching the confluence of both fields, resulting in the development of quantum deep learning and quantum-inspired deep learning methodologies. The procedure was as follows:

- A pre-trained network was loaded with all its layers frozen to act as a feature extractor, with only the weights of the classifier being updated while training.
- During network initialization, the size of the input vector for Quantum Net was defined, and this network was added as the classifier layer to the model.
- Cross-entropy was chosen as the loss function, the Adam optimizer was placed to update the model's weights at each training step, and the learning rate scheduler was set to decay the learning rate by a gamma factor at each step size.
- The model was then trained against this new configuration.

The key parameters of the quantum learning model used in this study, including learning rate (0.01), batch size (32), and step size (0.1), were selected and tuned based on a combination of experimental experiments and a careful review of the relevant scientific literature. In the initial phase, a grid search approach was used to identify the appropriate range for each parameter. Subsequently, fine-tuning of these parameters was performed to optimize the model performance on the validation set. The final parameters selected provided a favorable balance between the speed of the model training process and the classification accuracy obtained in our experiments. Table 5 presents the model quantum learning setup hyperparameters used in this work to diagnose prostate cancer. Hyperparameters help control the model learning process, thus essentially determining the general performance of the model. The settings are on how often the model shall be trained on the entire dataset, the number of samples used per update, how usually the learning rate shall be adjusted, and the optimization algorithm to be used. These conditions are vital to the successful training of the model to diagnose prostate cancer correctly.

Table 5. The hyperparameters of the quantum learning model

Step	#Epochs	#Batch size	Step size	Initial learning factor	The solver
0.4	40	32	15	0.00611	Adam

Prostate cancer was detected satisfactorily using the quantum learning model after 800 training iterations. The quantum learning model returned an average root mean squared error of 0.1321, which is very little average error in prediction. The model had an accuracy rate of 97.84%, hence correctly classifying almost 98% of the cases as either having or not having prostate cancer. Symmetric Mean Absolute Percentage Error was measured at 0.1398. It is a relative measure from a percentage point of view regarding how much of the model's predictions are from the fundamental values. A lower sMAPE value would mean higher predictive accuracy for the model. Table 6 shows excellent model performance regarding the accuracy, precision, recall, and F1-measure in diagnosing prostate cancer.

Table 6. Evaluation of PC diagnosis using the proposed model

Metric	Value (%)
Accuracy	**97.84**
Precision	**97.59**
Specificity	**87.50**
Recall	**96.43**
F1-measure	**97.01**

4.3. Comparison of the Proposed Method with Established Machine Learning Techniques for Prostate Cancer Diagnosis

In order to ensure a fair and comparable evaluation, all the comparison models listed in Table 7, including Multilayer Perceptron Neural Network (MLP), SVM, KNN, DT Decision Tree and NB, were re-implemented using the same prostate cancer dataset and consistent pre-processing techniques. In this regard, the dataset used was initially normalized to equalize the scale of the variables and avoid their disproportionate impact on the performance of the models. In addition, the same feature selection method based on the HHO algorithm that was used in the development of the proposed HHO-QL model was also applied to all the comparison models. This uniform approach to feature selection ensures that all models are trained with the same optimal set of features and their performance is not affected by unnecessary or unimportant variables. Thus, the performance comparison between the proposed model and existing models is made on a level playing field.

This study compares the performance of the proposed method with several machine learning techniques referenced in [30] for the diagnosis of prostate cancer, including Multi-Layer Perceptron (MLP), Radial Basis Function Neural Network, Decision Tree, Support Vector Machine, and K-Nearest Neighbor. Table 7 summarizes the accuracy results of these comparisons.

The table has shown that the Hybrid HHO-QL model has achieved an accuracy as high as 97.84%, outperforming all other methods tested in this research study, such as MLP, RBF, DT, SVM, and KNN. This model also outperformed some algorithms cited in reference [30]. Among these, the closest accuracy was obtained with Alshareef et al.'s approach using CIWO + DL, which had an accuracy of 97.19%. This places it as the nearest competitor to the Hybrid HHO-QL model.

Table 7. Comparison of the accuracy of the different algorithms

Algorithm	Accuracy (%)	References
Hybrid HHO - QL	97.84	**Present study**
MLP	91.36	**Present study**
RBF	92.08	**Present study**
DT	89.67	**Present study**
SVM	84.16	**Present study**
KNN	85.96	**Present study**
PLR-MC	94.60	**Alshareef et al., [49]**
SVM model	91.20	**Alshareef et al., [49]**
GA-KNN+SVM	85.71	**Alshareef et al., [49]**
Optimal DNN	96.21	**Alshareef et al., [49]**
CIWO[1]+ DL	97.19	**Alshareef et al., [49]**

[1]Chaotic invasive weed optimization

5. CONCLUSION

In this paper, we have proposed a hybrid model for the estimation of prostate cancer using clinical data. We used an initial benchmark dataset from Kaggle. We applied the HHO algorithm to select the most relevant features among the nine initial ones, considering only six as significant ones with a minimal error rate of 0.05. These selected features were used to train a Quantum Learning model for the diagnosis of prostate cancer. The proposed approach revealed superior accuracy to other machine learning methods, with an accuracy of 97.84%. More particularly, the RBF, MLP, DT, KNN, and SVM algorithms performed at an accuracy of 92.08%, 91.36%, 89.67%, 85.96%, and 84.16%, respectively. Notably, the hybrid method outperformed the accuracy of 97.17%, which the CIWO+DL Hybrid Algorithm achieved; therefore, it established the supremacy of our approach.

DECLARATION OF ETHICAL STANDARDS

The author of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Melisa Rahebi: Performed the experiments, analyzed the results, and wrote the manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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