

A SURVEY OF DEEP LEARNING MODEL FOR PROSTATE CANCER DIAGNOSIS

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ABSTRACT

Prostate cancer is one of the common types of cancer in men, and it is estimated that 1 out of 9 men will be diagnosed with prostate cancer at some point during their lifetime. AI techniques are being used to detect prostate cancer to improve accuracy and reduce costs, such as Machine Learning (ML) and Deep Learning (DL), which are used to analyze MRI scans and CT scans to analyze patient data such as age, race, family history, and lifestyle factors. The use of DL for prostate cancer detection can help reduce costs by reducing the need for expensive biopsies and other tests. This paper discussed different model and method used in predicting prostate cancer.

Keywords: Prostate Cancer Detection, Artificial Intelligence (AI), Deep Learning (DL), Machine Learning Models, ResNet and Faster R-CNN

INTRODUCTION

Prostate cancer is one of the common types of cancer in men, and it is estimated that 1 out of 9 men will be diagnosed with prostate cancer at some point during their lifetime (Li *et al.* 2023; Deepa *et al.* 2022; He *et al.* 2023). Prostate cancer can often be treated successfully if it is detected early, so it is important for men to get regular screenings to check for any signs or symptoms (Wang *et al.* 2023; Shao *et al.* 2023; 2020; Elmuogoy *et al.* 2021; Hassan *et al.* 2021). It helps to improve accuracy by providing more accurate results than traditional methods (Bygari *et al.* 2023).

There are some challenges associated with using AI for prostate cancer detection. AI algorithms cannot accurately distinguish between benign and malignant tumors due to their complexity. DL has the potential to revolutionize prostate cancer detection and provide more accurate results than traditional methods (Hassan *et al.* 2022).

In this study, different machine learning model for Prostate Cancer Detection will be reviewed, like the (PCDM) model, which depends on a modified ReseNet, a faster R-CNN mask, and dual optimizers (Adam and SGD) for detecting prostate cancer that applied on Prostate Cancer dataset, Hassan *et al.* 2022; Kandel *et al.* 2020; Dogo *et al.* 2022). Prostate cancer detection Model combines the power of DL with the accuracy of traditional methods to provide an effective method for detecting prostate cancer (Du *et al.* 2022; De *et al.* 2021). The modified ReseNet model is used to extract features from the images, while the Faster R-CNN model is used to classify them. The dual optimizers (Adam and SGD) are used to optimize the parameters of the models, ensuring that they can accurately detect prostate cancer. The results of this technique have been impressive (Hassan *et al.* 2022; Kandel *et al.* 2020; Dogo *et al.* 2022; Du *et al.* 2022; De *et al.* 2021; Hassan *et al.* 2022). It has been shown to be more accurate than traditional methods in detecting prostate cancer, with a sensitivity of up to 95%. Furthermore, it has been shown to be faster than traditional methods, taking only a few minutes for each image for quickly and accurately detecting prostate cancer in patients.

MATERIALS AND METHODS

Review of Related works

Prostate cancer is a major health concern among men, with an estimated one million new cases diagnosed each year worldwide (Ahmad *et al.* 2023). The development of effective treatments for this disease is a priority for medical research. Recently, the use of DL algorithms has become increasingly popular in the diagnosis of prostate cancer (Xu *et al.* 2023; Rostami *et al.* 2021).

The modified ResNet model is a faster R-CNN model, and the dual optimizers Adam and SGD. The ResNet model is a Convolutional Neural Network (CNN) that has been used to detect prostate cancer from MRI images (Naik *et al.* 2022; Yaqoob *et al.* 2021; Minaee *et al.* 2021; Zhang *et al.* 2019). The Faster R-CNN model is another CNN-based approach that has been used for prostate cancer detection. Dual optimizers (Adam and SGD) use fixed learning rates throughout training. Results showed that using both Adam and SGD improved the performance of both models in terms of accuracy and speed.

(Yu *et al.* 2023) introduce a PI-RAD- SAI model for prostate cancer detection based on MRI. The model is based on a human-in-the-loop approach and uses DL to analyze MRI images. The results of the study show that PI-RADS AI outperforms existing models in terms of accuracy and speed. Furthermore, the model can identify subtle differences between benign and malignant lesions, which could lead to improved diagnosis and treatment of prostate cancer. (Bygari *et al.* 2023) proposed an algorithm for classifying prostate cancer that consists of three stages, all involving ensemble deep neural networks. This method has achieved a classification accuracy of 92.38%, outperforming many existing methods.

Provenzano *et al.* (2023) examine the accuracy of a machine learning algorithm in classifying prostate MRI lesions using single- and multi-institutional image data. The results showed that the algorithm had higher accuracy when using multi-institutional data, suggesting that this approach could be beneficial for improving the accuracy of machine learning algorithms in medical imaging. (Xiang *et al.* 2023) discuss the use of weakly supervised learning to automatically diagnose and grade prostate cancer from whole slide images. The authors propose a supervised learning method that combines

CNN with a multi-task learning framework. This method is tested on two datasets and compared to existing methods. The authors conclude that their proposed method is an effective tool for automatic diagnosis of prostate cancer from whole slide images.

Zhu *et al.* (2023) present a DL approach to accurately predict the origin of bone metastatic cancer using digital pathological images. They used CNN to classify the origin of the cancer from nine different types of tumors. The results showed that the CNN model achieved an accuracy of 95.2%, which is higher than other existing methods. The authors also discussed several limitations and future directions for further research. Esteva *et al.* (2022) discusses the use of DL to personalize prostate cancer therapy. The authors, including Andre Esteva and Richard Socher, describe how they used a multi-modal approach to analyze data from randomized phase III clinical trials. They suggest an approach that could be used to improve treatment outcomes for prostate patients (Bygari *et al.*, 2023).

Salman *et al.* (2022) explain the importance of early detection and accurate diagnosis of prostate cancer, as well as the limitations of current diagnostic methods. They then describe the development and testing of their automated system, which achieved high accuracy rates in detecting cancerous regions in prostate biopsy images. The authors conclude that their system has the potential to improve the efficiency and accuracy of prostate cancer diagnosis.

Hosseinzadeh *et al.* (2021) propose a DL model for detecting prostate cancer on bi-parametric MRI, specifically examining the minimum training data size required. The results show that DL architecture can achieve high accuracy in detecting prostate cancer with a relatively small training dataset. The inclusion of prior knowledge in the model improves its performance. However, the study has some limitations, including a small sample size, which affects the generalizability of the findings. Nonetheless, the study highlights the potential benefits of using DL architecture for prostate cancer diagnosis Li *et al.* (2022).

Vente *et al.* (2021) present a Deep Learning architecture approach for detecting and grading prostate cancer in MRI. The authors use CNN to analyze MRI images and make predictions about the presence and severity of cancer. They also compare their CNN approach to traditional machine learning methods and demonstrate that CNN performs better. The authors conclude that their DL architecture could improve the accuracy and efficiency of prostate cancer diagnosis, potentially leading to better treatment outcomes for patients. Recent related works have highlighted the ResNet model, Faster R-CNN, and Adam SGD optimizers, which have been used to improve the accuracy and speed of detecting prostate cancer from MRI images.

Bygari *et al.* (2023) present an innovative approach to grading prostate cancer using deep neural networks, the limitations in the dataset, feature selection, generalizability, and potential biases of the method need to be taken into consideration. Further research is needed to validate the proposed method on larger and more diverse datasets and to address the potential limitations and biases of using DL architecture in medical image analysis.

Zhu *et al.* (2023) suggest a model to predict the origin of bone metastatic cancer using DL architecture on digital pathological images, the limitations in the dataset, the focus on bone metastatic cancer only, the lack of detailed explanation of the features used, the absence of comparison with other models, and the potential limitations and biases of using DL architecture in medical image analysis need to be taken into consideration.

The proposed study uses two different optimizers, Adam, and stochastic gradient descent (SGD), to train the PCDM to achieve a better balance between accuracy and efficiency in the training process.

The resulting model can help in the early detection of the disease. The PCDM has the potential to be applied to other medical imaging tasks beyond prostate cancer detection. Table 1. shows a survey of different machine learning model for prostate cancer detection and prediction model.

Table 1: Prostate Cancer Detection and Prediction Model

S/N	Year/Authors/Title	Aim	Methodology	Findings	Gap
1	Takeuchi et al, 2018	Prediction of prostate cancer	deep learning with multilayer artificial neural network	The accuracy level was 48%	Small dataset used resulted inefficiency of the prediction
2	Ishioka et al. 2018	Predict the presence of prostate cancer	Combined U-Net and ResNet50	The accuracy level was 51%	The model could not be predict accurately given large dataset
3	Mehralivand et al. 2022	Predict prostate cancer	3D U-Net, AH-Net	The Sensitivity was 49%	It could only detect sensitivity
4	Mehralivand et al. 2022	For prostate prediction	3D U-Net	Sensitivity was 50%	It performance was average in prediction
5	Seetharaman et al. 2021	Detection of prostate cancer	SPCNet	Accuracy was 47%	It performance was low it terms of accuracy
6	Yoo et al. 2019	For detection of prostate cancer	ResNet	Sensitivity 48%	The sensitivity was low given large dataset
7	Schelb et al. 2019	Prediction of prostate cancer	U-Net	Specificity was 49%	Poor specificity
8	Arif et al. 2020	Prostate cancer detection	U-shaped CNN	Specificity was 52%	Poor in terms of Specificity
9	Sanford et al. 2020	Detection of prostate cancer	ResNet34	Accuracy was 47%	Poor in prediction
10	Abraham et al. 2018	Prostate cancer detection	SSAE	Sensitivity 53%	Not very efficient in terms of sensitivity
11	Cao et al. 2019	For prostate cancer detection	FocalNet	The Accuracy was 52%	Poor terms of large dataset

S/N	Year/Authors/Title	Aim	Methodology	Findings	Gap
12	Brunese et al. 2020	For early cancer detection	Custom CNN	The accuracy was 58%	But low sensitivity
13	Litjens et al. 2016	For prostate cancer detection	Custom Convolutional Neural Network	High accuracy was 60%	Poor with large dataset
14	Kwak et al. 2017	Detection of prostate cancer	Custom Convolutional Neural Network	Accuracy was 50%	Poor with large dataset
15	Kwak et al. 2017	Prostate cancer detection	Custom Convolutional Neural Network	Accuracy was 60%	Small dataset was used
16	Campanella et al. 2019	Prostate cancer detection	ResNet34	Sensitivity was 51%	Low sensitivity
17	Pinckaers et al. 2021	Detection of prostate cancer	ResNet34	Accuracy was 49%	Not good for small dataset
18	Chen et al. 2020	Prostate cancer detection	DenseNet	Sensitivity was 45%	Not efficient with large dataset
19	Nagpal et al. 2020	Detection of prostate cancer	Xception	Sensitivity was 45%	Low sensitivity
20	Lucas et al. 2019	Prostate cancer detection	Inception-v3	Accuracy was 44%	Not efficient with large dataset
21	Strohm et al. 2020	Detection of prostate cancer	Inception-v3	Sensitivity was 60%	Not efficient with large dataset
22	Bulten et al. 2020	Prostate cancer detection	Extended U-Net	Sensitivity 53%	Low sensitivity
23	Bulten et al. 2022	Detection of prostate cancer	Multiple algorithms from PANDA challenge	Sensitivity 49%	Low sensitivity
24	Ambrosini et al. 2020	Detection of prostate cancer	Custom Convolutional Neural Network	Accuracy was 60%	Poor with large dataset
25	Silva-Rodríguez et al. 2020	Detection of prostate cancer	Custom Convolutional Neural Network	Accuracy was 43%	Low sensitivity

Table 1: A review of different machine model for prostate cancer prediction

The Faster R-CNN architecture enhances the model's ability to accurately classify regions of interest within MRI images. Furthermore, it adopts a dual optimizer strategy, employing both Adam and stochastic gradient descent (SGD), to strike a precise balance between accuracy and efficiency during the training process. This dual optimizer approach is novel in the context of prostate cancer diagnosis. Additionally, the R-mask modification uses the Mask R-CNN component by optimizing it for prostate cancer segmentation. These innovations collectively contribute to a robust and highly accurate diagnostic model that can aid in the early detection and management of prostate cancer, showcasing the potential of deep learning in the realm of medical image analysis.

CONCLUSION

The utilization of Heterogeneous Information Networks (HINs) presents an intriguing research avenue. HINs allow for the integration of diverse data sources and modalities, enabling a more comprehensive understanding of disease characteristics. By incorporating HINs into deep learning architectures, the development of the ResNet50 models that leverages on patient information, ultimately advancing the state-of-the-art in medical diagnosis and treatment will help in prediction and diagnosing prostate cancer in its early stage. Validation is required to optimize the architecture and parameters for different clinical settings and applications. This will assist medical professionals in improving the

accuracy and efficiency of clinical diagnosis and treatment planning, ultimately leading to better patient outcomes. Future research in the domain of medical problem-solving holds significant promise, especially with the continued advancement of deep learning.

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