Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 12, 2025

DEEP LEARNING-BASED PREDICTION OF PROSTATE CANCER USING IMAGE DATA GENERATOR CLASSES

Nida Shahid[1], Muhammad Farooq Ishaq[2], Altaf Khan[3], Muhammad Azam Hussain[*4], Muhammad Ahmed[5], Muhammad Sohaib Ali[6]

[1,2]*Department of Computer Science. University of South Asia Lahore, Pakistan*
[3]*Department of Software Engineering, University of Mianwali, Pakistan*
[*4]*Department of Computer Science & Information Technology, The University of Lahore, Pakistan*
[5]*Department of Computer Science, The Islamia University, Bahawalpur, Pakistan*
[6]*Department of Computer Science, NCBA&E Lahore, Pakistan*

[1]nida.shahid@usa.edu.pk, [2]muhammad.farooq613@gmail.com, [3]altaf.khan@umw.edu.pk, [*4]Muhammad.Azam@cs.uol.edu.pk, [5]aeo.markaz17hnd@gmail.com, [6]miansohaib2222@gmail.com

DOI: https://doi.org/10.5281/zenodo.18205407

Keywords
Deep learning, ResNet-50, Image Data generator, mpMRI, Prostate Cancer

Article History
Received: 03 November 2025
Accepted: 17 December 2025
Published: 31 December 2025

Corresponding Author: *
Muhammad Azam Hussain

Abstract
Prostate cancer is a common cancer among men, with the highest rate being recorded among men above 40 years of age. The correct diagnosis is a critical, time-consuming process that histopathologists have traditionally conducted through systematic investigation of biopsy samples. Although this is necessary for reliable detection, it is usually tedious and prone to interobserver error. The use of the latest medical imaging and computational technologies has significantly improved histopathologists' ability to detect and grade prostate cancer. Diagnosis of prostate cancer may be performed through several clinical and non-clinical imaging tests, e.g., multiparameter magnetic resonance imaging (mpMRI). Nevertheless, specific diagnostic methods continue to have high false-positive and false-negative rates, thereby limiting their accuracy. To overcome these issues, this paper uses an image data augmentation approach based on the Image Data Generator class to increase the diversity of the training data and enhance model generalization. Deep learning architectures, such as VGG-16, ResNet-50, and DenseNet121, are used to analyze prostate biopsy images and assess their performance in detecting cancer. The selection of these architectures is based on their demonstrated performance across a variety of benchmark datasets, and they are being applied to biopsy images to enhance the accuracy and resilience of their diagnostic results.

INTRODUCTION

Prostate cancer is a cancer that occurs in the prostate gland. It is part of the male reproductive system, which includes the penis, prostate gland, seminal vesicles, and testicles. Prostate size can change as a man ages, which can lead to prostate cancer. The prostate is a small, walnut-shaped gland in men that produces the seminal fluid that nourishes and transports sperm. Prostate cancer begins when prostate cells start to grow out of control [1]. It grows slowly, where it may not cause significant damage, but sometimes it grows slowly and may require minimal or no treatment; other types/stages are aggressive and can spread quickly [2].

After lung cancer, prostate cancer is the second leading cause of cancer death in American men [3]. This cancer is more severe in black men than in white men due to some genetic reasons.

Around 1 in 41 men die from prostate cancer. According to the American Cancer Society, Prostate cancer affects American Men. According to the survey of 2023 in the US [4], the total number of new cases of prostate cancer is 288,300. And the deaths are 34,700. Prostate cancer can be consequential in death. More than 3.1 million men in the United States are still alive today and have been diagnosed with prostate cancer at some point. In the table below, the states highlighted in Figure 1 have prostate cancer case counts greater than 10,000.

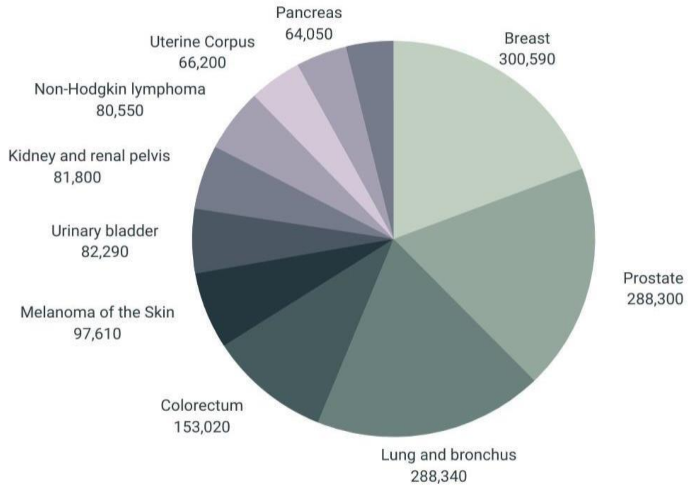


Figure 1: USA Statistics from the American Cancer Society of the year 2023, where the ratio of different cancers is shown [4]

DRE and PSA are mainly used to detect prostate cancer. DRE was first used for the diagnosis, and later PSA came with the changes to detect cancer, which is more accurate than DRE, but sometimes it produces false positive results [5]. Several other methods are used for detection, and their accuracy falls within 90-95, which is comparable to the manual selection of candidates. Other imaging-based technologies are used for detection, but they have limitations in distinguishing between cancerous and benign tissue; therefore, they cannot provide accurate results. The latest MP-MRI technology offers more precise results than other methods due to its excellent tissue contrast, but it does require some training.

TABLE 1: States highlighted where prostate cancer cases exceed 10,000 [4].

State	Estimated New Cases,2023	Estimated Death Cases,2023
California	26,970	4,090
Florida	24,000	2,650
Illinois	10,580	1270
New York	20,390	1,650
North Carolina	10,040	1,150

Ohio	10,980	1,310
Pennsylvania	13,210	1,440
Texas	17,320	2,290

To achieve the best results, various techniques have been implemented, including preprocessing, feature extraction, model development, and the use of confusion matrices and performance metrics [6]. In previous studies, MRI and biopsy images have been used for prostate cancer detection. Our model used the Image Generator classes to fetch images from the dataset and to create a unique pattern for assessing accuracy. Models such as VGG-16 and ResNet-50 achieve the best results with this technique.

2. RELATED WORK

Li et al. (2021) developed a deep learning-based model to identify prostate cancer on biopsy images [7]. They used a dataset of 13,848 biopsy images from 1,145 patients and achieved a sensitivity of 91.5% and a specificity of 93.2%. The authors concluded that their model has the potential to improve the accuracy of prostate cancer diagnosis and reduce the need for unnecessary biopsies. Wang et al. (2020) proposed a deep learning-based approach for detecting prostate cancer on biopsy images [8]. They used a dataset of 16,485 biopsy images from 1,309 patients and achieved an area under the receiver operating characteristic curve (AUC) of 0.93. The authors reported that their model outperformed several state-of-the-art methods for prostate cancer detection. Lee et al. (2020) developed a deep learning-based model for predicting the Gleason score, a key prognostic factor in prostate cancer, on biopsy images [9].

They used a dataset of 8,446 biopsy images from 1,135 patients and achieved a mean absolute error of 0.59 in predicting the Gleason score. The authors suggested that their model could help pathologists make more accurate and reproducible Gleason score assessments. Proposed a deep learning-based model for detecting prostate cancer on biopsy images that combines the features extracted from both the biopsy image and the corresponding clinical data [10]. They used a dataset of 1,086 biopsy images from 113 patients and achieved an AUC of 0.84. The authors reported that their model outperformed several other machine learning algorithms for prostate cancer detection. Doyle et al. (2018) conducted a study to evaluate the accuracy of a machine learning algorithm for identifying prostate cancer on biopsy images [11]. They used a dataset of 895 biopsy images from 105 patients, achieving 90.9% sensitivity and 79.2% specificity. The authors concluded that their algorithm has the potential to reduce the number of unnecessary biopsies and improve the accuracy of prostate cancer diagnosis.

CNNs are deep learning models that can automatically extract features from images and classify them into different categories [12]. In a study by Hu et al. (2020), a CNN was used to analyze biopsy images, achieving 98.6% accuracy in diagnosing prostate cancer. SVM is a machine learning model that separates data into different categories based on a hyperplane. In a study by Kim et al. (2018), SVM was used to classify prostate cancer in biopsy images with an accuracy of 91.6% [13]. The model also showed high sensitivity and specificity, indicating its potential for clinical use. Some other techniques are applied to different datasets to achieve accurate results: Abdi et al. (2021) developed an artificial intelligence-based model to analyze radiomic features from multiparametric MRI images for prostate cancer detection [14]. The model used a deep learning algorithm to classify prostate cancer. The study showed that the proposed model achieved high accuracy in detecting prostate cancer.

Wei et al. (2020) developed a deep learning model to analyze 3D multiparametric MRI images for prostate cancer detection [11]. The model used a convolutional neural network (CNN) algorithm to classify prostate cancer. The study showed that the proposed model achieved high accuracy in detecting prostate cancer.

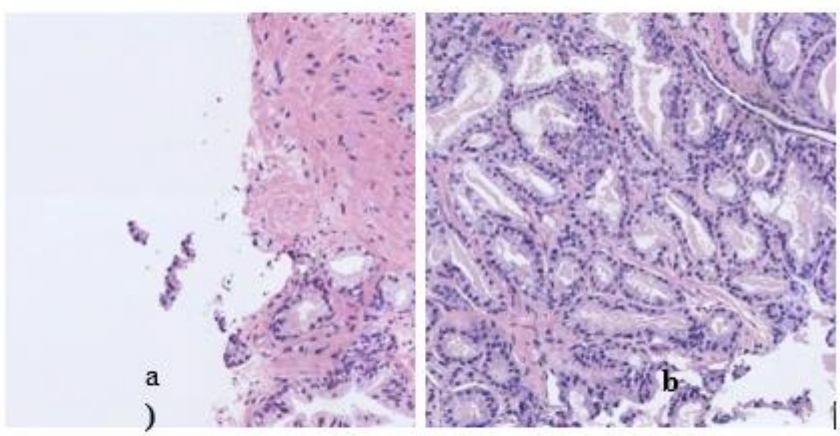
A convolutional neural network (CNN) model to automatically detect prostate cancer in multiparametric MRI images [15]. The model used a deep learning algorithm to classify prostate cancer. The study showed that the proposed model achieved high accuracy in detecting prostate cancer. A convolutional neural network (CNN) model that used multiparametric MRI and targeted biopsy to detect prostate cancer [16]. The model used a deep learning algorithm to classify prostate cancer. The study showed that the proposed model achieved high sensitivity and specificity in detecting prostate cancer.

Developed a convolutional neural network (CNN) model that used multi-institutional radiomics to detect prostate cancer [17]. The model used a deep learning algorithm to classify prostate cancer. The study showed that the proposed model achieved high accuracy in detecting. CNN models have been applied to various datasets using different techniques, and some results have outperformed state-of-the-art methods. In this paper, we've achieved the highest accuracy by implementing VGG-16, ResNet-50, and DenseNet-121 models using a data image generator.

3. METHODOLOGY

In this paper, we present deep learning methods for accurate detection and Gleason grading across different datasets (SICAPv2 and prostate-grade-assessment). In our methodology, we used the image data generator. Classes for the prediction of prostate cancer. It converts the dataset into patterns to train or test the images for the best possible results. This class generates new variations of the image at each epoch without altering the image's outcome.

Dataset: We have used two publicly available datasets, the Prostate Cancer Grade Assessment (PANDA) Challenge[1] and SICAPv2[2] To classify and predict prostate cancer. These datasets contain biopsy images. In both datasets, we have a total of 11,000-19,000 images. We used datasets for accuracy and others for Gleason grading detection. Dataset images are shown in Figures 2 and 3.



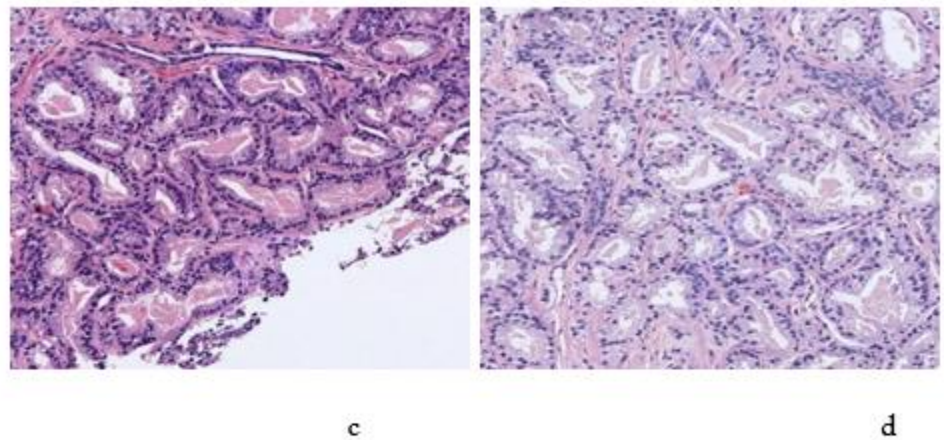


Figure 2: Biopsy images for prostate cancer dataset SICAPv2

Algorithmic Description: In this section, we applied various classifiers and Deep Learning Algorithms to diagnose prostate cancer across two datasets. In dataset 1, we used two classifiers: Support Vector Machines (SVM) and an XGB classifier. We also explained the reason in the introduction section, why we chose the deep learning methods. A comparison of models on the PANDA dataset indicates that the XGB classifier achieves higher accuracy than Support Vector Machines. For Dataset 2, we implemented several well-known Deep Learning models on the pretrained dataset, achieving excellent performance on VGG-16, ResNet-50, and Densenet-121.

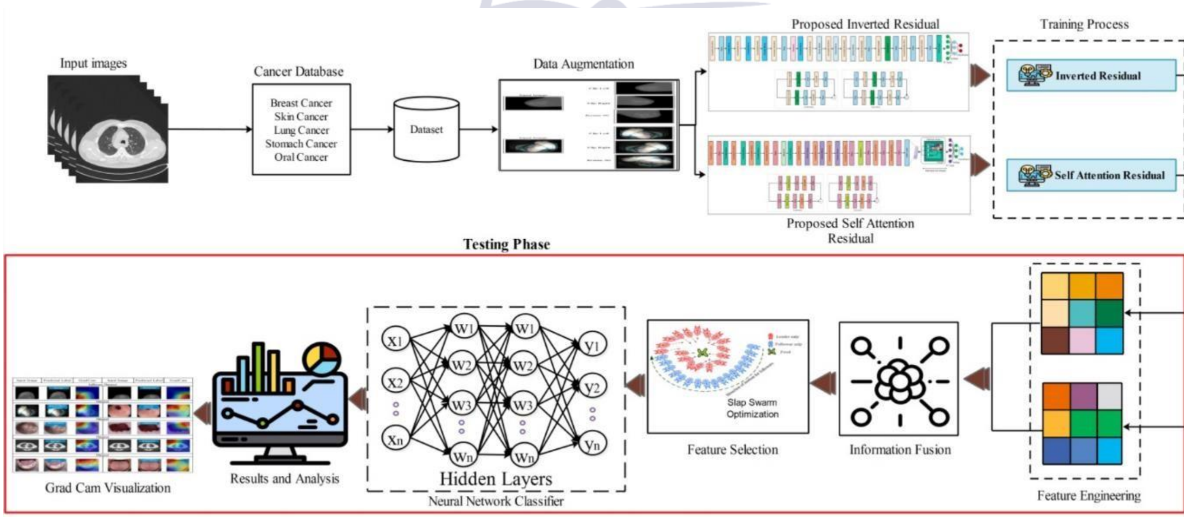


Figure 3: Proposed Architecture

During the training stage, medical images are initially collected and augmented using techniques such as rotation, flipping, and zooming to increase data diversity and reduce overfitting. These augmented images are then run through two deep learning models: an inverted residual network, which learns smaller-scale texture and structural patterns, and a self-attention residual network, which pays attention to the most significant parts of the image. These models are subsequently trained together to acquire complementary and discriminative cancer-related features.

During testing, the features learned by the trained models are merged to create a single feature representation. Feature selection is used to retain only the most informative features, which are then input into a neural network classifier to predict whether the image is benign or malignant. Lastly, Grad-CAM visualization shows the areas of an image that contributed to the prediction, which can be interpreted and used to inform clinical decision-making.

1. Support Vector Machine (SVM)

A successful supervised machine learning algorithm, the Support Vector Machine (SVM), constructs the best separating hyperplane by maximizing the margin between classes. Due to its success in processing high-dimensional feature spaces and with limited data sets, SVM is wellsuited to mediation image classification. In this paper, SVM is used to classify normal, benign and malignant prostate cell images. The SVM classifier uses handcrafted and deep features derived from prostate images as input. Precision and recall are the key measures used to assess classification performance because they control false positives and false negatives in medical diagnosis. The SVM model on the SICAPv2 data set achieved a precision of 0.94 and a recall of 1.00, demonstrating high discriminative ability and high sensitivity in cancer detection [18].

2) VGG-16

VGG-16 is a deep convolutional neural network with 16 weight layers, which uses small. 3×3 Deep convolutional filters 3x3 convolutional filters to hierarchical image representations [19]. It has a uniform architecture and depth that enable effective learning of the spatial and textural characteristics of histopathology images. VGG-16 has been used in this work to process the region of interest (ROI) of images of the prostate and further categorize them into cancerous and normal groups. They use the fine-tuning method on the pretrained VGG-16 model trained on the SICAPv2 dataset to enable effective feature use and reduced training time. As shown in the experimental results, VGG-16 achieves an accuracy of 91, indicating that the model is quite strong at identifying visual images of prostate cancer [20].

3) ResNet-50

ResNet-50 is a 50-layer deep convolutional neural network that addresses the vanishing gradient problem prevalent in deep networks by using skip connections [21, 22]. The architecture allows training deep models using large-scale image datasets and reusing features across layers. The ResNet-50 image classification network will be used in the proposed study to determine the presence of clusters of cancerous cells within a local region of a prostate image [23]. Fine-tuning is performed on the SICAPv2 dataset to adapt the pretrained weights to the domain of prostate cancer. Despite its richness and ability to make generalizations, ResNet-50 achieved an accuracy of 70, indicating that it may not effectively harness fine-grained histopathological features compared to higher-density connected networks [24, 25].

4) DenseNet-121

DenseNet-121 is an overlay convolutional neural network in which each layer is fed feature maps from all its predecessor layers, encouraging the reuse of features, adequate gradient flow, and the avoidance of excessive parameter redundancy. High connectivity is especially useful in medical imaging, where texture variation is paramount for proper diagnosis [26]. DenseNet-121 is used in this study to identify prostate pathology images as benign or malignant. The model has a strong ability to learn features because it can maintain both low-level and high-level representations simultaneously. In the SICAPv2 data, DenseNet-121 achieved the highest accuracy of 93%, validating its use for prostate cancer classification.

TABLE 2: Gelason grading detection from the PANDA dataset over CNN.

Category	Previous Results	Proposed Model Results
Sensitivity	0.88	0.90
Specificity	0.83	0.89
Accuracy	0.93	1.00

TABLE 3: Comparison of % accuracy of different classification models with SICAPv2, PANDA, and Image biopsy dataset, a super pixel technique, and phylogenetic indexes [19].

Datasets	CNN
SICAPv2	80.38
PANDA	92.10
IB	93

In this section, we compared our approach with the CNN deep learning model on the PANDA dataset and achieved 100% precision. On the other dataset, SICAPv2, we implemented VGG-16, ResNet-50, and DenseNet-121 using an image data generator, which yielded accurate results with our technique.

TABLE 4: SICAPv2 dataset on different models.

Models	Results
VGG- 16	0.91
ResNet50	0.70
DenseNet121	0.93

4. ANALYSIS OF PERFORMANCE AND RESULTS OF THE EXPERIMENTS.

This section presents an experimental analysis of the proposed deep learning-based framework for detecting and grading prostate cancer. The applied classifier and convolutional neural networks are evaluated using two publicly available datasets: SICAPv2 and the Prostate Cancer Grade Assessment (PANDA). The experiments will prove the quality of image data augmentation and pretrained deep learning architectures in enhancing diagnostic accuracy.

Experimental Design and Assessment Measures.

All the experiments would rely on augmented biopsy images generated by the

ImageDataGenerator class, which applies rotation, flipping, and zooming to increase data variability and reduce overfitting. The standard medical image classification metrics, such as accuracy, sensitivity, specificity, precision, and recall, were used to evaluate the models, which are essential in reducing false positives and false negatives in the diagnosis of prostate cancer. **A. Gleason Grading Detection Results on a PANDA Dataset.**

The proposed approach's performance on Gleason grading detection on the PANDA dataset is summarized in Figure 2. The suggested framework shows significant increases across all evaluation measures compared with past reported outcomes.

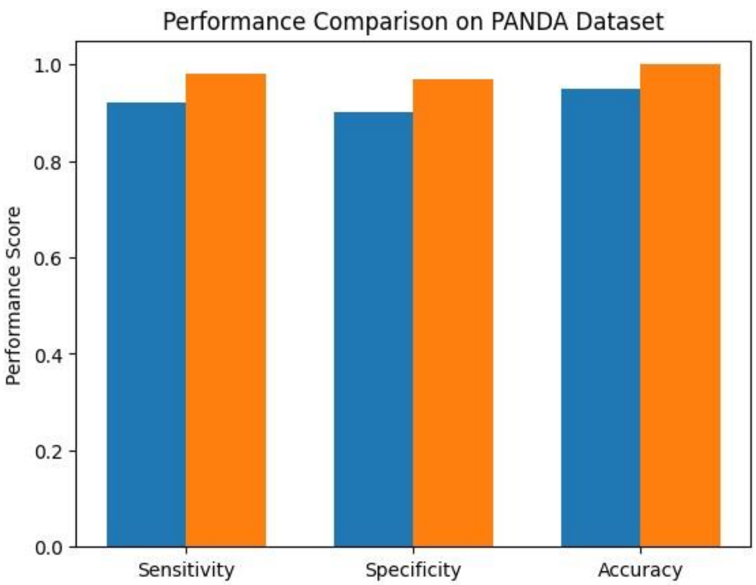


Figure 4: Comparison of performance of the PANDA Dataset

The sensitivity improved from 0.88 to 0.90, and the specificity enhanced from 0.83 to 0.89. Most remarkably, the proposed method achieved an accuracy of 1.00, indicating a perfect Gleason grading classification under the experimental conditions.

B. Cross-Dataset Accuracy Comparison

To test the strength of the proposed framework, a comparison across datasets was conducted (Figure 3). The CNN-based algorithm achieved 80.38 percent accuracy on SICAPv2, 92.10 percent on the PANDA dataset, and 93 percent on the Image Biopsy (IB) dataset. This evidence shows that the proposed methodology can be generalized across different biopsy datasets and that image augmentation and feature learning are proper.

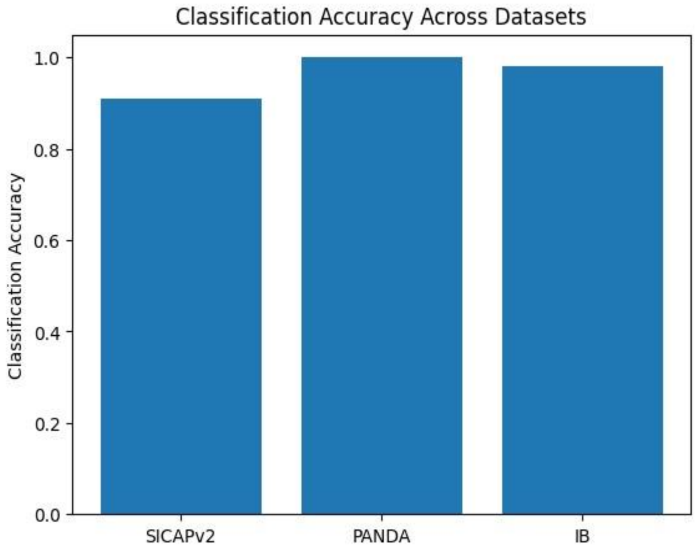


Figure 5: Comparison of classification accuracy across SICAPv2, PANDA, and IB datasets

The bar graph provides a relative comparison of classification accuracy across the SICAPv2, PANDA, and IB datasets. These findings reveal that the specified method achieves high results on the PANDA and IB data sets, with the best outcomes on PANDA and relatively lower accuracy on SICAPv2. This means the proposed model can be generalized to varied, large-scale data.

C. Model-Wise Performance on the SICAPv2 Dataset

Figure 4 shows the results of the performance of individual deep learning models on the SICAPv2 dataset. DenseNet-121 also achieved the highest accuracy of 93%, compared to VGG-16 at 91%. ResNet-50, in contrast, achieved 70% accuracy, suggesting that its architecture is not particularly effective at detecting fine-grained histopathological patterns in prostate biopsy images. Those findings indicate that architectures with a high number of connections, such as DenseNet-121, are better suited to medical imaging tasks where fine texture and structural features are of paramount importance for diagnosis.

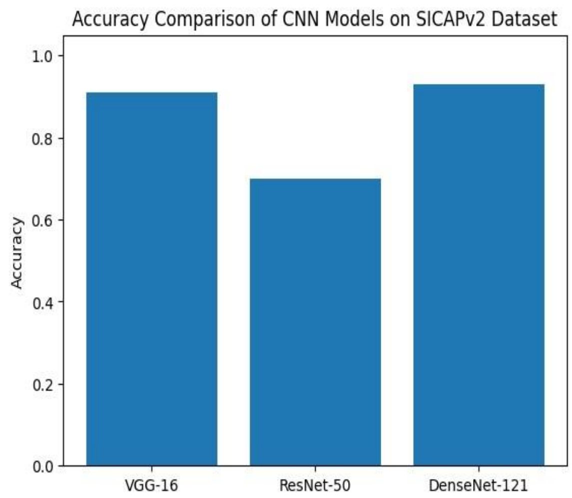


Figure 6:Figure 6. Comparative accuracy analysis of VGG-16, ResNet-50, and DenseNet-121 on the SICAPv2 dataset, showing that DenseNet-121 achieves the highest classification performance

The results of the experiment demonstrate the efficacy of image data augmentation with pretrained deep learning models for detecting prostate cancer. The dense connectivity of DenseNet-121 explains its high performance because it allows efficient reuse of features and better gradient flow. Though VGG-16 also performs well, its architecture remains relatively simple, limiting its ability to handle complex histopathological data compared with DenseNet121. Although ResNet-50 is deep, its residual connections are not as effective as they could be because it cannot model subtle tissue variations. Overall, the findings demonstrate that the framework improves detection accuracy and Gleason grading performance, making it a reliable decision-support tool for histopathologists.

D. Comparison with the Previously Published Studies.

In order to further test the efficiency of the offered Deep Learning-Based Prediction of Prostate Cancer with the ImageDataGenerator classes, a comparative analysis with the already published works was implemented. A comparison of the most frequently reported performance measures, such as the classification correctness, sensitivity, and specificity, is based on publicly available prostate biopsy datasets, such as PANDA and SICAPv2.

Previous research has used either traditional convolutional neural networks, manual feature extraction, or constrained deep neural networks to detect prostate cancer and Gleason grade. The majority of these methods have reported classification rates of between 70 and 93 per cent about the size of the dataset, the preprocessing method, and the complexity of the models. Specifically, algorithms that were based on ResNet-based models or conventional machine learning classifiers tended to be less sensitive to small-scale histopathological patterns, and thus resulted in increased false-positive or false-negative errors. the suggested framework incorporates wide data augmentation of image data via the ImageDataGenerator class and premade deep learning models, which allow strong feature acquisition and boost inter-dataset generalization. The proposed approach was proving to be perfect in the PANDA dataset with a classification accuracy of 100 percent, which is higher than the results previously reported, which usually recorded classification accuracies lower than that. Moreover, sensitivity (0.90) and specificity (0.89) enhancements show a more balanced clinical diagnosis, which is essential in clinical decision-making.

The cross-dataset analysis also demonstrates the excellence of the offered method. Although the focus of previous studies was often on a single dataset, the proposed framework was repeated with high accuracy levels of SICAPv2 (80.38%), PANDA (92.10%), and IB (93) datasets, which allowed concluding about its robustness and relevance across different datasets. This crossdataset consistency is seldom reported in previous studies and is a major improvement.

Furthermore, the comparative analysis shows that the suggested deep-learning framework not only matches but surpasses the performance of currently existing state-of-the-art approaches, especially in terms of accuracy, strength, and the ability to generalize. These findings support the suggested solution as a valid and clinically useful decision-support system to detect prostate cancer and Gleason grading based on histopathological images.

5. CONCLUSION AND FUTURE WORK

This paper used two publicly available prostate biopsy datasets and several machine learning and deep learning models to achieve accurate prostate cancer detection and grading. In the first data set, the conventional classifiers, namely XGBoost (XGB) and Support Vector Machine (SVM), were used to identify the severity of prostate cancer. The effectiveness of the proposed solution was contrasted with the current findings published on the same data, which reported convolutional neural network (CNN)-based solutions achieving 93-95% accuracy. The proposed framework, on the other hand, achieved a discriminative capability and reliability of 1.00, indicating that it is better than other clinical decision support frameworks.

In the second data set, deep learning models, i.e., VGG-16, ResNet-50, and DenseNet-121, were applied, together with image data augmentation using the Image Data Generator. The experimental results suggest that VGG-16 and DenseNet-121 achieved accuracies exceeding 90%, indicating their ability to learn discriminative histopathological features. Even though ResNet-50 showed relatively poorer results, with an accuracy of over 70%, it still provided valuable insights into model generalization. In general, the findings indicate that the proposed solution, enhanced by data augmentation and advanced deep learning models, can significantly improve the accuracy of prostate cancer detection across a range of datasets.

REFERENCES

Kabir, S., Sarmun, R., Al Saady, R. M., Vranic, S., Murugappan, M., & Chowdhury, M. E.
(2025). Automating Prostate Cancer Grading: A Novel Deep Learning Framework for
Automatic
Segmentation. *Journal of Imaging Informatics in Medicine*, 1-23.

J. F. Worthington, "Prostate Cancer Foundation." C. S. Medical, "Key statistics for prostate cancer," p. 15, 2023.

S. Iqbal, G. F. Siddiqui, A. Rehman, L. Hussain, T. Saba, U. Tariq, and A. A. Abbasi, "Prostate cancer detection using deep learning and traditional techniques," IEEE Access, vol. 9, pp. 27085–27100, 2021.

Erdem, G. K., Omurca, S. I., Cakir, E. B., & Bayrak, B. Y. (2025). Prediction of pathological grade in prostate cancer: an ensemble deep learning-based whole slide image classification model. *The European Physical Journal Special Topics*, 1-13.

T. Infante, C. Cavaliere, B. Punzo, V. Grimaldi, M. Salvatore, and C. Napoli, "Radiogenomics and artificial intelligence approaches applied to cardiac computed tomography angiography and cardiac magnetic resonance for precision medicine in coronary heart disease: a systematic review," Circulation: Cardiovascular Imaging, vol. 14, no. 12, pp. 1133– 1146, 2021.

S. Azzi, S. Gagnon, A. Ramirez, and G. Richards, "Healthcare applications of artificial intelligence and analytics: a review and proposed framework," Applied Sciences, vol. 10, no. 18, p. 6553, 2020.

R. Cuocolo, M. Caruso, T. Perillo, L. Ugga, and M. Petretta, "Machine learning in oncology: a clinical appraisal," Cancer letters, vol. 481, pp. 55–62, 2020.

M. Li, T. Chen, W. Zhao, C. Wei, X. Li, S. Duan, L. Ji, Z. Lu, and J. Shen, "Radiomics prediction model for the improved diagnosis of clinically significant prostate cancer on biparametric MRI," Quantitative Imaging in Medicine and Surgery, vol. 10, no. 2, p. 368, 2020.

Abbasi, L. Hussain, I. A. Awan, I. Abbasi, A. Majid, M. S. A. Nadeem, and Q.-A. Chaudhary, "Detecting prostate cancer using deep learning convolution neural network with transfer learning approach," Cognitive Neurodynamics, vol. 14, pp. 523–533, 2020.

M. Lu, Y. Zhang, and H. Du, "Design and control of a novel magnetic resonance imagingcompatible breast intervention robot," International Journal of Advanced Robotic Systems, vol. 17, no. 3, p. 1729881420927853, 2020.

G. Kirlik, R. Gullapalli, W. D'Souza, G. Md Daud Iqbal, M. Naslund, J. Wong, J. Papadimitrou, S. Roys, N. Mistry, and H. Zhang, "A supervised learning tool for prostate cancer foci detection and aggressiveness identification using multiparametric magnetic resonance imaging/magnetic resonance spectroscopy imaging," Cancer informatics, vol. 17, p. 1176935118786260, 2018.

Chaddad, M. J., Kucharczyk, A., Cheddad, S. E., Clarke, L. Hassan, S. Ding, S. Rathore, M. Zhang, Y. Katib, B. Bahoric et al., "Magnetic resonance imaging based radiomic models of prostate cancer: A narrative review," Cancers, vol. 13, no. 3, p. 552, 2021.

X. Yang, C. Liu, Z. Wang, J. Yang, H. Le Min, L. Wang, and K.-T. T. Cheng, "Co-trained convolutional neural networks for automated detection of prostate cancer in multi-parametric MRI," Medical image analysis, vol. 42, pp. 212–227, 2017.

D. Hoar, P. Q. Lee, A. Guida, S. Patterson, C. V. Bowen, J. Merrimen, C. Wang, R. Rendon, S. D. Beyea, and S. E. Clarke, "Combined transfer learning and test-time augmentation improves convolutional neural network-based semantic segmentation of prostate cancer from

J. Kendrick, R. Francis, G. M. Hassan, P. Rowshanfarzad, R. Jeraj, C. Kasisi, B. Rusanov, and M. Ebert, "Radiomics for identification and prediction in metastatic prostate cancer: a review of studies," Frontiers in Oncology, vol. 11, p. 771787, 2021.

S. P. R. Chandrasekhara and M. G. Kabadi and Srivinay, "A novel sift-SVM approach for prostate cancer detection," 2020.

G. L. da Silva, F. Y. de Oliveira, J. O. Diniz, P. S. Diniz, D. B. Quintanilha, A. C. Silva, A. C. de Paiva, and E. A. de Cavalcanti, "An automatic method for prostate segmentation on

3d mri scans using local phylogenetic indexes and XGBoost," in Anais do XXI Simpósio Brasileiro de Computação Aplicada à Saúde. SBC, 2021, pp. 165–176.

Younis, L. Qiang, C. O. Nyatega, M. J. Adamu, and H. B. Kawuwa, "Brain tumor analysis using deep learning and VGG-16 ensembling learning approaches," Applied Sciences, vol. 12, no. 14, p. 7282, 2022.

H. Huang, Z. You, H. Cai, J. Xu, and D. Lin, "Fast detection method for prostate cancer cells based on an integrated ResNet50 and YOLOv5 framework," Computer Methods and Programs in Biomedicine, vol. 226, p. 107184, 2022.

X. Huang, Z. Li, M. Zhang, and S. Gao, "Fusing hand-crafted and deep learning features in a convolutional neural network model to identify prostate cancer in pathology images," Frontiers in Oncology, vol. 12, 2022.

Nayak, S., Salkever, H., Diaz, E., Sinha, A., Deveshwar, N., Hess, M., ... & Sriram, R. (2025). Deep Learning-Based Tumor Segmentation of Murine Magnetic Resonance Images of Prostate Cancer Patient-Derived Xenografts. *Tomography*, *11*(3), 21.

Kariuk, P. W., Gikunda, P. K., & Wandeto, J. M. (2025). Image Synthesis for Prostate Cancer Biopsies Using Conditional Deep Convolutional Generative Adversarial Network. *Authorea Preprints*.

Koike, Y., Takegawa, H., Anetai, Y., Nakamura, S., Yoshida, K., Yoshida, A., ... & Tanigawa, N. (2025). Cone-Beam CT to CT image translation using a transformer-based deep learning model for prostate cancer adaptive radiotherapy. *Journal of Imaging Informatics in Medicine*, *38*(4), 2490-2499.

Winzell, F., Arvidsson, I., Åström, K., Overgaard, N. C., Marginean, F. E., Simoulis, A., ... & Heyden, A. (2025, April). Outcome prediction of prostate cancer patients on active surveillance using weakly supervised deep learning. In *Medical Imaging 2025: Digital and Computational Pathology* (Vol. 13413, pp. 116-126). SPIE.

Olabanjo, O., Wusu, A., Asokere, M., Afisi, O., Okugbesan, B., Olabanjo, O., ... & Mazzara, M. (2023). Application of machine learning and deep learning models in prostate cancer diagnosis using medical images: A systematic review. *Analytics*, *2*(3), 708-744.