Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 7, 2025

AI-DRIVEN APPROACH FOR EARLY PROSTATE CANCER DETECTION AND DIAGNOSIS

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DOI: https://doi.org/10.5281/zenodo.16526795

Keywords
Prostate Cancer, Deep learning Models (YOLOv11), MRI, Histopathological

Article History
Received on 24 April 2025
Accepted on 11 July 2025
Published on 26 July 2025

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Abstract
Prostate cancer develops in the prostate glands in men, located below the bladder. Prostate cancer is becoming the prominent cause of death among men. It grows slowly and may not show any symptoms in the early stage. Many procedures are being used to treat Prostate cancer, but they are not getting better results yet at the early stage. Deep learning models, such as YOLO, have a significant impact on medical imaging due to their high accuracy and real-time object detection capabilities. The study supports the integration of advanced AI models (YOLOv11) into clinical workflows for prostate cancer diagnosis at an early stage. The model is very efficient, achieving a 92.56% validation accuracy, average 98.61% Precision, average 93.91% Recall, average 96.19% F-1 score, and Area under the Curve (AUC) 96%-to-98%.

INTRODUCTION

Air pollution has been increasing progressively due to urbanization and population growth. Air pollution is a major global challenge [1]. Air pollution not only has an effect on the environment but also on human health. Some studies have revealed that air pollution is the cause of cancers and chronic metabolic diseases. Carbon dioxide (CO2), Carbon monoxide (CO), nitrogen oxides (NO_2 and NOx), ozone (O_3), and sulfur dioxide (SO_2) are common air pollutants [2]. These pollutants have a bad impact on the immune system and are a main cause of numerous diseases [3]. Prostate cancer is the second commonly diagnosed cancer in men globally [4]. Prostate cancer develops in prostate glands (small walnut-shaped reproductive organs) placed beneath the bladder and in the anterior of the rectum. The seminal fluid is produced by the prostate gland. The seminal fluid combines with sperm to make semen. The prostate gland assists sperm fertility and motility [5]. The growth of prostate cancer is mostly related to older age, particularly in men above the age of 50 [6]. It is an important cause of cancer-related death among men worldwide. In many persons, prostate cancer grows slowly and remains limited to the gland, causing little or no damage in its early stages. It may remain asymptomatic for years, making early detection mostly challenging without the aid of screening tools [7]. However, there are more destructive forms of prostate cancer that multiply quickly and have the potential to spread in the surrounding tissues and distant organs, such as bones, lymph nodes, lungs, and liver, which severely degrades the diagnosis [8].

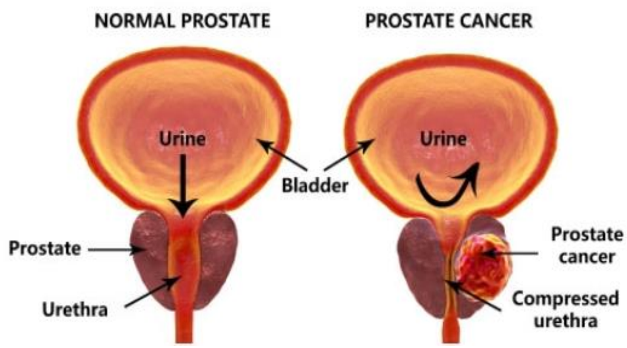

Figure 1:Prostate Cancer

As the disease progresses, patients may face a range of urological and systemic symptoms. These contain common urination, especially at night (nocturia), trouble in starting or stopping urination, weak or interrupted urine flow, a burning sensation while urinating, blood in the urine (hematuria) or semen (hematospermia), pain or difficulty in the lower back, hips, or thighs, and in some cases, erectile dysfunction [8]. In advanced cases, involuntary weight loss, weakness, and bone pain may occur due to its spread.

Several risk factors are related to prostate cancer growth. These include age, family history of prostate cancer [7], inherited genetic mutations, and many environmental and lifestyle factors such as diets, smoking, alcohol consumption, and obesity [9]. Hormonal imbalances, mostly including testosterone and dihydrotestosterone (DHT), may also play a part in cancer initiation and development [4].

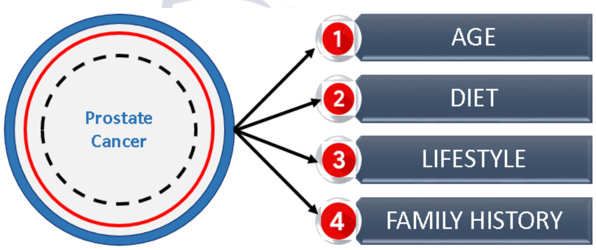

Figure 2: Factors Affecting Prostate Cancer

Early and accurate detection of prostate cancer is important for timely involvement and enhanced survival results. The screening methods contain the prostate-specific antigen (PSA) blood test, which measures PSA levels in the bloodstream. Raised levels may indicate cancer or other prostate abnormalities—and the digital rectal examination (DRE), where a physician examines the prostate through the rectum to find any abnormalities [10]. If these tests raise doubts of distortion, a series of positive diagnostic actions may be engaged, such as multi-parametric magnetic resonance imaging (MRI), computed tomography (CT) scans, and trans-rectal ultrasound (TRUS)-guided prostate biopsies. These techniques help visualize the prostate, identify unsure cuts, regulate the amount of the disease, and allocate a Gleason score to measure tumor aggressiveness. Treatment plans are adapted based on various factors, including cancer stage, histological grade, PSA levels, patient age, and personal preferences [11].

Several treatment alternatives are accessible for prostate cancer. These contain radical prostatectomy (surgical removal of the prostate gland), external beam radiation therapy (EBRT), internal radiation therapy (brachytherapy), androgen deprivation therapy (ADT), chemotherapy with drugs like docetaxel or cabazitaxel, immunotherapy, and newer methods such as focal therapies and high-intensity focused ultrasound (HIFU) [12]. Robotic-assisted laparoscopic surgery has further revolutionized prostate cancer treatment by offering greater precision, reduced blood loss, fewer complications, and quicker recovery compared to traditional open surgery [13]. Despite the accessibility of various therapeutic options, the choice of treatment must balance oncological control with quality-of-life concerns, particularly concerning urinary and sexual function.

Prostate cancer is being treated using both traditional and ono-traditional methods. Traditional treatments like surgery, radiation, and chemotherapy are usually used and supported by medical research, but they frequently cause severe side effects like drowsiness and other health problems. Newer treatment methods such as HIFU, cryotherapy, immunotherapy, and using AI are becoming more popular because they target cancer better and have fewer side effects. Recently, deep learning (DL) methods like ResNet, RNN, and CNN have been used to study prostate cancer using MRI and tissue images. Some models, like PI-RADSAI and others, have shown very high accuracy in detecting cancer. Conversely, most of these models cannot detect cancer in real time, which is a big limitation.

Study Gap:

1. The existing DL models (e.g., ResNet, RNN, Mask R-CNN, EfficientNet-b7) are built for static image investigation and are not suitable for real-time object detection.
2. Regardless of high accuracy, these models have deficient clinical combination due to computational complexity.
3. There is limited research on lightweight, real-time, and explainable AI models that can be effectively applied in practical object diagnostic workflows.

In current years, progressions in artificial intelligence (AI), Machine learning, Deep learning, and computer vision have exposed big potential in prostate cancer diagnosis and management [14]. The YOLO (You Only Look Once) deep learning model is one of the most inspiring tools because of its capability in real-time object detection [15].

Objective of Study:

1. To build a model for dynamic image investigation and suitable for real-time object detection.
2. To build a model achieving higher accuracy and reducing the computation complexity.
3. To build a model so that it can be applied practically to object diagnostic workflows.

The proposed model automatically detects and focuses on cancerous regions with high accuracy and speed. The YOLOv11 Deep learning model will outperform in handling medical imaging data (MRI and histopathological images). By examining image data, YOLOv11 can support radiologists and pathologists in detecting early-stage tumors, measuring tumor margins, and assisting decision-making for biopsy or treatment planning. Moreover, the deep learning YOLOv11 model can give automated grading of cancer severity, prediction of tumor progression, and patient risk stratification. However, challenges persist, including the need for large, annotated datasets, model generalization through various imaging platforms, data imbalance, and confirming transparency in decision-making for clinical trust and acceptance.

ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 7, 2025

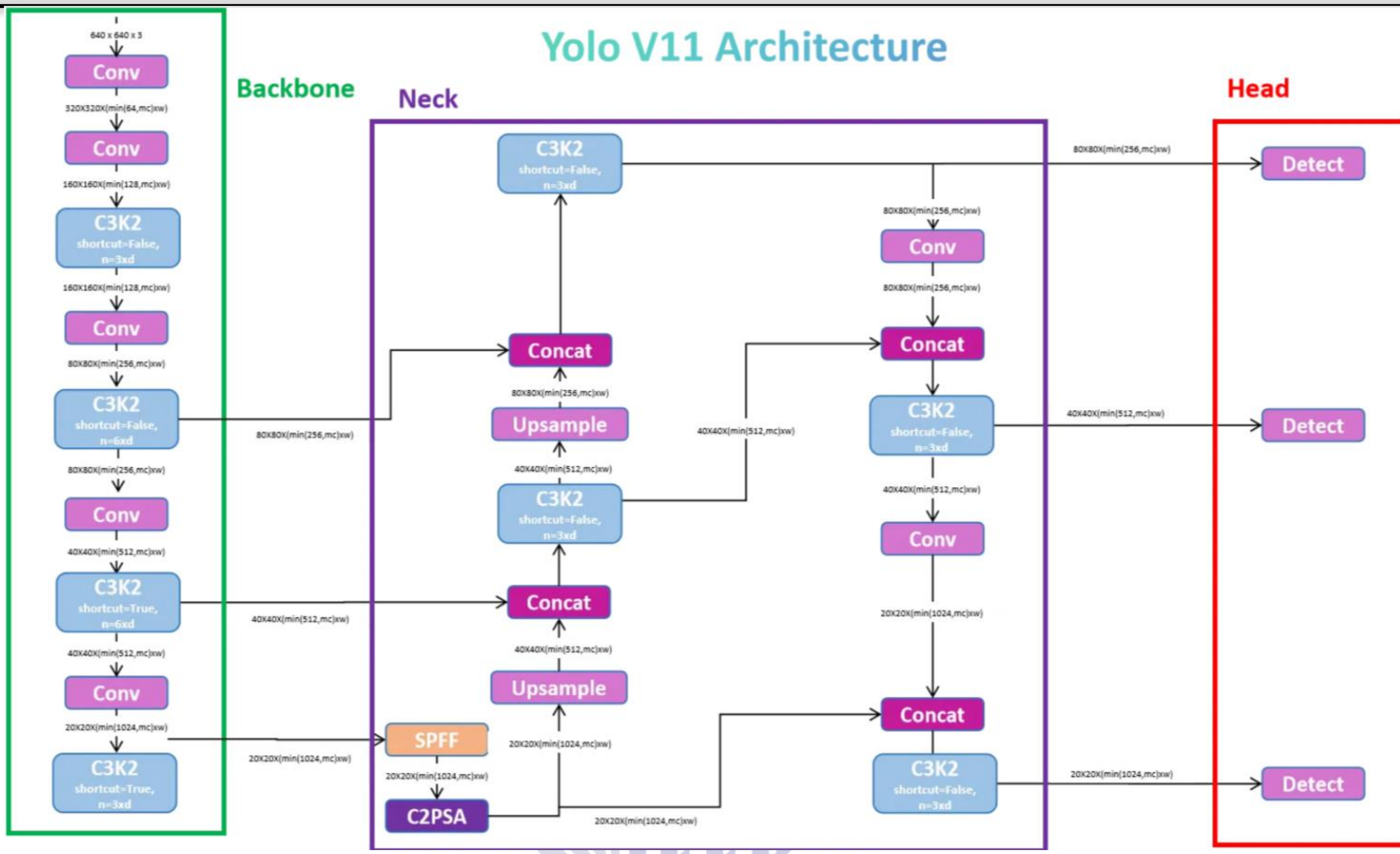

Figure 3:Yolov11 Architecture

The diagram demonstrates the architecture of a complete computer vision framework centered around the YOLOv11 model. S Nikhileswara Rao et al. The Yolov11 model consists of three main modules. The initial module, C3K2, achieves early feature extraction, likely using convolutional layers optimized for efficiency. This is followed by the C2PSA module, which incorporates parallel split attention mechanisms to increase the model's focus on important spatial and semantic features within the image. The features are then further refined by the SPPF (Spatial Pyramid Pooling – Fast) module, which allows multi-scale feature aggregation, permitting the model to detect objects of varying sizes more effectively.

These improved features are then passed into the YOLOv11 core architecture, which serves as the central processing unit of the system. YOLOv11 processes the input features and generates outputs for multiple computer vision tasks. These include object detection, instance segmentation, image classification, pose estimation, oriented object detection, and object tracking. By integrating attention mechanisms and multi-scale pooling within an efficient backbone, the system ensures robust performance across a variety of vision applications. This design makes YOLOv11 not only versatile but also suitable for real-time deployment in complex environments. As research expands, the integration of AI (YOLOv11 model) will enhance clinical consequences. Public awareness campaigns, regular exercise, and diet may also decrease the problem of prostate cancer and increase the quality of life.

Literature Review

Traditional and non-traditional treatment methods are being used globally. Traditional treatments such as surgery, radiation therapy, chemotherapy, and hormone therapy have been used for many years and are supported by strong clinical evidence [16]. These methods are good for removing cancerous cells, especially in the early stages. They are commonly accessible in hospitals and are frequently the first choice endorsed by doctors. Conversely, traditional treatments can also have major side effects, such as fatigue, urinary problems, erectile dysfunction, and an overall impact on quality of life. Alternatively, non-traditional methods, such as high-intensity focused ultrasound (HIFU), cryotherapy, immunotherapy, targeted therapy, and the use of artificial intelligence (AI) in analysis, offer inspiring alternatives [17]. Non-traditional methods have fewer side effects compared to traditional methods. Non-traditional methods can be better in targeting cancerous cells while preserving healthy tissue. Furthermore, lifestyle variations and loyal care can increase patient well-being. Around one million new cases of prostate cancer are being diagnosed yearly [18]. Recently, the use of Deep learning algorithms has become popular in the diagnosis of prostate cancer [19] [20]. Numerous studies have applied DL models like **ResNet**, RNN, **Faster R-CNN**, **Mask R-CNN [21][22][23],** and **dual optimizers (Adam and SGD)** to examine MRI and pathology images of the prostate. These models have established enhanced accuracy and speed for detecting cancerous cells. For example, the **PI-RADSAI model** uses a human-in-the-loop method to distinguish between benign and malignant lesions, attaining an accuracy of 88%. In contrast, a cooperative model was established using UNet, Xception, and EfficientNet-b7, reaching 92.38% accuracy. The CNN model is also used to diagnose prostate cancer, attaining 95.2% accuracy [24]. But these models are not good for real-time object detection.

The proposed model will provide better results. It consists of an input unit used to fetch the images. After fetching the images input unit transfers the data to the Detection Unit. Detection unit (deep learning model (YOLOv11)) used for classification. It uses a neural network to classify the data speedily and accurately in just one step. The working of the model is shown in the figure.

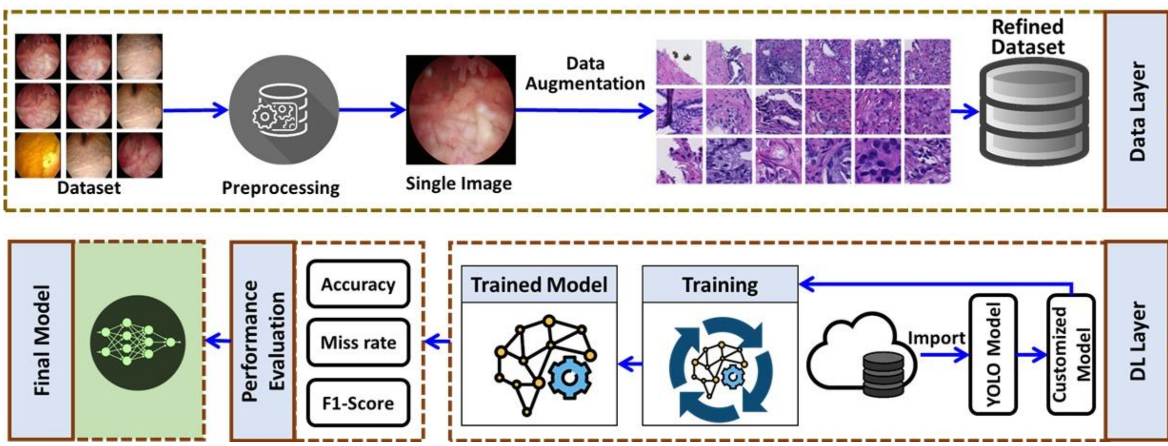

Figure 4: Proposed Model

Model Working:

Prostate Imaging Data Acquisition: Input images, e.g., Ultrasound or MRI images, are used to detect the abnormalities in the prostate gland. **The model** used preprocessed images (augmentations) to increase the quality and prepare for training. These preprocessing steps help the model to achieve its best performance, prevent overfitting, and remove irrelevant images.

Deep Learning Model (YOLOv11): The YOLOv11 model is trained with augmented and preprocessed data, and it is used for detections and classifications. It uses bonding boxes and class probabilities to identify the normal and abnormal regions in the prostate images. The final step delivers the three types of output. Classification, Diagnosis, and Clinical Examination**.**

Classification	Label the condition (e.g., healthy, benign, malignant).
Diagnosis	Supports or assists in medical diagnosis.
Clinical Examination	Integrates model findings into the doctor's evaluation for decision-making.

Dataset and Resources:

The dataset (namely Prostate Cancer) is collected from the Robow flow site. It has 100 observations, out of which 8 are numeric variables, one ID, and one categorical variable. It consists of a large number of prostate cancer-related pictures. Out of 100%, 70% pictures are used for training, 10% for testing, and 20% images are used for validation. In this review paper, for the validity and authenticity of data, articles are downloaded from MDPI. IEEE Access, Springer, Science Direct, The Lancet, RSNA, Scientific Reports Journals, and Google Scholar.

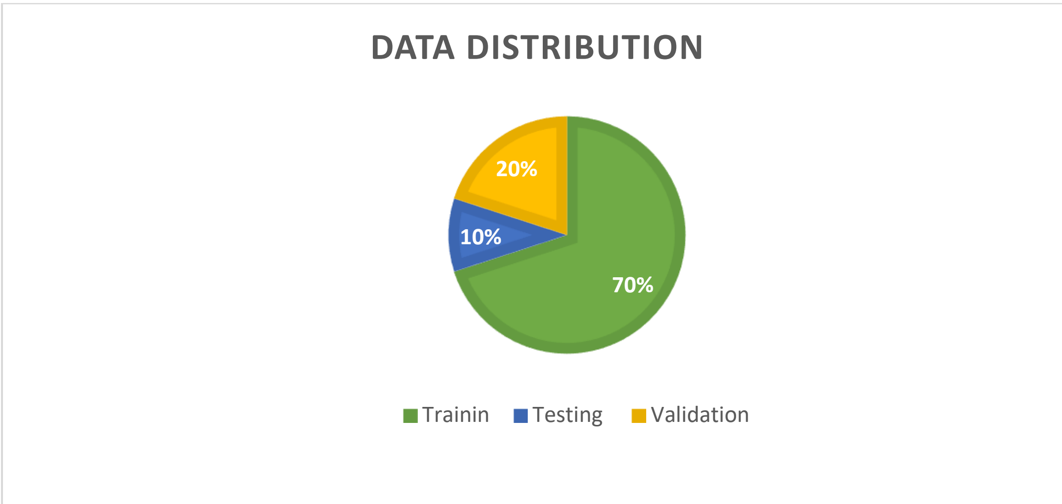

Figure 5: Data Distribution

Performance Metrics:

The performance of the proposed model was evaluated by F-1 Score, Precision, Recall, and Accuracy.

Table 1: Performance Metrics Table

Metric	Formula	Explanation
Precision	$\frac{tp}{tp + fp}$	Measure the correctness of the model.
Recall	$\frac{tp}{tp + fn}$	Handle the classification problems of the classes.
Accuracy	$\frac{tp + tn}{tp + tn + fp + fn}$	Measure the correctness of a classification model.
F1-Score	$2 * \frac{Precision * Recall}{Precision + Recall}$	Measure the harmonic mean of Precision and Recall of the model.

Performance Evaluation:

Performance evaluation refers to how well an AI system accomplishes its intended tasks. Recall, Precision, F-1 Score, and Accuracy can determine the performance evaluation.

Accuracy – Percentage of correct predictions.

Precision & Recall – Trade-off between false positives and false negatives.

F1 Score – Harmonic mean of precision and recall.

Confusion Metric:

It is an essential tool for evaluating the performance of a **classification model** in AI/ML. It delivers a complete breakdown of correct and incorrect predictions, helping to calculate model accuracy, precision, recall, and other key metrics. For **binary classification** (Positive vs. Negative), the matrix is a **2×2 table**:

Table 2: Confusion Metrics

	True Cancer	True Background
Predicted Cancer	1633	106
Predicted Background	23	00

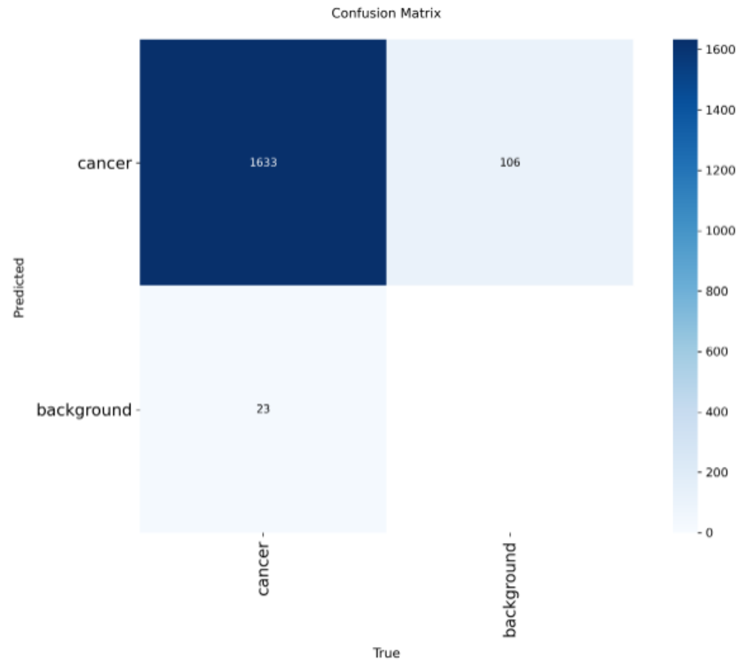

Figure 6: Confusion Matrix

F-1 Confidence Curve:

The **F1-Confidence Curve** (or **F1-Threshold Curve**) is a useful visualization tool that displays how the **F1-score** of a classification model change as the **prediction confidence threshold** varies. This helps in selecting the optimal threshold for balancing precision and recall.

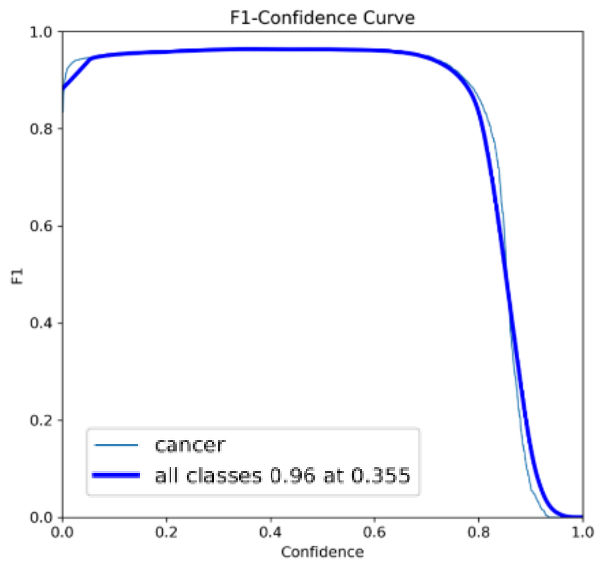

Figure 7: F1-Confidence Curve

Precision-Recall Curve:

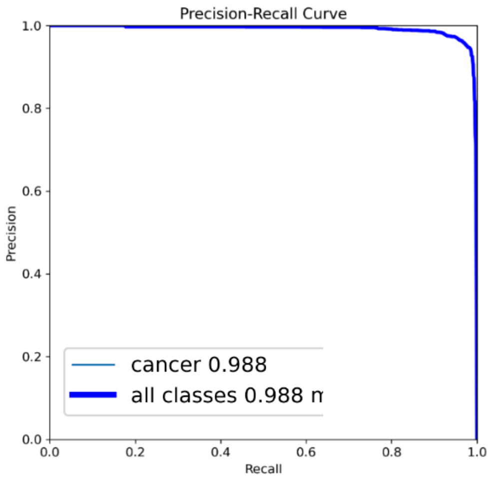

Figure 8: Precision-Recall Curve

The **Precision-Recall (PR) Curve** is an acute evaluation tool for classification models, specifically for imbalanced datasets where the ROC curve can be misleading. It sketches a graph of precision (y-axis) against recall (x-axis) at different classification thresholds, enlightening the trade-off between precision and recall.

Training Results:

The results in the graphs show the model is successfully trained, illustrating strong performance in classification and localization on new, unseen data.

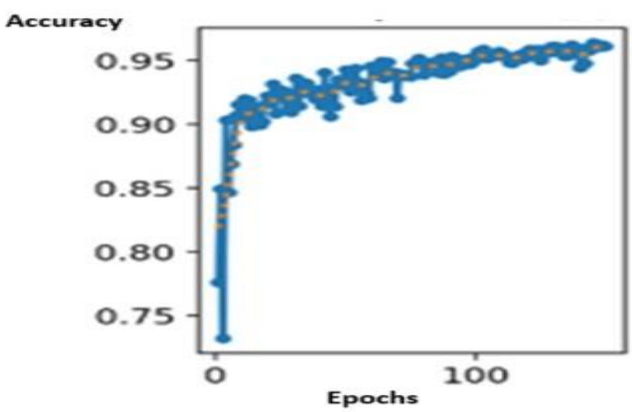

Figure 9: Accuracy

Performance of different deep learning models on different datasets

Year	Authors	Model	Dataset	Precision	Recall	F-1 Score	Training Accuracy	Validation Accuracy	AUC
2025	Gamze Korkmaz Erdem [25]	DenseNet169	WSI-based classification	92.19	91.16	90.59	91.16		
2024	Hossam Magdy Balaha	CNN	ISUP Grade-wise Prostate Cancer	88.58	89.22	88.87	88.91		97.27
2025	Noëlie Debs et al.	3D nnU-Net	Prostatex	55Avg.					83
2022	Mehmet Emin Salman et al.	Yolo general-purpose							89

2025	Young Joon Lee et al.			57.7	80.2	67		50.5	
2023	Provenzano et al.[26]	ResNet (ML)	Prostatex-2						82-98
2022	Salman et al. [27]	Yolo	Prostate cancer					89	
Our Model		**YOLOv11**	**Prostate cancer**	**98.61**	**93.91**	**96.19**	**98.8%**	**92.65**	**96-98**

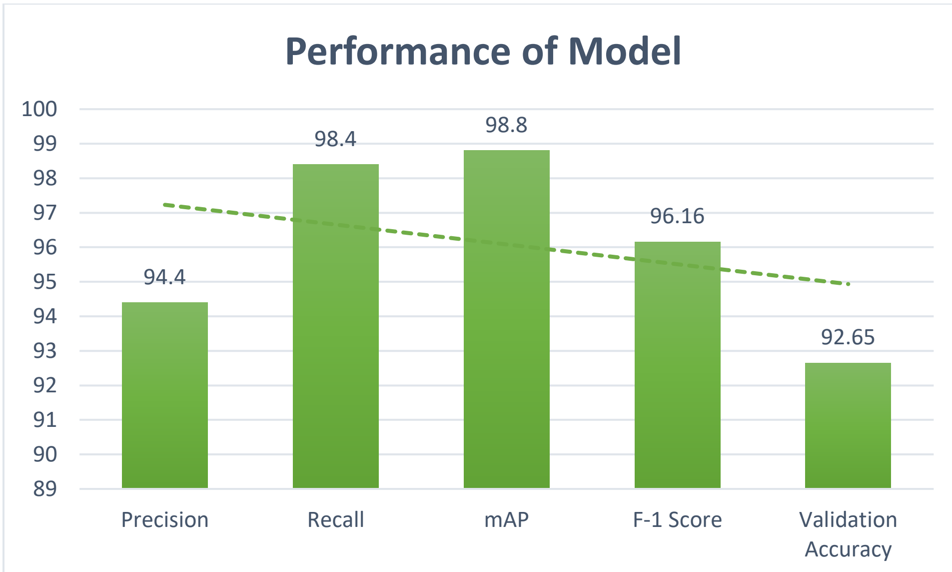

Figure 10:Performacne of Proposed Model

Conclusion:

Prostate cancer is a dangerous disease in humans because it remains silent at its earlier stages without showing any symptoms. So it's significant to take instant attention to control and cure it at the initial stage. The traditional and non-traditional methods have proven useful, but have some side effects. Use of AI with these methods/techniques, such as Resnet, Unet, CNNs, RNNs, is significantly increasing because they have a remarkable impact on the diagnosis of prostate cancer, having no side effects. Among all the Deep learning models, the YOLOv11 model is best because of its real-time application and high speed. Our proposed model gives an end-to-end deep learning solution. It speedily gets images, processes them through the detection unit, and provides highly accurate results at the earliest stage, enabling better treatment plans. The performance of the proposed model is very good for all the classes, having an accuracy of 92.65, a Precision of 98.61, a Recall of 93.91, and an F-1 score of 96.19. The system is very efficient because it can detect prostate cancer at the earliest stage with the highest accuracy.

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