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An Automated Prostate-cancer Prediction System (APPS) Based on Advanced DFO-ConGA$_2$L Model using MRI Imaging Technique

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ABSTRACT: The prostate cancer is a deadly form of cancer that assassinates a significant number of men due of its mediocre identification process. Images from people with cancer include important and intricate details that are difficult for conventional diagnostic methods to extract. This work establishes a novel Automated Prostate-cancer Prediction System (APPS) model for the goal of detecting and classifying prostate cancer utilizing MRI imaging sequences. The supplied medical image is normalized using a Coherence Diffusion Filtering (CDFilter) approach for improved quality and contrast. The appropriate properties are also extracted from the normalized image using the morphological and texture feature extraction approach, which helps to increase the accuracy of the classifier to 99%. A precision of 99.1, recall of 98.9, and F1-score of 99 are achieved. In order to train the classifier, the most important properties are also selected utilizing the cutting-edge Dragon Fly Optimized Feature Selection (DFO-FS) algorithm. Using this method greatly improves the overall disease diagnosis performance of the classifier with faster processing. More specifically, the provided MRI input data are used to categorize the prostate cancer-affected and healthy tissues using the new Convoluted Gated Axial Attention Learning Model (ConGA$_2$L) based on the selected features. This study compares and validates the performance of the APPS model by looking at several aspects using publicly available prostate cancer data.

Keywords: Prostate Cancer Detection, Artificial Intelligence (AI), Deep Learning, Magnetic Resonance Image (MRI), Automated Prostate-cancer Prediction System (APPS), Coherence Diffusion Filtering (CDFilter), Dragon Fly Optimized Feature Selection (DFO-FS), and Classification

1. INTRODUCTION

The prostate is a male reproductive organ around the size of a walnut that discharges and generates alkaline fluid [1, 2]. Parts of the urethra encircle the gland, which is situated in the pelvis where the urinary tract lies on the upper side and the pelvic region is on the side that is posterior. The internal skeletal muscles reach the apex of the diaphragm. It is divided into two areas: the base, which is located adjacent to the bladder, and the apex, which is located adjacent to the ureteral sphincter. Prostate cancer [3] can be diagnosed in a number of methods such as digital rectal examination, PSA test, biopsy, transrectal ultrasound, MRI, genomic tests, CT scan, or bone scan. Screening tests are used for symptoms of urinary tract cancer; however, most men are experiencing persistent inflammation after the test. Nonetheless, a lot of guys devote all of their lives without receiving a prostate cancer diagnosis [4]. Prostate cancer has been detected for in the beginning of the 1990s via a digital rectal exam (DRE). Its implication has been associated with a significant improvement. It is also feasible to differentiate both benign and malignant cells with this screening method [5]. Although it cannot detect malignancies in other regions or segments of the prostate, the DRE can be beneficial in pinpointing tumors located in the posterior region. One diagnostic procedure that is utilized is prostate-specific antigen (PSA) that initially became available in the first decade of the 1990s and has the potential to lower death rates as well as numerous other issues. It has begun turning into highly contentious. False-positive PSA test results are common, as can lead to health issues such as discomfort and inflammation. For asymptomatic males, when the effects might go unnoticed for a lifetime [6], PSA may be helpful. When employed in medical screening, a structured randomized technique beneath transrectal ultrasonography (TRUS) aids in the detection of small as well as low-grade carcinomas. It

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is still challenging to screen a large number of individuals due to its low sensitivity.

Moreover, the prostate cancer can be effectively diagnosed in a number of ways with Computer-Aided Design (CAD) [7, 8]. Recently, deep learning and machine learning techniques have been successfully employed by researchers to find anomalies in medical imaging. CAD is one of the most advanced and useful medical disease diagnostic and categorization technologies when compared to other disease diagnosis technologies. Numerous studies have shown that MRI imaging is a reliable method for identifying the type or degree of prostate cancer. Evidently, utilizing MRI to figure out the severity of cancer is more difficult than having a reliable expert determine it [9]. Intelligent algorithms and MRI scans are being applied in a number of recent studies to determine or assess the type and extent of malignancies, particularly prostate cancer, in an effort to decrease errors made by humans, speed up diagnostics, and enhance operational precision and efficacy. In fact, Artificial Intelligence (AI) assists in collecting vital clinical data that physicians can use to make significant and essential decisions regarding medical prediction, diagnosis of diseases, and surgical results. The term AI [10-12] refers to the ability of the computer to simulate intelligent actions with little to no input from humans and to accomplish a task using information that is supplied. AI has many subfields, in which Machine learning (ML) is one of such subfields; it deals with algorithms that dynamically obtain information from data in order to build intelligence in systems. The following four primary groups are useful for categorize machine learning types: reinforcement learning, supervised learning, semi-supervised learning, and unsupervised learning [13]. The machine receives data from an observer who also labels the different sorts of data in supervised learning.

The machine tries to identify a pattern from the data provided to the anticipated output once the inputs and results are defined. Without the aid of a trainer or labels designating various kinds of data, the machine makes connections among data and discovers patterns in unsupervised learning. A learning model [14, 15] known as semi-supervised learning examines how machines adapt if confronted with both labeled and unlabeled data. The goal of semi-supervised learning is to derive algorithms with a mix of labeled and unlabeled input. Deep Learning (DL) approaches are more sophisticated and effective than machine learning models. These days, researchers highly prefer DL because of its improved prediction outcomes in medical condition diagnosis applications [16]. The most popular neural networks for prostate cancer detection are Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), and Deep Belief Network (DBN). It still faces significant challenges, though, including the need for more training data, high computing complexity, long prediction times, and overhead [17-20]. Therefore, the goal of the proposed work is to construct an automated tool for prostate cancer diagnosis that is both lightweight and successful by utilizing a unique deep learning technique combined with a meta-heuristic model. The following outlines the main goals of the proposed work:

- For the purpose of detecting and categorizing prostate cancer using MRI imaging sequences, a novel Automated Prostate-cancer Prediction System (APPS) model is created in this work.
- For better quality and contrast, a Coherence Diffusion Filtering (CDFilter) technique is also utilized to normalize the input medical image.
- In order to improve the accuracy of the classifier, the morphological and texture feature extraction model is also used to extract the relevant characteristics from the normalized image.
- In addition, the most necessary attributes are chosen using the state-of-the-art Dragon Fly Optimized Feature Selection (DFO-FS) algorithm in order to train the classifier. With faster processing, the overall disease diagnosis performance of the classifier is significantly enhanced by employing this technology.
- To be more precise, the new Convoluted Gated Axial Attention Learning Model (ConGA$_2$L) is used to classify the prostate cancer-affected and healthy tissues from the provided MRI input samples based on the selected features.
- This study uses the public dataset of prostate cancer to examine a number of parameters in order to compare and validate the performance of the proposed APPS model.

The remainder of this work has been separated into the following sections: In order to investigate various intelligence algorithms utilized for prostate cancer diagnosis and classification, a thorough literature analysis is presented in Section 2. It also looks into the benefits and drawbacks of each model according to its results and prediction rate. Together with the general flow and algorithmic explanations, Section 3 provides the comprehensive justification for the suggested APPS paradigm. Furthermore, utilizing a range of assessment metrics, Section 4 compares and confirms the performance and outcomes of the APPS model. In Section 5, a comprehensive summary of the paper is presented, along with recommendations for further research.

2. RELATED WORKS

This section examines some of the most recent models found in the literature that are used to categorize and predict prostate cancer using various imaging modalities. On the basis of the conventional methodologies' prediction accuracy and outcomes, it also evaluates the issues and difficulties they encountered.

Li, et al [16] presented a detailed study of segmentation, machine learning and deep learning techniques for significantly predicting the probability rate of prostate cancer. The study found that the field of computer vision in medical imaging has experienced a surge in attention due to the quick advances in ML and DL. Since prostate MRI is the preferred method for lesion detection and remains in line with the trend towards tailored specimens. Also, it is more suited for regional ablation therapy to improve clinical outcomes, hence it is a desirable imaging modality for use in DL applications. With the adoption of data analytics and federated learning techniques for predicting risk with prostate cancer, it has an incredible potential to mitigate variation among observers in the detection of lesions. Lee, et al [17] used a reinforcement learning strategy to predict prostate cancer more accurately. The researchers also looked into several models and structure types that are employed in the precise identification and categorization of prostate cancer. Tataru, et al [18] analyzed the recent trends in AI for developing an automated prostate cancer diagnosis system. AI has proven to be highly precise when used in medical imaging, both in recognizing prostate abnormalities and anticipating clinical results including lifespan and adaptability to treatment. The huge quantity of data collected from the genome of prostate tumors requires rapid, reliable, and precise system capacity, which automated learning approaches provide. It might be difficult to determine the toxicity of radiation therapy for patients, despite it being a crucial component of treatment for prostate cancer. Moreover, AI might be used to forecast the way patients react to the negative side effects of their treatment. With the use of these methods, practitioners may be able to schedule radiation treatments more effectively. Erdem and Bozkurt [19] offered a comparison analysis to look into various deep learning and machine learning methods for a precise prostate cancer prediction. SVM, NB, KNN, RF, LDA, LR, MLP, and DNN are some of the machine learning and deep learning approaches used for disease prognosis in this work. Deep Learning algorithms constitute one of the methods that can be thought of as the more sophisticated version of artificial neural networks (ANN). It is developed with numerous hidden layers interposed with regard to the input and output layers and is referred to as a deep feed-forward neural network.

Nagpal, et al [20] built a novel deep learning algorithm that can accurately diagnose prostate cancer and calculate its score. A two-stage deep learning model is used in this work to predict and classify diseases. Salman, et al [21] implemented a deep learning system based on Yolo for the automated detection and categorization of prostate cancer. The primary use of the Yolo architecture in this work is to segment the input image containing the tumor-affected area. Furthermore, data fusion is carried out in order to accurately identify cancer from the input and make decisions. Nonetheless, its primary drawbacks are its poor forecast accuracy and extremely complicated categorization process. Bosma, et al [22] utilized a semi-supervised learning approach to identify and predict the class of prostate cancer from MRIs. This paper demonstrates a report-guided pseudo label training approach for MRI-based practical prostate cancer recognition model using radiology reports. The fundamental technique is universal and is not restricted to MRIs, radiology reports, or clinically relevant prostate cancer. The proposed training method can be applied to any identification problem with identifiable structures of interest and healthcare information reflecting these outcomes, hence minimizing the manual annotation workload.

Roest, et al [23] carried out a thorough investigation on the various deep learning methods for prostate cancer diagnosis. The MRI scans are utilized in this evaluation to verify the categorization algorithms' output. This study indicates that the effectiveness of deep learning models using bigger training datasets is vital, as most DL research to date has been conducted using very small datasets. It has been demonstrated that collaborative decision-making between physicians and deep learning could improve detection efficiency. Hosseinzadeh, et al [24] unveiled an intriguing automatic diagnosis technique for prostate cancer from MRIs that uses deep learning and requires little training data. In this study, an effective lesion identification is achieved by the application of a cascaded deep learning technology. Furthermore, an anisotropic multi-planar 3DUNet model is utilized to efficiently segment the image for accurate diagnosis. Nevertheless, the high computational complexity of the proposed model reduces the overall effectiveness of the cancer prediction system. To help patients with confined prostate cancer make clinical decisions, the authors in [25] created a computerized, personalized risk identification algorithm.

This approach can apply both time-varying and dynamic input information as well as combines the analytical interpretation of quantitative regression methods with the figurative ability inherent in deep learning. Bertelli, et al [26] applied a hybrid learning algorithm integrated with radiomics feature for prostate cancer diagnosis. Here, the standard CNN that suits 2D data has been used for cropping slices from each tumor tissue. According to the findings of the study, ML and DL methods used on MR imaging appeared to be beneficial tools for predicting severity of prostate cancer. Mehralivand, et al [27] used a deep learning technique with AI support to predict prostate cancer from biparametric MRIs. Authors in [28] proposed a meningioma brain tumor detection method using Adaptive Neuro Fuzzy Inference System (ANFIS) classification based on enhanced MRI images, multi-resolution transformation via Curvelet transform, feature extraction, and morphological operations. Enhancing the sensitivity and positive prediction values of disease detection is the aim of this research.

[29] explores enhancing breast cancer detection using transfer learning techniques on unclassified medical images, achieving high classification performance on the ICIAR 2018 dataset and surpassing previous benchmarks in accuracy, precision, recall, F1-score, sensitivity, and specificity. [30] focuses on leveraging machine learning and image processing to create a precise and straightforward automated system for accurately classifying and predicting lung cancer stages from CT images, addressing issues faced by existing tumor detection frameworks, using adaptive median

filtering, feature extraction, and the Stacking Ensemble Learning Classification (SELC) algorithm while evaluating performance through various measures. The following Table 1 reviews a few of the recent state of that art methodologies used for prostate cancer diagnosis.

Table 1. Review of literature with recent state of the art techniques

Ref	Methodology	Parameters considered	Findings
[31]	2D UNet model with lesion segmentation	Kappa, dice, and model performance accuracy.	Not effective in prediction, and high time consumption.
[32]	CNN-VGG Network	Positive prediction value, negative prediction value and ROC.	Classification complexity and precise predictions results.
[33]	Machine learning model	AUC, accuracy and training loss.	Improved diagnostic accuracy and AUC.
[34]	Deep learning algorithm with augmentation model	Training and validation accuracy.	A significant number of samples are required for prediction.
[35]	Machine learning algorithm	Positive prediction value and sensitivity.	Improved accuracy in diagnosis, and prolonged time consumption.

This research review looks at how traditional approaches struggle with particular problems including higher classification complexity, longer prediction times, and reduced efficiency. Therefore, the goal of the proposed study is to develop a robust and efficient automated method for the identification and categorization of prostate cancer.

3 PROPOSED METHODOLOGY

This section provides the overall flow diagram and algorithmic details for the proposed Automated Prostate-cancer Prediction System (APPS) model. The development of an automated and incredibly successful detection technique for the identification and categorization of prostate cancer from MRI images is the original contribution of the paper. The suggested APPS model differs from earlier literature efforts in that it uses many image processing techniques for accurate prostate cancer prediction throughout preprocessing, feature extraction, optimization, and classification stages. The flow of the proposed APPS model is shown in Fig 1, which uses the following approaches for an effective prostate cancer diagnosis:

- Coherence Diffusion Filtering (CDFilter) based image normalization
- Morphological and texture feature extraction
- Dragon Fly Optimized Feature Selection (DFO-FS)
- Convoluted Gated Axial Attention Learning Model (ConGA$_2$L)
- Performance evaluation

The Imaging Data Commons (IDC) (Imaging Data), a publicly accessible prostate MRI imaging database, is being used in this study to predict and classify diseases [36]. The data is gathered from 26 subjects and consists of 22,036 images. Following the acquisition of the input samples, the distinct image normalization model, CDFilter, is utilized to eliminate noise and enhance the overall image quality and contrast. The overall disease detection performance results of the suggested system are significantly enhanced by the adoption of this filtering technique. In order to extract the needed and desired set of features from the filtered image, the morphological and texture feature extraction model is used.

This feature extraction improves the performance gain of the classifier and produces better prediction outcomes. 25 features are obtained from the input images. Furthermore, only the features required to train the classifier were chosen using the contemporary meta-heuristic approach called DFO. Around 5 features are selected using this approach. It efficiently minimizes the dimensionality of the image with fewer features, which considerably increases the training speed and accuracy of the classifier. Furthermore, the newly developed classifier algorithm, called ConGA2L, is used to correctly and with a lower false prediction rate classify the prostate cancer-affected and healthy tissues from the provided samples. Incorporating various distinct image processing techniques, such as CDFilter, DFO, and ConGA2L, significantly improves the prostate cancer diagnosis capability of the APPS framework. Using the proposed APPS model has several benefits, including improved disease prediction accuracy, a decreased false positive rate, and portability. The data is split as 60% for training, 20% for validation, and 20% for testing.

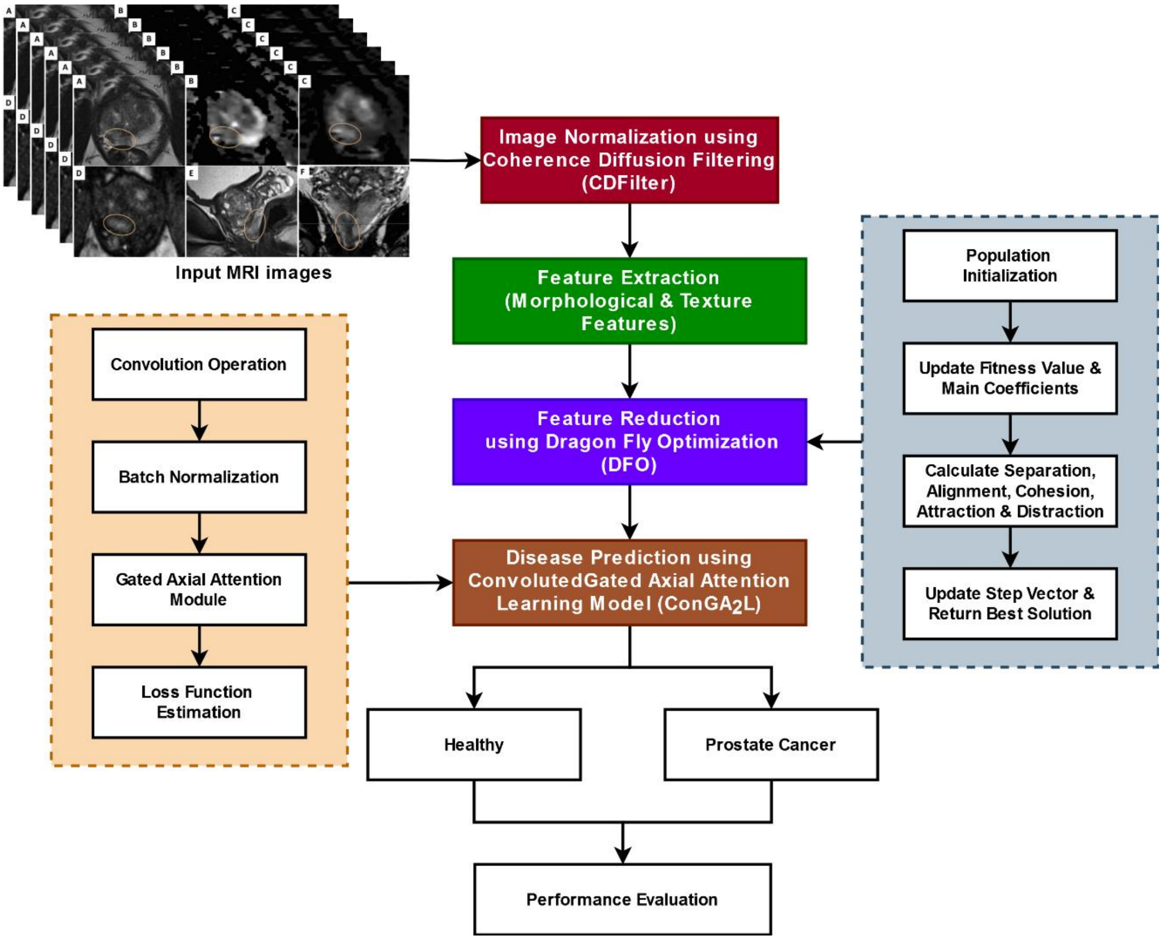

Figure 1. Flow of the proposed APPS model

A. COHERENCE DIFFUSION FILTERING (CDFILTER) FOR PREPROCESSING

The proposed method uses CDFilter, an advanced preprocessing model, for both contrast enhancement and noise reduction. Preprocessing and noise filtering are essential steps in medical imaging applications to achieve better classification performance. Numerous filtering techniques are used in the current research to reduce noise and improve quality. However, the issues with traditional methods are related to high complexity, inadequate filtering, and the existence of noise. In order to ensure an accurate diagnosis of prostate cancer, the proposed effort intends to adopt a new CDFilter technique to preprocess and normalize the input MRI images. To increase the degree of contrast in targeted MRI scans, the noise in the homogenous level regions must be decreased and the smoothness should be enhanced. To maintain the edge, the magnitude of the scalar diffusion constant around the acute edges of the quadratic diffusion filters needs to be reduced. But this will result in noisy edges. On the other hand, the diffusion tensor has been employed by anisotropic augmenting diffusion filters to change the diffusion along the image structures. The method of diffusion filtering employs an organized matrix as a diffusion tensor to direct the distribution. It depends on the incorporation of structural description that includes local coherence of structures.

B. MORPHOLOGICAL AND TEXTURE FEATURE EXTRACTION

Following filtering, from the normalized images, a collection of 14 morphological and 11 texture features are extracted for a reliable disease diagnosis. To extract visual and concealed properties from images for further analysis, the extraction of features is performed. Diminishing the dimensionality and extracting knowledge from extensive medical image datasets are the primary objectives. A feature extraction approach is employed to derive pertinent and required information from these methods, which contain a variety of data types. Here, both the texture and morphological features are extracted from the preprocessed samples for making an effective prediction. The regional distribution of gray images is analyzed through the statistical oriented feature extraction technique. A first order and higher-order approach are separated into this category. The variance and mean are employed as prediction properties in the first order approach. Other fundamental statistical techniques that are used in image processing include mean, median, and mod. Moreover, the higher-level static information estimates the characteristics that can be found at specific locations. The list of features extracted in this stage are represented in Fig 2.

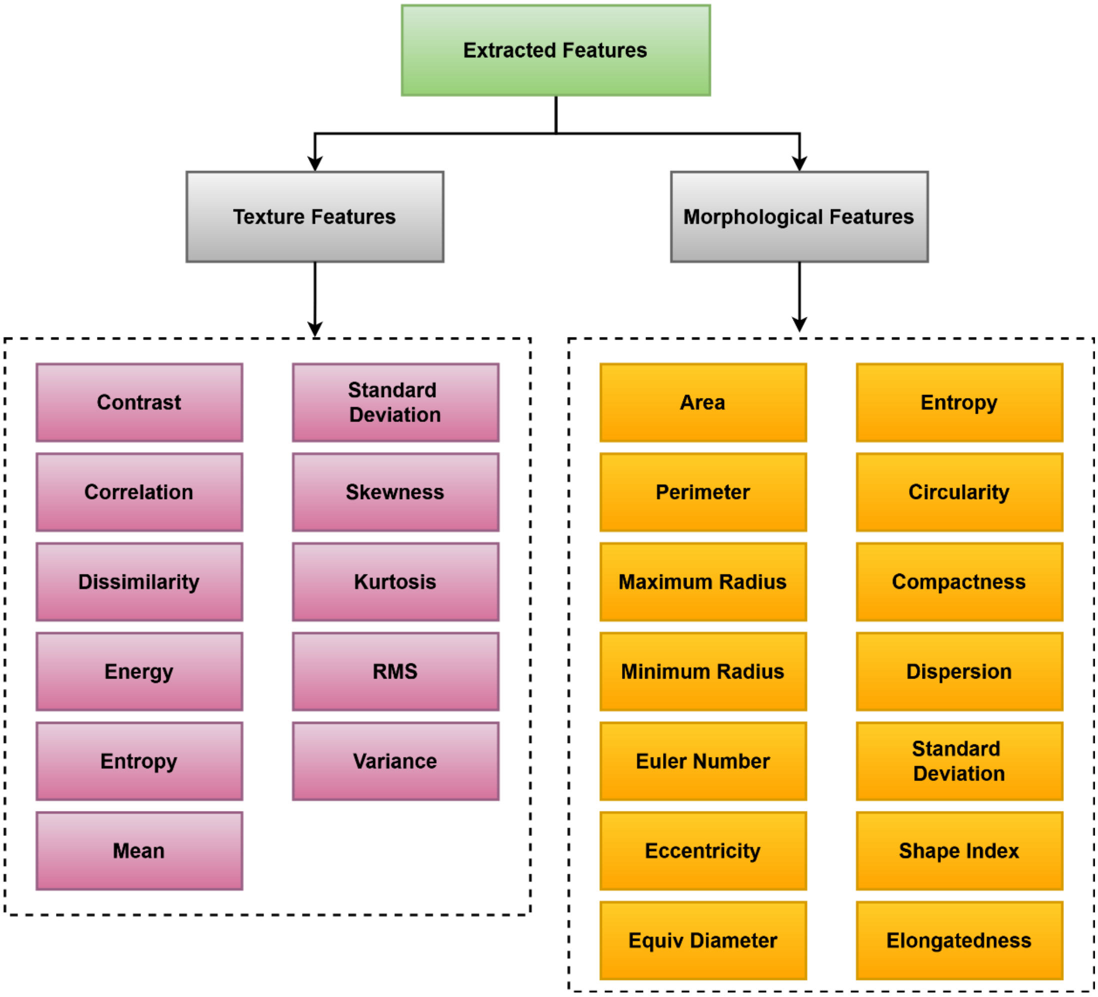

Figure 2. List of extracted features

C. Dragon Fly Optimized Feature Selection (DFO-FS) Algorithm

After extracting the required features, the DFO-FS algorithm is used for choosing the necessary and prevalent features from the extracted set. The main purpose of implementing this algorithm is to reduce the dimensionality of features for improving the accuracy of classifier with less computational burden. In earlier research studies, numerous feature selection as well as meta-heuristic algorithms are applied for feature selection. But the majority of approaches face the problems associated with the factors of extended time to reach the best optimal solution, searching complexity, and lower efficiency [37]. Hence, the proposed work aims to apply a unique and modern algorithm, known as DFO-FS for feature selection. A novel optimization technique based on swarms mimics the movement and foraging patterns of idealized dragonflies. In recent times, an iterative DFO has been developed that makes use of random values to alter its five substantial coefficients. The survival-of-the-fittest theory can be applied to this current mechanism by using additional functions such as simple, quadratic, and harmonic. In order to address feature selection issues, the strategy employs different approaches for altering the values of each of its principal indices. Dragonflies travel in small groups in the wild in search of food. We refer to this process as the hunting mechanism. Larger swarms of dragonflies move using a process known as migration mechanism, in which they fly together in an identical direction. Moreover, the following five key operators are used to characterize the swarming behavior of dragonflies:

- Separation
- Alignment
- Cohesion
- Attraction
- Distraction

The system that keeps the search agents apart in the neighborhood is called separation. The following equation displays the separation pattern as it has been mathematically modeled [38]:

$$\mathfrak{S}_i = -\sum_{j=1}^{\hbar} \wp - \wp_i \tag{1}$$

Where, j indicates the neighbor, $\mathfrak{S}_i$ indicates the separation behavior, and $\wp_i$ denotes the vector value. Consequently, the way that the velocity of the particular search agent correlates with that of the other agents that are searching in the vicinity is known as alignment. The following equation displays the synchronized behavior that has been analytically represented:

$$\mathfrak{A}_i = \frac{\sum_{j=1}^{\hbar} v_i}{\hbar} \tag{2}$$

Where, $\mathfrak{A}_i$ denotes the speed of neighbor j. Cohesion describes the way people move from their local neighborhood to the mass center. It describes the propensity of people to move towards the nearest point of mass. The following statement presents a mathematical representation of the Cohesion behavior $\mathfrak{C}_i$:

$$\mathfrak{C}_i = \frac{\sum_{j=1}^{\hbar} a_i}{\hbar} - \wp \tag{3}$$

The concept of attraction describes how a food source draws in the people who fly in its direction. Below is a representation of the formal modeling of this behavior:

$$\mathfrak{F}_i = \mathfrak{f}_s - \wp \tag{4}$$

Where, $\mathfrak{f}_s$ denotes the location of food source, and $\mathfrak{F}_i$ represents the attraction behavior. Distraction is an expression used to describe the inclination of people to flee from an attacker. The subsequent equation illustrates how the distraction between the enemy and the ith solution is quantitatively modeled:

$$\mathfrak{L}_i = e_p + \wp \tag{5}$$

Where, e_p denotes the position of enemy. Moreover, the position of dragonflies is updated according to the step vector as illustrated in the following equation:

$$\Delta\wp_{k+1} = (x\mathfrak{S}_i + y\mathfrak{A}_i + z\mathfrak{C}_i + v\mathfrak{F}_i + m\mathfrak{L}_i) + \omega\Delta\wp_k \tag{6}$$

Where, x, y, z, v, m are the weight values of the aforementioned swarming behaviors, which are computed according to the following models:

$$x, y, z = 2 \times \tau \times G \tag{7}$$

$$v = 2 \times \tau \tag{8}$$

$$\omega = 0.9 - itr \times \frac{(0.9-0.4)}{Mx_{itr}} \tag{9}$$

Where, $m = G$, and the parameter τ is computed as shown in the following model:

$$G = \begin{cases} 0.1 - \frac{0.2 \times itr}{Mx_{itr}} & if(2 \times itr) \leq Mx_{itr} \\ 0 & Otherwise \end{cases} \tag{10}$$

Where, τ is the random number. Moreover, the position of individual is estimated based on the following model:

$$\wp_{k+1} = \wp_k + \Delta\wp_{k+1} \tag{11}$$

Where, $\wp_{k+1}$ denotes the updated position, and k denotes the present step. According to the best position, the optimal solution is identified and used for picking the required features from the normalized image.

D.CONVOLUTED GATED AXIAL ATTENTION LEARNING MODEL ($CONGA_2L$)

The newly developed and exclusive $ConGA_2L$ deep learning-based classification technique is used to classify the prostate cancer-affected and normal tissues from the provided samples. Numerous learning approaches are reported to be employed in earlier studies for disease prediction, according to the literature review. The suggested $ConGA_2L$ technique is used for an efficient disease diagnosis in comparison to these methods. Moreover, the distinct characteristics of adopting this technique are simple to implement with less computational burden. Convolutional structures' innate inductive desire prevents them from successfully modeling distant interactions in images. Self-attention techniques have been employed by transformer structures to acquire incredibly expressive characteristics and encode relationships that are far apart.

In this instance, the capacity of the network to express and identify network characteristics is enhanced with the addition of the transformer structure. Here, an axial attention-based approach has been used to expand the present framework. With the accurate location information captured by the extra positional biases in Query, Key, and Value, distant relationships are recorded. In addition to effectively computing non-local context, axial attention can effectively encode positional biases into mechanisms and capture remote interactions in input attribute graphs. However, as it is difficult to learn from experiments with small-scale data sets, which often occur in the segmentation of medical images, it is not always correct when recording distant interactions. When adding neighboring positions to the associated codes, searches, and results, efficiency may suffer if the relative locations received were not encoded correctly. As a result, the suggested ConGA2L model now has an enhanced axial block that facilitates efficient position control. This technique greatly improves APPS performance and yields accurate categorization results.

4. RESULTS AND DISCUSSION

This section uses a range of evaluation metrics to test and analyze the performance of the proposed APPS model. Moreover, this work uses publically available dataset for performance assessment and analysis, which is referred to as the prostate MRI image database. There are 230 MRI images of patients in this collection, each with a unique description and category. Additionally, the final set of images includes patient MRIs that are utilized for classification. The Health Insurance Portability and Liability Act (HIPPA) regulations recorded this set of data. The positive and negative prediction scores for the conventional and suggested deep learning models used to diagnose prostate cancer are shown in Tables 2. The most important parameter used to evaluate the accuracy of disease prediction is the confusion matrix of the classifier, which is often created using the previously described measures. The suggested APPS model outperforms the other current classifier approaches in terms of enhanced positive prediction and lower negative prediction values, as demonstrated by the anticipated estimations.

Table 2. Confusion Matrix of predictive value

	Positive	Negative
Positive	TP (58)	FP (2)
Negative	FN (6)	TN (114)

(a) VGG 16

	Positive	Negative
Positive	TP (46)	FP (14)
Negative	FN (12)	TN (108)

(b) Inception V3

	Positive	Negative
Positive	TP (51)	FP (9)
Negative	FN (15)	TN (105)

(c) ResNet

	Positive	Negative
Positive	TP (59)	FP (1)
Negative	FN (4)	TN (116)

(d) Proposed

True Positive Rate, also known as sensitivity, indicates whether or not the persons being examined are positively tested. It is expressed mathematically as shown in below:

$$\boldsymbol{TPR = \frac{TP}{TP+FN}} \tag{12}$$

TNR, also known as specificity, indicates that negative tests were correctly recognized. It can be expressed mathematically as illustrated below:

$$\boldsymbol{TNR = \frac{TN}{FP+TN}} \tag{13}$$

Consequently, the positive and negative prediction values are estimated by using the following equations:

$$\boldsymbol{PPV = \frac{TP}{TP+FP}} \tag{14}$$

$$\boldsymbol{NPV = \frac{TN}{TN+FN}} \tag{15}$$

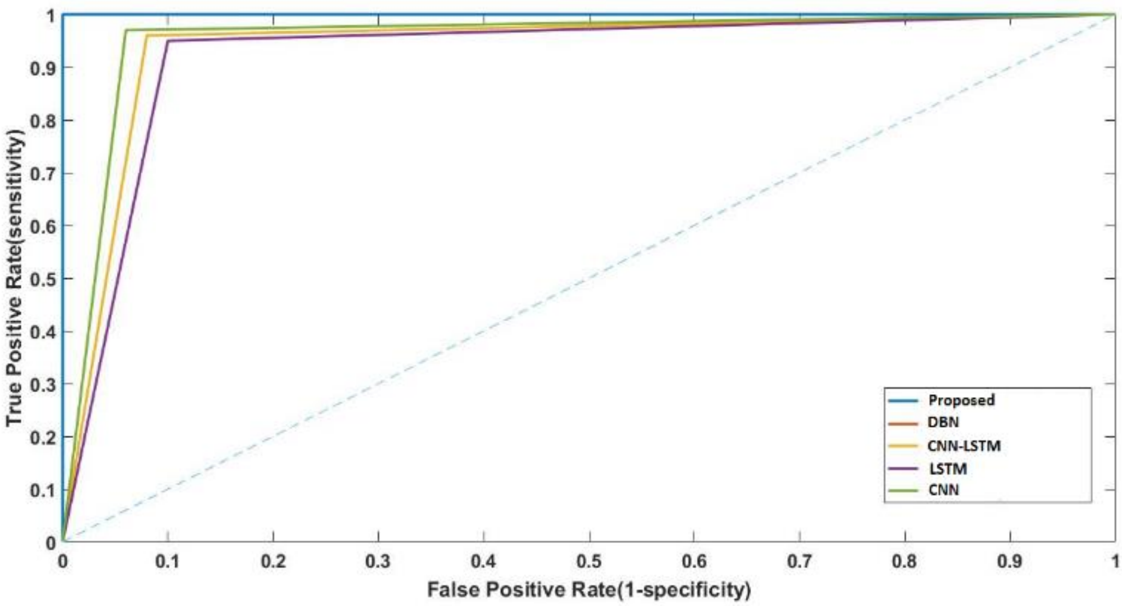

Figure 3. ROC analysis

The Receiver Operating Characteristics (ROC) of both the suggested and traditional deep learning methods for diagnosing prostate cancer are shown in Fig 3. A common technique for classifier validation is ROC analysis. An area under a curve is thought to represent a portion of a square unit. The AUC has a value between 0 and 1. A realistic classifier ought to have a value higher than 0.5, with 90% to 100% being represented by a value between 0.9 and 1.0. Plotting the ROC in accordance with specificity and sensitivity makes it an excellent test. The y-axis governs the actual positive rate of prostate cancer, while the x-axis reflects the false positive rate. When compared with alternative deep learning methods, the findings show that the ROC of the suggested APPS model has significantly improved to 0.99. Several performance measure types in this study are validated through the use of the following models:

$$\boldsymbol{Accuracy} = \frac{(\boldsymbol{TP}+\boldsymbol{TN})}{(\boldsymbol{TP}+\boldsymbol{TN}+\boldsymbol{FP}+\boldsymbol{FN})} \times \mathbf{100} \tag{16}$$

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP}+\text{FN})} \times 100 \tag{17}$$

$$\text{Specificity} = \frac{\text{TP}}{(\text{TP}+\text{FP})} \times 100 \tag{18}$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP}+\text{FP})} \times 100 \tag{19}$$

$$\text{F1} - \text{Score} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{20}$$

Where, TP – True positives, TN – True negatives, FP – False positives, and FN – False negatives. Additionally, the overall performance outcomes of the suggested and current deep learning approaches employed for prostate cancer diagnosis are compared in Table 3 and Fig 4. These results also show that, in comparison to the other deep learning methods, the suggested APPS model yields better prediction outcomes. The primary means of achieving better performance results is the implementation of an effective feature extraction and optimization strategy.

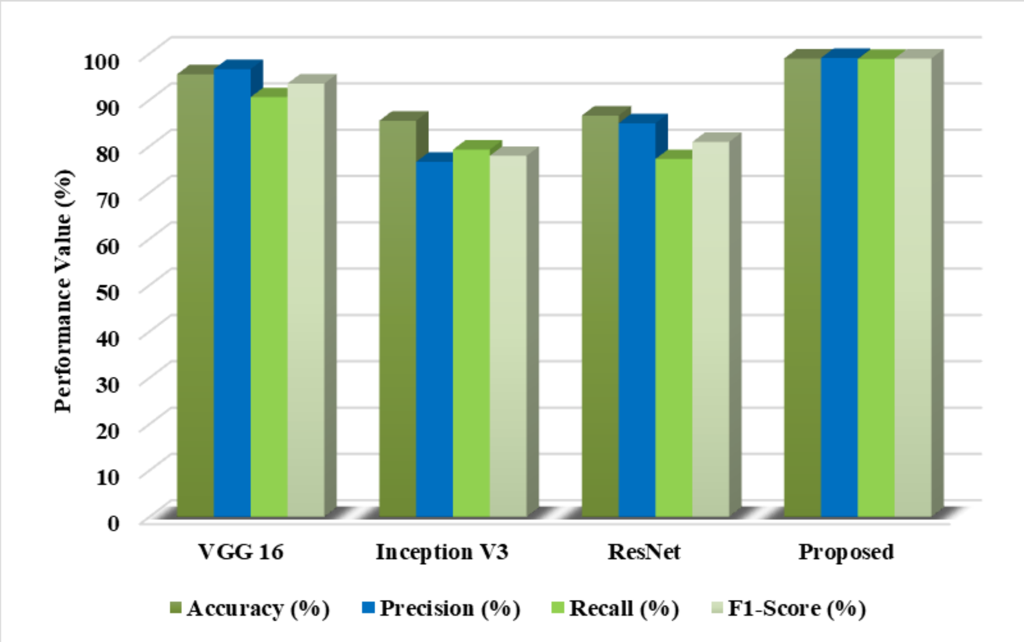

Figure 4. Performance study of conventional and proposed deep learning models used for prostate cancer diagnosis

Table 3. Comparative analysis

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG 16	95.56	96.67	90.63	93.55
Inception V3	85.56	76.67	79.31	77.97
ResNet	86.67	85	77.27	80.95
Proposed	99	99.1	98.9	99

Furthermore, Fig. 5 verifies the training and testing accuracy of the suggested APPS model in relation to different epoch counts. Generally speaking, the accuracy of the classifier throughout training and testing processes determines how well it predicts diseases. Therefore, it is essential to accurately classify the normal and prostate cancer-affected tissues from the provided images in order to increase accuracy at both the training and validation stages. The findings show that the suggested system significantly increases the overall training and testing accuracy of APPS.

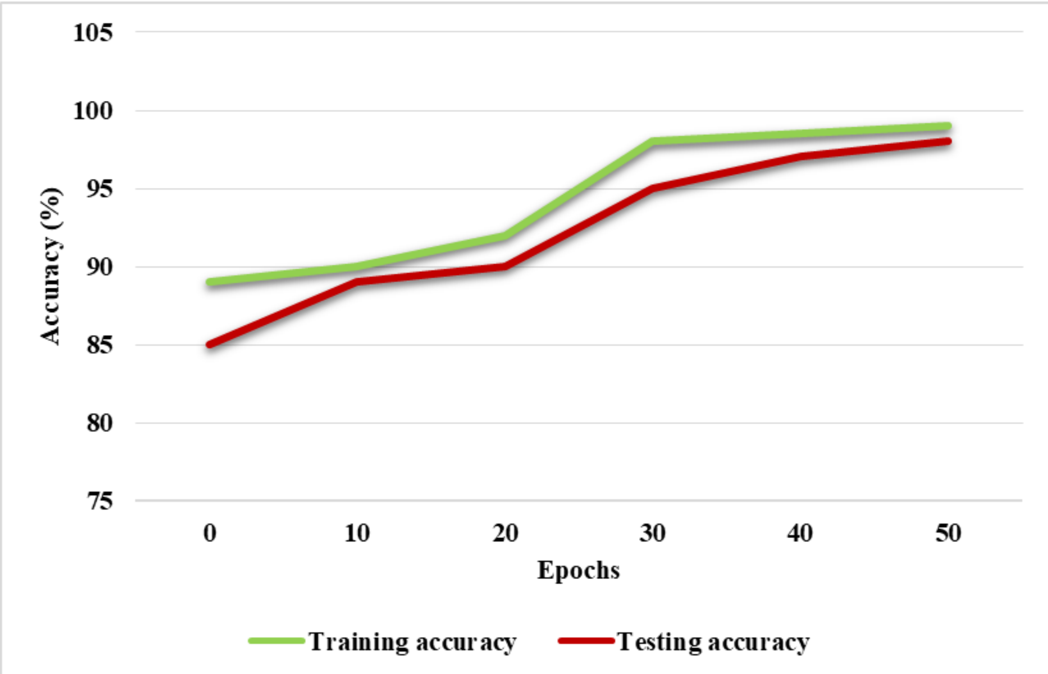

Figure 5. Training and testing accuracy

Table 4. Comparative study among the classification approaches with the texture based features

Methods	Sensitivity	Specificity	Accuracy	MCC
Kernel-NB	89.5	78.97	82.23	64.07
DT	69	89.71	83.31	60.14
SVM	85.50	94.18	91.50	80
KNN	85	90.83	89.03	74.75
BT	87	89.26	88.56	74.23
Proposed	99.1	99	99	98.9

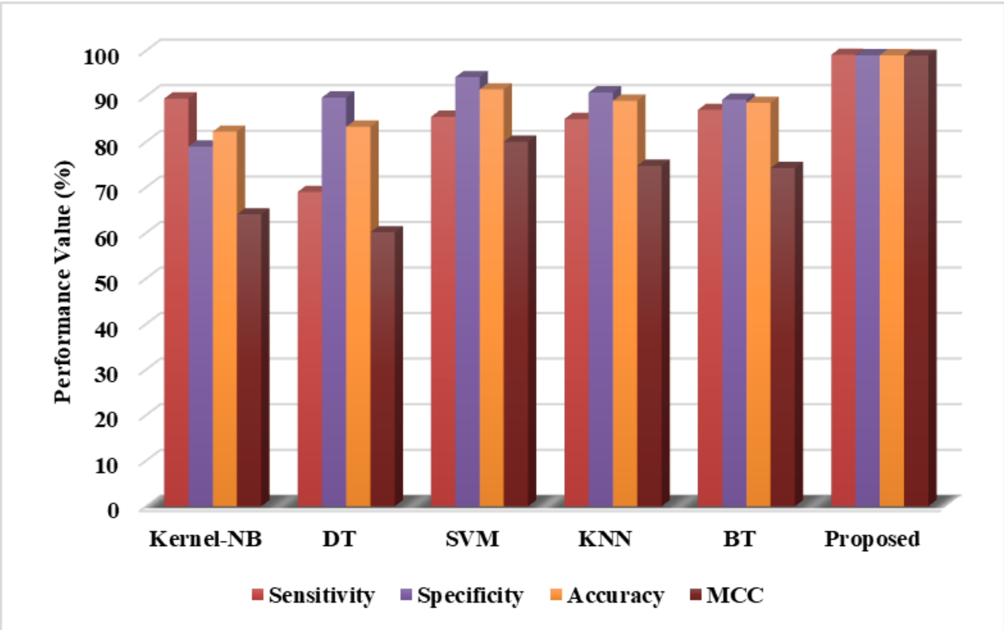

Figure 6. Performance comparison of some of the prevalent machine learning approaches for prostate cancer detection

Fig 6 and Table 5 shows a performance comparison analysis of the most prominent machine learning approaches used for prostate cancer diagnosis. For this evaluation, metrics such as sensitivity, specificity, accuracy, and Matthews Correlation Coefficient (MCC) are analyzed. Similarly, the other parameters evaluated and compared with the same machine learning models are PPV, NPV, AUC, and FPR, as shown in Fig 7 and Table 6. Sensitivity measures how accurately the model identifies actual positive cases, while specificity measures how accurately it identifies actual negative cases. Accuracy, on the other hand, measures the overall correctness of the model's predictions. MCC provides a balanced measure of a model's performance, which is particularly useful for imbalanced datasets. Positive Predictive Value (PPV) represents the ratio of correctly predicted positive cases to the total predicted positive cases, while Negative Predictive Value (NPV) represents the ratio of correctly predicted negative cases to the total predicted negative cases. The Area Under the Curve (AUC) measures the model's ability to distinguish between classes and is often used for binary classification. Lastly, the False Positive Rate (FPR) measures the ratio of falsely predicted positive cases to the total actual negative cases.

According to this comparison, the proposed APPS model is more competent at managing big dimensional datasets with superior performance outcomes in terms of high accuracy, PPV, AUC, and lower FPR.

Table 5. Comparison based on the parameters of PPV, NPV, FPR and AUC with the texture based features

Methods	PPV	NPV	AUC	FPR
Kernel-NB	65.57	94.39	93.22	21.03
DT	75	86.61	85.17	10.29
SVM	86.80	93.56	95.33	5.81
KNN	80.57	93.12	94.69	9.17
BT	78.38	93.88	94.32	10.74

Proposed	99	98.5	99	2.10

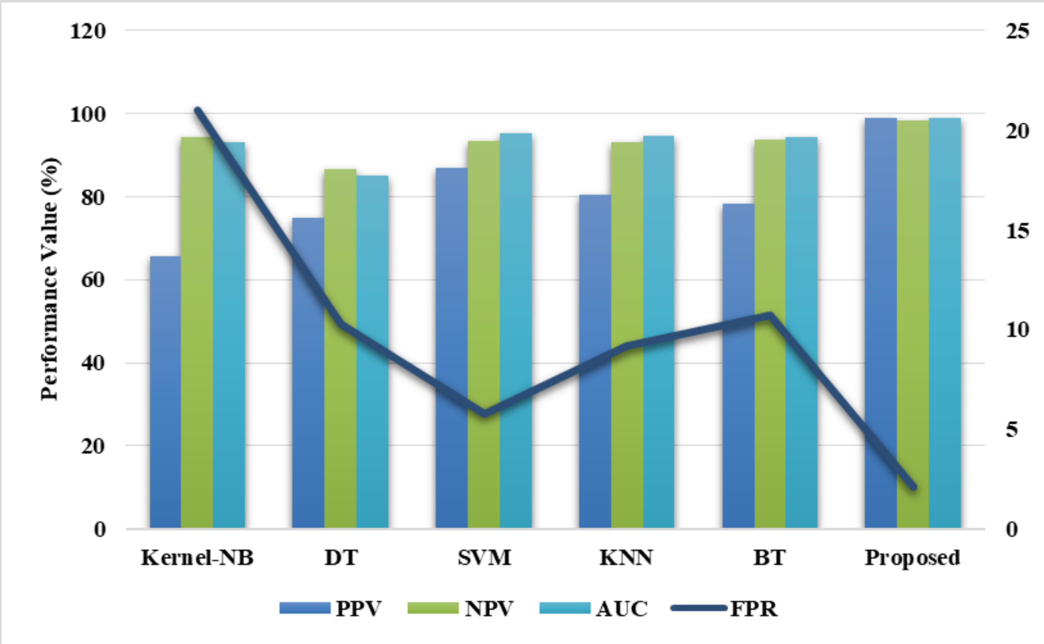

Figure 7. Comparative assessment based on PPV, NPV, AUC and FPR values

Table 6. Comparative study among the classification approaches with preprocessing

Methods	Sensitivity	Specificity	Accuracy	MCC
Kernel-NB	82	76.51	78.21	57.86
DT	80.5	91.28	87.94	71.78
SVM	85.6	91.28	89.8	76.58
KNN	86	94.63	91.96	81.09
BT	84.5	92.62	90.11	76.91
Proposed	99.1	99.3	99	99.1

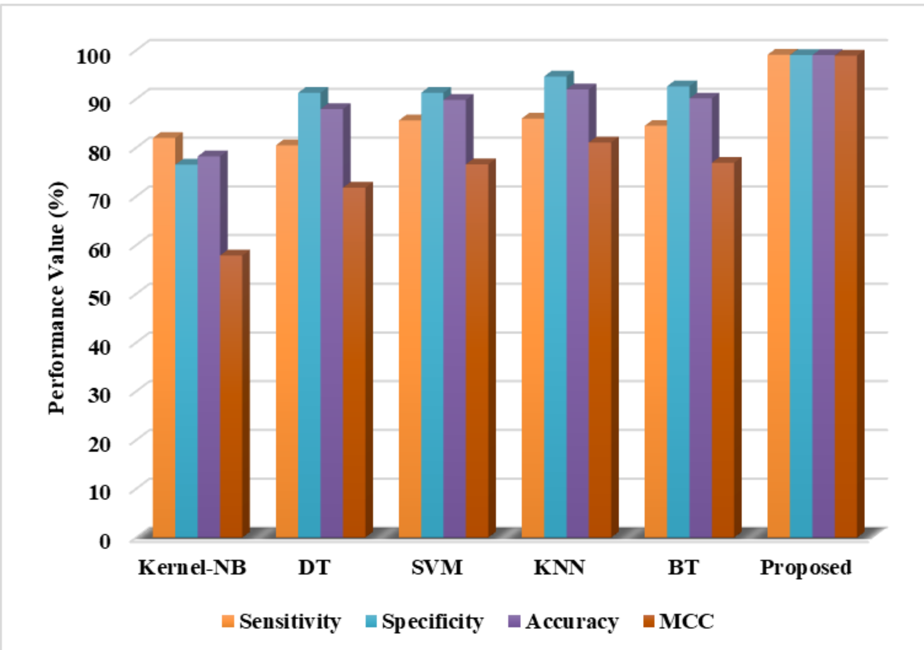

Figure 8. Performance comparison of some of the prevalent machine learning approaches for prostate cancer detection with preprocessing

Table 7. Comparison based on the parameters of PPV, NPV, FPR and AUC with preprocessing

Methods	PPV	NPV	AUC	FPR
Kernel-NB	60.97	90.48	88.13	23.49
DT	80.5	91.28	89.69	8.72
SVM	81.6	93.79	95.47	8.72
KNN	87.76	93.79	96.74	5.36
BT	83.36	93.03	95.39	7.38
Proposed	99	98.2	99.2	1.64

The overall effectiveness of the suggested machine learning techniques and the standard methods with the addition of image preprocessing are also contrasted in Fig. 8 and Table 7. As a result, as illustrated in Fig. 9 and Table 8, the PPV, NPV, AUC, and FPR measures are also validated and compared. The suggested APPS model works better than the traditional methods overall, according to the comparing data.

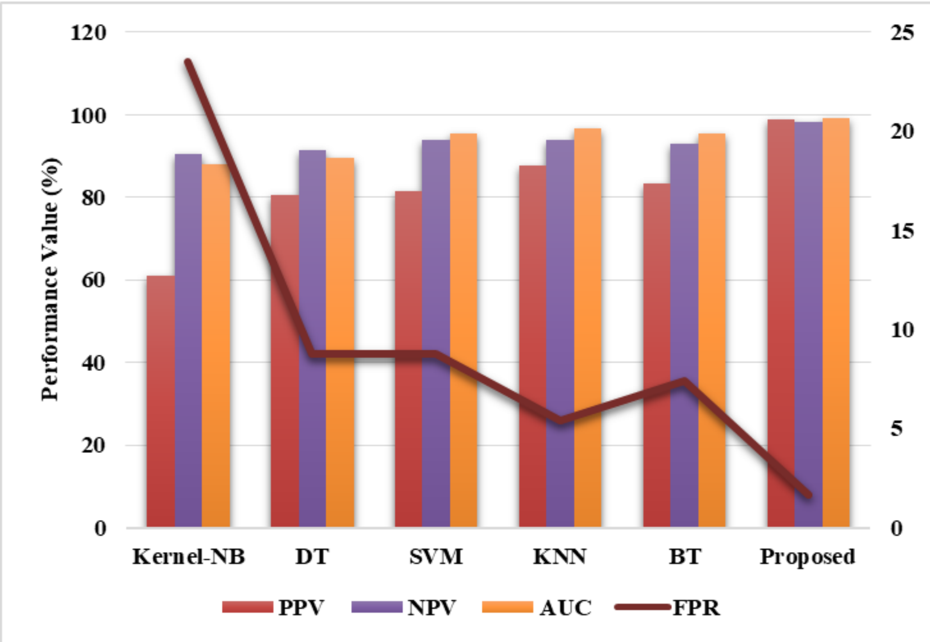

Figure 9. Comparative assessment based on PPV, NPV, AUC and FPR values with preprocessing

The precision, recall, f1-score, and FPR values for the suggested APPS model are assessed in Table 8 in relation to the classifications of prostate cancer and healthy tissues. Next, the relevant values are shown in Figures 10 and 11. The results show that the suggested APPS model offers better performance outcomes with a lower FPR. The primary factor improving the results in the suggested model is the integration of many modules, including preprocessing, feature extraction, and optimization.

Table 8. Performance study of the proposed APPS model using prostate cancer dataset

Type of class	Precision	Recall	F1-Score	FPR
Healthy tissue	98.3	98.9	98.8	0.056
Prostate cancer	99	99.1	99	0.012

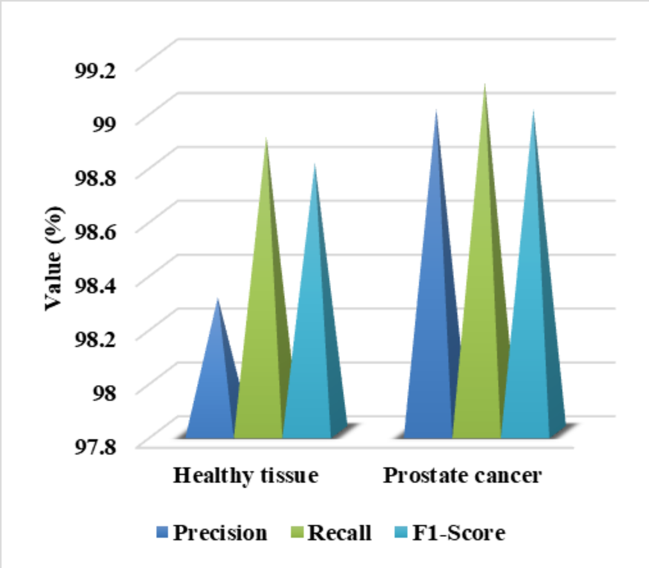

Figure 10. **Performance evaluation for healthy and prostate cancer tissues**

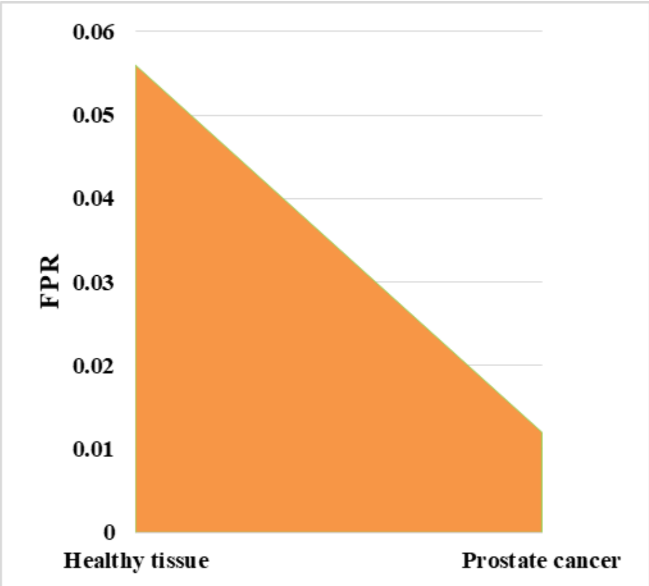

Figure 11. FPR analysis for healthy and prostate cancer classes

5. CONCLUSION

This study looked at the prostate cancer, which is one of the leading causes of cancer-related fatalities in males and whose signs are comparable to the symptoms of benign growth. The diagnosis of illnesses is one of the main issues confronting healthcare today. This study is crucial due to the fact that are currently no clear criteria for evaluating signs of prostate cancer, and the diagnostic tools available have an exceptionally low prediction probability. The novel contribution of the paper is the development of an automated and remarkably successful detection technique for the recognition and classification of prostate cancer from MRI images. Throughout the preprocessing, feature extraction, optimization, and classification phases, the proposed APPS model employs a variety of image processing approaches to accurately predict prostate cancer, setting it apart from previous literature efforts. This work uses the publicly available prostate MRI imaging data to predict and categorize illnesses. After the input samples are acquired, noise is removed and overall image quality and contrast are improved by applying the unique image normalization model, CDFilter. Using this filtering strategy greatly improves the overall disease detection performance outcomes of the suggested system. The morphological and texture feature extraction model is used to extract the required and desirable collection of features from the filtered image. Better prediction results and a higher performance gain for the classifier are obtained from this feature extraction. Additionally, the DFO meta-heuristic technique was used to choose only the characteristics needed to train the classifier. With fewer features, it effectively reduces the dimensionality of the image, thereby boosting the accuracy and training speed of the classifier. Additionally, from the submitted samples, the prostate cancer-affected and healthy tissues are classified accurately and with a lower false prediction rate using the recently created classifier algorithm, ConGA2L. Including multiple unique images processing methods, including DFO, ConGA2L, and CDFilter, greatly enhances the prostate cancer diagnosis performance of the proposed APPS framework. A few advantages of utilizing the suggested APPS model include its mobility, reduced false positive rate, and enhanced disease prediction accuracy.

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