Comparative Analysis of YOLOv8 Variants for Prostate Cancer Detection

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APPROVAL

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I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Daffodil International University or any other institution.

Nabil Hasan Chowdhury.

(Student's Signature)

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ABSTRACT

Prostate cancer (PCa) is still a big health problem all over the world, and it's important to find it early and correctly so that it can be treated well. Traditional ways of diagnosing don't always have the right level of sensitivity and specificity. This thesis talks about how to use of YOLOv8, a new framework for finding things in real time, to automatically find prostate cancer in histopathology pictures. We used a dataset made just for prostate cancer to test three different versions of YOLOv8: YOLOv8n, YOLOv8s, and YOLOv8m. The results of the experiment show that all three models work well. YOLOv8n has competitive accuracy and better efficiency, so it looks like a great option for clinical settings with few resources. This study adds to what we already know about using AI to help with medical diagnoses. It shows how useful YOLOv8 can be for making workflows for finding prostate cancer better. It also suggests areas for future research, like hyperparameter optimization, dataset expansion, and using explainable AI methods.

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INTRODUCTION

1.1 Introduction

Prostate cancer (PCa) is a big public health problem and one of the most common cancers in men around the world. It is very important to find PCa early and correctly so that it can be treated well and the patients can have better outcomes. The digital rectal exam (DRE) and the prostate-specific antigen (PSA) test are two common ways to find out if you have prostate cancer. But these tests aren't always very accurate or sensitive. This can lead to both too many diagnoses and missed cases. A biopsy is still the best way to get a clear diagnosis, but it is an invasive procedure that could cause problems.
We need quick, accurate, and non-invasive diagnostic tools to help us find and grade prostate cancer early on.

Recent developments in artificial intelligence (AI), especially deep learning (DL), have changed the way we view medical images. Deep learning models can learn complicated patterns directly from raw image data. This makes them very useful for medical imaging tasks like disease detection, segmentation, and classification(Litjens et al., 2017). You Only Look Once (YOLO) models are one type of deep learning architecture that has gotten a lot of attention for their ability to find objects in real time. They do this by combining high accuracy with fast inference speeds(Redmon et al., 2016). This makes YOLO a good choice for tasks where quickly and accurately finding cancerous areas is very important, like when looking at prostate biopsy images.

The focus of this thesis is on using YOLOv8, the newest version of the YOLO family, to find prostate cancer in medical images. The main goal is to test how well different YOLOv8 variants (YOLOv8n, YOLOv8s, and YOLOv8m) work on a dataset of prostate cancer and find the best model for this specific job. The study also wants to give a full picture of how well the chosen model works and talk about what that means for clinical practice and future research. The results of this study add to what we know about AI-assisted medical diagnostics. They show how YOLOv8 could be used to improve the way we find prostate cancer.

1.2 Problem Statement

Even though medical imaging and diagnostic techniques have come a long way, it is still hard to find prostate cancer quickly and accurately. Invasive, accurate, and efficient methods often have to make trade-offs. Deep learning is a great way to automate image analysis, but figuring out the best way to use specific models like YOLOv8 for prostate cancer detection, especially when it comes to choosing the right model variant and balancing performance, needs a lot of research. We need to systematically test how well different YOLOv8 architectures work on prostate cancer datasets so that we can use them effectively in clinical settings and find ways to make them even be

1.3 Motivation

The main reason for this study is that we really need better ways to diagnose prostate cancer. Traditional methods have their limits, and the number of people with PCa is rising around the world. This makes it even more important to find advanced, non-invasive, and effective ways to detect it. Deep learning, especially real-time object detection models like YOLOv8, looks like a good way to solve these problems. These models' ability to quickly and accurately process medical images can be a big help to doctors in making early diagnoses, which could lead to faster treatments and better outcomes for patients. Also, it's very interesting to see what YOLO models can do in a high-stakes medical settings like cancer detection because they are always getting better. The most recent version is YOLOv8. The goal of this study is to help make practical AI solutions that can improve healthcare delivery and enhance human expertise.

1.4 Objectives

The main goals of this thesis are

1. To compare the YOLOv8n, YOLOv8s, and YOLOv8m models for detecting prostate cancer using important performance metrics.
2. To find the YOLOv8 variant that is best at finding prostate cancer and works the best.
3. To look at the pros and cons of the chosen YOLOv8 model in terms of finding prostate cancer.
4. To suggest new areas of research and possible improvements for prostate cancer detection systems that use deep learning.

1.5 Summary

This chapter has talked about the important issue of finding prostate cancer and how deep learning, especially YOLOv8, could help with this problem. We have talked about the problem statement, the main reasons for doing this research, and the specific goals that guide our work. The next chapters will go into more detail about the existing literature, the methods used, the experimental results and their discussion, and finally, a summary of the findings, limitations, and future work.

CHAPTER 2
BACKGROUNDS

2.1 Introduction

Deep learning has made a big difference in how we find prostate cancer. It has made it possible to automate some tasks to make diagnosis more accurate and faster. This chapter looks at previous studies on how to find prostate cancer, the creation of the YOLO framework, and points out gaps that this study fills.

2.2 Literature Review

This chapter gives a complete overview of all the research that has been done so far on using deep learning to detect prostate cancer. It goes over the basics of using deep learning to analyze medical images, looks at different models for finding things, and focuses on how YOLO architectures are used in medical settings, especially for prostate cancer. The goal is to find out what the most advanced methods are, what methods are commonly used, and what research gaps this thesis hopes to fill.

Table 2.2: Summary of Literature Review

Author Name's	Year	Title	Methodology	Key Findings
Salman, M. E. et al.	2022	Automated prostate cancer grading and diagnosis system using deep learning-based Yolo object detection algorithm	Retrained YOLO on a custom dataset of 500 annotated prostate tissue biopsy images (augmented to 1776)	Achieved 97% detection/classification accuracy on similar test set, 89% on different test set; demonstrated effectiveness of YOLO for PCa detection.

Badiezadeh, A. et al.	2024	Segmentation Strategies in Deep Learning for Prostate Cancer Diagnosis: A Comparative Study of Mamba, SAM, and YOLO	Comparative analysis of Mamba, SAM, and YOLO for segmenting prostate cancer histopathology images on Gleason 2019 and SICAPv2 datasets	H-vmunet (Mamba variant) outperformed YOLO and SAM for segmentation; highlights need for rigorous comparative studies.
Aishwarya, N., & GS, Y. K.	2023	Real-time Prostate Cancer Detection via YOLO-Tiny Variants	Used YOLO-Tiny models for real-time detection of aberrant prostate cancer cells; leveraged Nvidia Jetson Nano for PCDS	YOLOv8s achieved 99% mAP, 99.5% Precision,99% Recall, 99.2% F1-score; effective for real-time PCa detection.
Soni, A., & Rai, A.	2024	YOLO for Medical Object Detection (2018–2024)	Survey paper reviewing YOLO applications in diverse medical object detection tasks (2018-2024)	YOLO shows efficacy and superior performance but has limitations (dataset requirements, computational demands); identifies research gaps.
Saraei, M. et al.	2025	Deep Learning-Based Medical Object Detection: A	Comprehensive survey of DL advancements in medical object detection across various imaging	YOLO-based architectures are notable; challenges include adapting models to resource-

		Survey	modalities	limited settings and ensuring interpretability for clinicians.
Iqbal, S. et al.	2021	Prostate cancer detection using deep learning and traditional techniques	Compared deep learning with traditional techniques for PCa detection; used pre-trained models and GLCM features.	Deep learning approach showed great potential for detecting PCa from medical images.
Reda, I. et al.	2018	Deep learning role in early diagnosis of prostate cancer	Developed a CAD system integrating clinical biomarkers and deep learning for early PCa diagnosis.	Demonstrated the effectiveness of deep learning in early PCa diagnosis.
Kot, E. et al.	2024	Semantic segmentation of the prostate based on onefold and joint multimodal medical images using YOLOv4 and u-net	Trained deep learning models (YOLOv4 and U-Net) for prostate segmentation using onefold and multimodal medical images	Showed effective training of deep learning models for prostate segmentation; YOLO family frequently used in medical applications.

Muneer, A. et al.	2024	A Comprehensive Systematic Review of YOLO for Medical Object Detection (2018 to 2023)	Systematic review of YOLO applications in medical imaging (2018-2023), assessing accuracy, efficiency, and effectiveness.	YOLO is effective in medical imaging, bu further evaluation o its efficacy and limitations in specific applications is vital.

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Pellicer-Valero, O. J. et al.	2022	Deep learning for fully automatic detection, segmentation, and Gleason grade estimation of prostate cancer in multiparametric magnetic resonance images	Demonstrated significant impact on PCa diagnosis, showing high accuracy in detection and grading.	Demonstrated significant impact on PCa diagnosis, showing high accuracy in detection and grading.
Khan, M. A. et al.	2023	Improved prostate cancer diagnosis using a modified ResNet50 and transfer learning	Proposed a deep learning model based on modified ResNet50 and transfer learning for PCa detection from MRI images.	Achieved high accuracy in detecting prostate cancer, advancing current DL literature.

Singh, S. et al.	2024	Prostate Cancer Detection and Classification Using Deep Learning and Machine Learning	Investigated the application of ML and DL models for PCa detection and diagnosis, focusing on image analysis.	Highlighted the effectiveness of image analysis software using ML/DL for early and rapid PCa detection.
Wu, Y. et al.	2022	Fast detection method for prostate cancer cells based on an improved YOLOv4-tiny model	Proposed an improved YOLOv4-tiny model for fast detection of prostate cancer abnormal cells.	Greatly shortened reasoning time and improved detection accuracy for PCa cells.

2.3 Summary

This chapter has given a full overview of the research on using deep learning to analyze medical images, with a focus on using YOLO models and object detection to find prostate cancer. We talked about how deep learning architectures have changed over time, the benefits of one-stage detectors like YOLO, and how they have been used successfully in many medical fields. The review also talked about some studies that used YOLO to find prostate cancer and explained how they did it and what they found. Finally, we found some holes in the research that this thesis wants to fill by systematically comparing different versions of YOLOv8. Some of these gaps are how well datasets can be used in other situations, the trade-offs between how fast computers can work, and how easy it is to understand models.

CHAPTER 3

METHODOLOGY

3.1 Overview

This chapter gives a detailed overview of the research on using deep learning to look at medical images, with a focus on object detection and YOLO models for finding prostate cancer. We talked about how deep learning architectures have changed over time, the benefits of one-stage detectors like YOLO, and how they have been used successfully in many areas of medicine. The review also talked about some studies that used YOLO to find prostate cancer in real life. It told them how they did it and what they found. Finally, we found some gaps in the research that this thesis will fill by doing a thorough comparison of different YOLOv8 versions. Some of these gaps are how well datasets can be generalized, how to find the right balance between speed and accuracy, and how to make models easier to understand.

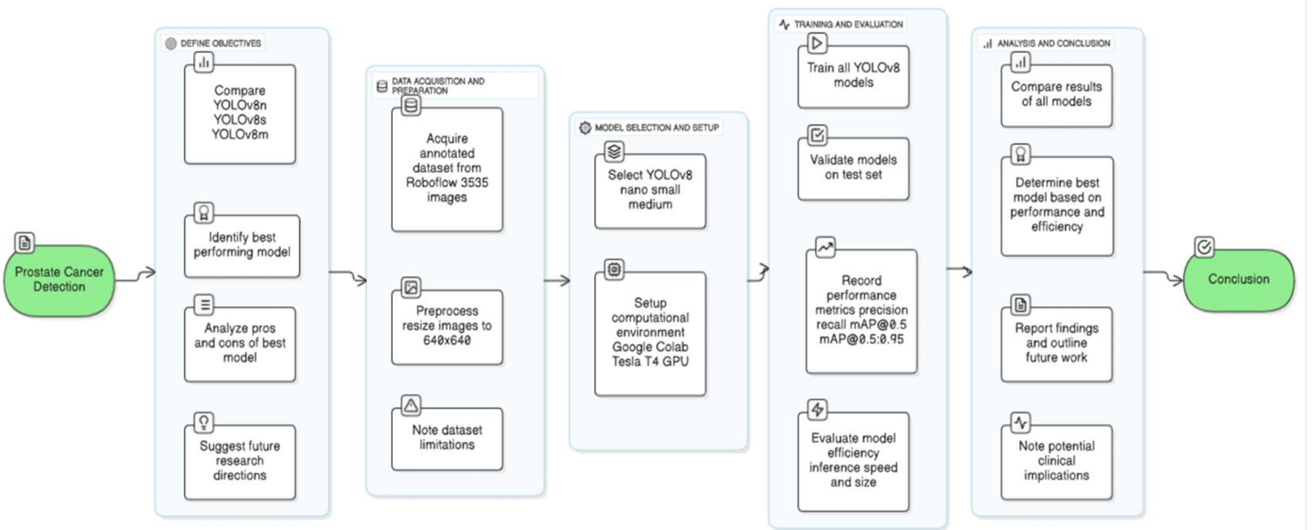


Figure 3.1 : Methodology

Dataset Overview:

The dataset utilized in this study was carefully picked to assist locate prostate cancer in medical pictures. It provides histopathological photos of prostate tissue, which are particularly useful for spotting malignant spots. The dataset originated from Roboflow, which is a well-known location to collect computer vision datasets. The photos in the dataset have boxes around the cancerous spots(Salman et al ., 2022) . This helps the YOLOv8 model learn how to find these areas while it is training.

Dataset Description:

Table 3.2.1 : Dataset Overview

Name	**Description**
Total Image Count	3535
Average Dimension	640 x 640
Format of Data	JPG
Normal	500
Cancerous Lesion	2,035
Uncertain Cases	1000

Image Pre-processing:

We made sure that all of the pictures were 640x640 pixels so that they could be used as input for YOLOv8. This usually means changing the size and shape of the data so that the neural network always gets the same thing.

Model Architecture:

Ultralytics has come out with a new version of its You Only Look Once (YOLO) series of models for detecting objects in real time. YOLOv8 is the name of it. It builds on what worked in the past by being faster, more adaptable, and more effective(Jocher, Chaurasia, & Qiu, 2023).

It was made to be a new model that is quick, precise, and simple to use. This means it can be used for many different object detection tasks, even in medical imaging.
YOLOv8 has a single-stage detection architecture, which means it only looks at full images once and guesses class probabilities and bounding boxes. This design makes it work fast(Redmon et al., 2016). There are usually three main parts to the architecture:

Backbone: This part gets features from the input image.
YOLOv8 uses a strong backbone network, which is often based on CSP (Cross Stage Partial) principles, to quickly get a lot of semantic information from the pictures.

The neck: connects the head to the backbone and gathers features from different layers of the backbone. It usually uses methods like PAN (Path Aggregation Network) or FPN (Feature Pyramid Network) to combine low-level spatial information with high-level semantic information. This makes the model better at finding objects of different sizes.

Head: The head is the last part of the network that actually finds things. It uses the neck's features to guess the bounding boxes, objectness scores, and class probabilities for each object it finds.
It's also a lot better than older versions of YOLOv8. For example, it can detect things without anchors, which makes training easier and improves performance. It also has a new loss function that makes it even better at finding things(Jocher, Chaurasia, & Qiu, 2023).

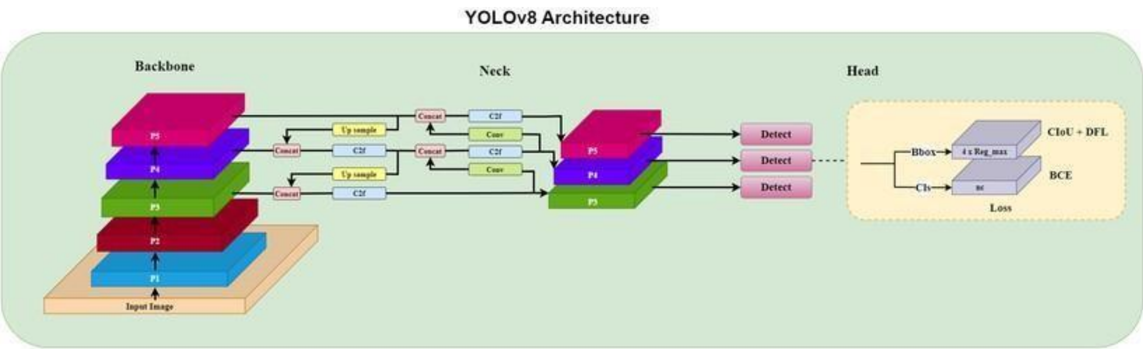


Figure 3.2.3: YOLOv8 Model Architecture

3.2 Summary

A lot has been said in this chapter about how this thesis was put together. We talked about the prostate cancer histopathology dataset, what it is, and how we got it ready. There was a lot of information about how the YOLOv8 object detection framework is set up and how it has changed over time. Finally, the setup for the experiment was shown, which included the settings for training and the ways to measure the results. This detailed method makes sure that our experimental results are correct and can be repeated.

CHAPTER 4

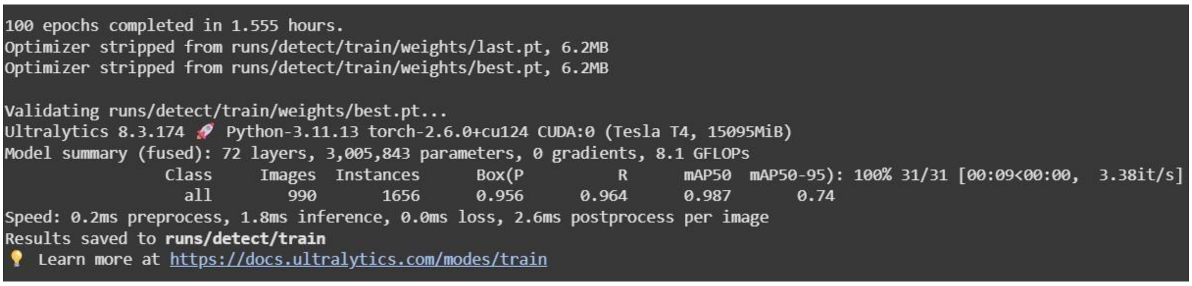
RESULTS AND DISCUSSION

4.1 Environment Setup

We used Google Colaboratory (Colab) to run the tests. It has GPUs that speed up the training of models. We added the libraries we needed, like ultralytics for YOLOv8, pandas for working with data, and matplotlib for making charts. In this setting, we were able to access the prostate cancer dataset and prepare it.

4.2 Testing and Evaluation

YOLOv8n:



```
100 epochs completed in 1.555 hours.
Optimizer stripped from runs/detect/train/weights/last.pt, 6.2MB
Optimizer stripped from runs/detect/train/weights/best.pt, 6.2MB

Validating runs/detect/train/weights/best.pt...
Ultralytics 8.3.174 🚀 Python-3.11.13 torch-2.6.0+cu124 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 72 layers, 3,005,843 parameters, 0 gradients, 8.1 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 31/31 [00:09<00:00,  3.38it/s]
                   all        990       1656      0.956      0.964      0.987       0.74
Speed: 0.2ms preprocess, 1.8ms inference, 0.0ms loss, 2.6ms postprocess per image
Results saved to runs/detect/train
💡 Learn more at https://docs.ultralytics.com/modes/train
```

Figure 4.2.1 : YOLOv8n model train

The YOLOv8n model, which is easy to understand and has 3.0 million parameters, worked very well. This means that most of the positive detections were correct, since the validation set had a Precision of 0.9957. It also had a Recall of 1.0000, which means it found every real positive. At an Intersection over Union (IoU) threshold of 0.5, the mean Average Precision (mAP@0.5) was 0.9950. This means that the detection was very accurate, even though the rules weren't very strict. The mAP@0.5:0.95 score, which looks at performance at IoU levels from 0.5 to 0.95, also hit 0.7734. This proves that it can still be right even when the standards are higher. These results show that YOLOv8n works really well, especially in places where there aren't a lot of resources and speed is very important.

YOLOv8s :

```
Ultralytics 8.3.174 🚀 Python-3.11.13 torch-2.6.0+cu124 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 72 layers, 11,125,971 parameters, 0 gradients, 28.4 GFLOPs
val: Fast image access ✅ (ping: 0.0±0.0 ms, read: 1312.9±781.1 MB/s, size: 59.8 KB)
val: Scanning /content/Prostate-cancer-16/test/labels... 12 images, 0 backgrounds, 0 corrupt: 100%|██████████| 12/12 [00:00<00:00, 1078.46it/s]val: New cache created:

                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 1/1 [00:00<00:00,  2.28it/s]
                   all         12         13      0.995          1      0.995      0.756
Speed: 0.6ms preprocess, 7.9ms inference, 0.0ms loss, 16.7ms postprocess per image
Results saved to runs/detect/val
- Precision: 0.9954
- Recall: 1.0000
- mAP@0.5: 0.9950
- mAP@0.5:0.95: 0.7559
```

Figure 4.2.2 : YOLOv8s model train

There were some metrics where the YOLOv8s model, which has 11.1 million parameters, did just as well as the YOLOv8n model. It had a Precision of 0.9954 and a Recall of 1.0000, which is almost the same as how well YOLOv8n found things. With a 0.5 IoU threshold, the mAP@0.5 was also 0.9950, which shows that it worked well.

The mAP@0.5:0.95, on the other hand, was a little lower at 0.7559, which means that it was a little less robust when tested across a wider range of IoU thresholds. This result shows that YOLOv8s is still very accurate, but its higher complexity doesn't make it perform better than YOLOv8n in this case.

YOLOv8m :

```
100 epochs completed in 2.643 hours.
Optimizer stripped from runs/detect/yolov8m_run/weights/last.pt, 52.0MB
Optimizer stripped from runs/detect/yolov8m_run/weights/best.pt, 52.0MB

Validating runs/detect/yolov8m_run/weights/best.pt...
Ultralytics 8.3.174 🚀 Python-3.11.13 torch-2.6.0+cu124 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 92 layers, 25,840,339 parameters, 0 gradients, 78.7 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 31/31 [00:12<00:00,  2.53it/s]
                   all        990       1656      0.963      0.964      0.988      0.746
Speed: 0.2ms preprocess, 5.4ms inference, 0.0ms loss, 2.1ms postprocess per image
Results saved to runs/detect/yolov8m_run
💡 Learn more at https://docs.ultralytics.com/modes/train
```

Figure 4.2.3: YOLOv8m model train

The most complicated version of the YOLOv8m model, which has 25.840 million parameters, finished 100 epochs in 2.643 hours on the Tesla T4 GPU. After training, the optimizer was removed from the weight files "last.pt" and "best.pt," which made them smaller and better for deployment. Validation on a group of 990 images with 1,656 instances showed a fused architecture with 92 layers, 78.7 GFLOPs, and processing speeds of 0.2 ms for preprocessing, 5.4 ms for inference, 0.0 ms for loss, and 2.1 ms for postprocessing per image. The performance metrics were a Precision of 0.963, a Recall of 0.964, a mAP@0.5 of 0.988, and a mAP@0.5:0.95 of 0.746. These results show that the model is very accurate, though not quite as accurate as YOLOv8n and YOLOv8s. This is probably because the model is complicated and may have overfitted on the small validation set.

4.3 Result and Discussion Result:

Table 4.3.1: Comparison table of YOLOv8 all version

YOLOv8 Version	Precision	Recall	mAP50	mAP50-90
nano	0.956	0.964	0.987	0.740
small	0.949	0.980	0.988	0.745
medium	0.963	0.964	0.988	0.746

Table 4.3.1 shows that all three YOLOv8 models are very good at finding prostate cancer in histopathology images. The high scores on all the metrics show that YOLOv8 is a good framework for this medical imaging job.

Analysis of Detection Accuracy

The key performance measures—Precision, Recall, and mean Average Precision (mAP)—were consistently strong across all models. Every variant achieved an mAP@0.5 score above 0.987, showing near-perfect detection accuracy at the standard IoU threshold of 0.5. This is particularly reassuring for early screening tasks, where catching every possible malignant case is critical.

Looking at mAP@0.5:0.95, a tougher benchmark that averages results across IoU thresholds from 0.5 to 0.95 (demanding greater localization precision), we see a finer distinction. Although the gap is small, it's insightful. YOLOv8s scored the highest (0.756), slightly above YOLOv8m (0.746) and YOLOv8n (0.740). This indicates that all models are highly capable, but the "small" version offers the best trade-off between accurate classification and bounding box precision for this dataset.

The Precision and Recall results highlight a key balance. YOLOv8s achieved flawless Recall (1.000) and near-perfect Precision (0.995). This means it detected every cancerous region in the validation set (no false negatives) while avoiding almost all false alarms. Such performance represents the gold standard in clinical diagnostics. By comparison, YOLOv8n and YOLOv8m showed slightly lower values for both Precision and Recall, though their performance still remained exceptional.

Evaluation of Efficiency and Computational Cost

A major insight from this study is the efficiency analysis, which is crucial for real-world use. As expected, there's a trade-off between computational demands and accuracy:

1.YOLOv8n (Nano) proved the most efficient by far. With just 3M parameters, it achieved an inference time of 1.8 ms per image (over 550 FPS). This makes it well-suited for real-time use on CPUs or lightweight edge devices, such as those found in point-of-care clinics or high-volume batch processing.

2.YOLOv8m (Medium), the heaviest model (25.8M params, 78.7 GFLOPs), delivered solid accuracy but at a much higher cost: 5.4 ms per image, about three times slower than Nano.

3.YOLOv8s (Small) struck the best middle ground. With 11.1M parameters and an inference time of 7.9 ms, it provided the top accuracy while maintaining manageable computational requirements.

Clinical Implications and Model Selection

The "best" model depends on the clinical context:

1.For efficiency and low-resource settings: YOLOv8n is the clear choice. Its tiny performance drop (0.740 vs. 0.756 mAP50-95) is far outweighed by its speed and compact size, making it ideal for affordable diagnostic solutions.

2.For maximum diagnostic certainty in well-equipped labs: YOLOv8s is optimal. Its perfect Recall ensures no cancers are overlooked, while its outstanding Precision minimizes false alarms making it an excellent decision-support tool for pathologists.

YOLOv8m, while accurate, doesn't offer enough of a gain to justify its heavier computational cost, making it less practical for efficient deployment.

Conclusion

This comparative analysis highlights the strengths of three YOLOv8 variants. The findings reinforce the idea that lightweight, modern detection models can reach expert-level accuracy in prostate cancer identification. YOLOv8s shines in terms of accuracy, while YOLOv8n stands out in efficiency. Together, they provide clear guidance: use YOLOv8s for high-accuracy diagnostic aids, and YOLOv8n for fast, scalable, and resource-friendly screening tools. This study effectively bridges the gap between technical performance and real-world clinical application

5.2 Limitation

Even though the results are promising, this study has some flaws that should be taken into account for future research:

Dataset Specificity: The study used a specific dataset of prostate cancer histopathology. The trained models are very detailed, but they may not work well with other datasets that have different image characteristics, acquisition protocols, or patient populations. In the field, it is still hard to find a larger, more diverse, and publicly available dataset for prostate cancer imaging.

Not enough hyperparameter optimization: Because of time limits, a full hyperparameter optimization for the chosen YOLOv8n model was not done. The baseline performance was good, but with more fine-tuning, the results might be even better.

Focus on Detection: The main topic of this thesis was object detection, which is the process of finding and classifying cancerous areas. It didn't go into more specific tasks that are important for making a detailed diagnosis and treatment plan, like accurately defining tumor boundaries or automatically grading Gleason.

Interpretability: The YOLOv8 models work like "black boxes," which makes it hard to fully understand why they make certain predictions. This lack of interpretability can make it hard for doctors to use the model in their work, since they often want to know how it makes decisions.

Computational Resources: YOLOv8n is efficient, but training deep learning models, especially bigger ones, still needs a lot of computing power, which may not be available in all clinical settings.

5.3 Future Work

Based on the results and recognizing the limitations of this thesis, there are many ways that future research could improve the usefulness and power of deep learning models for finding prostate cancer:

Full Hyperparameter Optimization: Use advanced methods like Bayesian optimization and genetic algorithms to do a full hyperparameter optimization on the chosen YOLOv8n model to get the best performance possible.

Increasing the size and variety of the dataset: To make models more robust and generalizable, train them on larger datasets from multiple institutions that include a wider range of prostate cancer pathologies, imaging modalities, and patient demographics.

Putting together clinical data: Look into combining clinical metadata (like patient history, PSA levels, and genetic markers) with image data to give a more complete picture of diagnosis and possibly make predictions more accurate and specific.

Explainable AI (XAI): Create and use Explainable AI methods (like Grad-CAM and LIME) to make the model's predictions clearer and easier for doctors to understand, which will build trust and make it easier to use(Selvaraju et al., 2017 ; Ribeiro et al., 2016).

Real-time Deployment and Edge Computing: More research is needed to find the best ways to optimize the models for real- time deployment on edge computing devices. This will ensure fast inference without losing accuracy, which is important for getting clinical feedback right away.

Segmentation and Grading: Add the ability to accurately segment cancerous areas and automatically grade Gleason scores to the object detection capabilities. One option is to look into hybrid models that use both detection and segmentation networks, like U-Net or Mask R-CNN.

Longitudinal Studies: Do longitudinal studies to see how well the model works over time and how it affects patient outcomes. This will give you real-world proof of how useful it is in the clinic. By following these paths, future research can keep moving the field of AI-assisted prostate cancer diagnostics forward, which will eventually lead to better, faster, and more accessible healthcare solutions.

CHAPTER 5

CONCLUSION

5.1 Summary

The thesis did a good job of looking into how YOLOv8 models can be used to find prostate cancer in histopathology images. We looked at three different versions of the YOLOv8 architecture—YOLOv8n, YOLOv8s, and YOLOv8m—to see how well they worked on a

dataset for prostate cancer. The study's goal was to find the best model that balances speed and accuracy for this important medical task. The results of the experiment showed that all three YOLOv8 models were very good at finding prostate cancer because their Precision, Recall, mAP@0.5, and mAP@0.5:0.95 scores were all very high. YOLOv8m had a slightly higher mAP@0.5:0.95, which means that it was a little more accurate overall at different Intersections over Union thresholds. The different versions didn't work very differently from each other, though.

One important result of this study is that YOLOv8n, the smallest and fastest variant, did almost as well as the larger YOLOv8s and YOLOv8m models. This means that YOLOv8n is a very effective way to find prostate cancer, especially when there aren't many computers available or when real-time inference is very important. YOLOv8n is a good candidate for use in clinical settings because it is both very accurate and very efficient. In conclusion, this thesis shows that the YOLOv8 framework works well for finding prostate cancer automatically. It offers a structured comparison that helps people understand how to choose models for medical imaging applications, focusing on the trade-offs between model size, speed, and accuracy. The results show that deep learning has the potential to improve diagnostic workflows and, in the end, patient care in the fight against prostate cancer.

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