

Prostrate Cancer Classification: A Deep Learning Approach Deep Learning Model for Prostate Cancer Classification

Rooh Ullah*, Dr. Muhammad Salim Javed**, Dr. Mahmood ul Hassan***

* IIC University Technology Kingdom of Cambodia, Lecturer in CS, The University of Agriculture Peshawar

** IIC University Technology Kingdom of Cambodia

*** Assistant Professor, Department of Computer Skills, Deanship of Preparatory Year, Najran University

Corresponding: * roohullah.orc@gmail.com

Abstract

Purpose: The present study was conducted to explore the performances of DL models in PET images of patients with BCR PC. The purpose of the study was to examine the efficiency of DL model in the classification of prostate cancer in normal, abnormal and discriminating by PET scans for the presence of tumor recurrence or metastases among the cancer patients.

Methods: The study was conducted in the Shaukat Khanum Cancer Hospital Peshawar. The study has included 268 random patients were examined in the process of CT/PET. The data were collected from the patients from January 2020 to October 10th 2021, 239 were found with Prostate Cancer. The data showed that 29 in 239 were found two F-fluciclovine CT/PET having median of 201+100.0 (40 to 211) days between their treatment through scans. PET images have been categorized into normal, abnormal groups with the help of their clinical reports. Convolution neural network (CNN) models were trained using two different architectures, a 2D-CNN (ResNet50) using single slices (slice-based approach) and the same 2D-CNN and a 3D-CNN (ResNet-14) using a hundred slices per PET image (case-based approach). Models' performances were evaluated on independent test datasets.

Results: The results suggested that the 2D CNN sliced based approached were used two data sets i.e. training and test data. The sensitivity of the data set showed and confirms the presence of abnormality i.e. 91.2% (criterion of 0.531) while the curve area is found 0.862 (p-value: .00). Statistical results showed about 99% of the loss function and accuracy of the results. The results of 2D-CNN cased-based approach showed sensitivity analysis and specificity of the training data showed about 90.9% & 91.1% respectively (criterion 108.9) and the area curve was found 0.684 (p-value: .00). The results for the accuracy and loss function showed about 99.1% and 0.17% in the training data set while 88.19% and 47.64% for the test data sets.

Introduction

Medical studies argued that the prostate can be considered as the walnut sized gland and this gland always secretes a fluid which is alkaline in nature. This gland has been found in pelvis and the rectum has been on the posterior side, on the upper side there is a bladder and this gland has been found surrounded by different parts of urethra (Erickson et al., 2017). The studies reported that the skeletal muscles are starting from diaphragm to the apex. This structure has different regions. The region which is near to the bladder called as the base and that part of gland which is near to the urethral sphincter has been called as apex (Schwyzer et al., 2018). This is obvious that the four lobes of the prostate can be considered as the peripheral zone (PZ), central zone (CZ), transition zone (TZ) and the anterior fibro muscular trauma, among the above zones there exists about 70%, 25% and 5% of tissues respectively. The last one has no glandular tissues (Kirienko et al., 2018). The medical studies showed that the higher the glandular tissue found, there will be

a higher risk of prostate cancer (Nobashi et al., 2019). This has been concluded that the proliferation of the cells leads to prostate cancer.

Machine learning (ML) techniques are revolutionising healthcare, with diagnostic imaging seeing the most massive development and effect. Deep learning (DL) methods, such as convolutional neural networks (CNNs), have demonstrated excellent effectiveness in handling computer vision issues and have thus been effective in medical fields with a lot of visual input (Erickson et al., 2017). Recent research have used ML and 18Ffluorodeoxyglucose (FDG) computed tomography (PET) have shown impressive outcomes in lung and brain cancer tumor detection and constructing (Nobashi et al., 2019), lesion classification (Nakagawa et al., 2019) and reaction forecasting classification of non-focal procedures like Alzheimer's classification methods (Liu et al., 2018), and cardiovascular incident estimation (Juarez-Orozco et al., 2020).

Even though most prior researchers have examined at the efficiency of ML in FDG PET examinations, this study looks at the effectiveness of DL in PET experiments using 18F-fluciclovine, a PET radiopharmaceutical licenced by the US FDA for evaluating biochemical recurrence (BCR) of prostate cancer (PC) (Gusman et al., 2019). Both 2D-CNN and 3DCNN architectures were tested in this study for detecting aberrant 18F-fluciclovine uptake on PET scans of patients with BCR of PC.

Cancer is an universal issue that impacts patients with clinical and management issues. Cancer is more likely in older adults who do not engage in physical activity. According to cancer statistics 2020 [5, there were 1, 806, 590 (almost 1.8 million) new cancer patients and 606, 520 (0.6 million) deaths reported in the current years. According to data, the mortality rate for four primary malignancies (prostate, breast, lung, and colorectal) climbed until 1990, then decreased gradually until 2017. Prostate cancer is the most common cancer within males and the second leading cause of deaths in the US. In 2019, there were 191, 930 new instances of prostate cancer in the US, with males accounting for 21% of the total. Prostate cancer was the most common cancer kind, accounting for 893,660 cases (Nakagawa et al., 2019).

In 2020, 321, 160 people in the United States are expected to die from cancer, with 33, 310 of those dying from prostate cancer. Age, family background, and lifestyle all have a role in prostate cancer. Asians are also less vulnerable than Europeans and African-Americans. The death rate has been reduced by active and effective procedures such as radical prostatectomy, radiation, and hormone therapy. Although active radiation is a viable treatment, it can have mental and emotional consequences (Li et al., 2018). There are numerous approaches to identify prostate cancer, including routine screening for urinary symptoms, which most men dislike because they cause persistent irritation. Many males, on the other hand, continue their whole lives without being diagnosed with prostate cancer (Liu et al., 2018). In the early 1990s, the digital rectal exam (DRE) has been used to screen for prostate cancer. As a result of its implications, a significant reduction has been documented. This screening test can also be used to identify between cancerous and non-cancerous cells (Juarez-Orozco et al., 2020).

The DRE can only detect malignancies in the posterior section of the prostate and cannot detect tumours in other areas or regions of the prostate (Gusman et al., 2019). PSA (prostate-specific antigen) is a diagnostic test for prostate cancer. It was first used in the early 1990s and has been shown to help minimize death and other problems. It is now proving to be extremely divisive. PSA screening frequently produces false-positive results as well as health problems like pain and

infection (Cookson et al., 2007). PSA can be beneficial for asymptomatic men whose symptoms may go unnoticed for the rest of their lives. The systematic randomized technique under transrectal ultrasonography (TRUS) is used in clinical diagnosis to detect tiny and low-grade tumors. Despite this, its low sensitivity makes screening a large population challenging (Nakagawa et al., 2019).

Material & Methods

Selection of Patients

The present study has included 268 random patients were examined in the process of CT/PET at Shaukat Khanum Hospital Peshawar between January 2020 to October 10th 2021, 239 were found with Prostate Cancer. The data showed that 29 in 239 were found two F-fluciclovine CT/PET having median of 201+100.0 (40 to 211) days between their treatment through scans. The remaining patients were treated with only 1 scan. F-fluciclovine were suggested in the process to confirm the suspected BCR after getting primary radiation therapy.

PET Scan Acquisition

The study has followed the standard procedure of (14). The patients have been informed for the standard procedure, they have been advised to no do exercise for 1 days and not to take any liquid or any food at least 4 hours before the imaging. The images have been derived by using Discovery 690 and MI models. The images were performed starting from the thigh all the way to the skull. The study also performed low-dozed CT scan.

PET Data Set

To get the accuracy of the mode, the study has taken the region of pelvis as this part has been affected most of the time in the prostate cancer. Resultantly, the number of slice per PET has been reduced to the pelvis region only. All the PET images consists of the 120 transaxial slice which included the bony pelvis and its soft tissue contents. The images have been managed by using MIM software.

PET Image Labeling

The entire images in the PET process have been labeled as normal and abnormal depends on the medial reports finding. The normal results included no radiopharmaceutical in the prostrate bed while the abnormal has included the radiopharmaceutical in the prostrate bed. The PET scans have been analyzed and interpreted as the per the standard procedure stated by the medical studies.

CNN Training

In this procedure, the DICOM transaxial slices have been converted to PNG format by using software. The study has used slice-based approach in this stage and at this stage only abnormal cases have been included and the expert opinion of the medical institute has been taken in the screening of images. Same numbers from the normal cases have been included to balance the situation. Training has been arranged by using different sets of same cases of normal and

abnormal cases. Model training has been done by using 2D-CNN training procedure at the Shaukat Khanum Cancer Hospital and Research Center at Lahore.

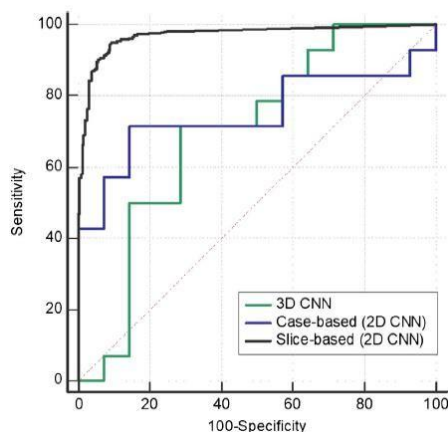
CNN Performance

At this stage the study has used Receiver Operating Characteristics (ROC) curve to test the data and examine the specificity and sensitivity. The average score of the PET scan for the normal and abnormal slices have been examined and probability of 0.05 has been allocated to perform the test on the data set.

Results & Discussions

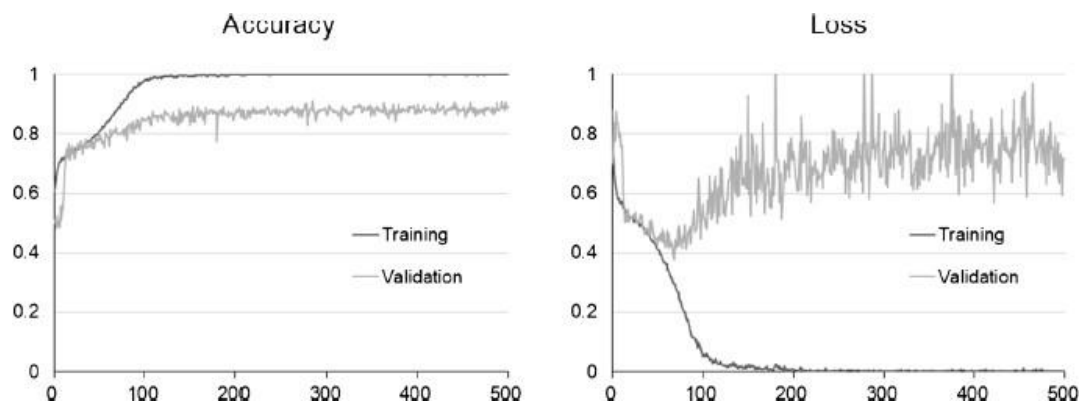
2D-CNN Sliced-Based

The finding of the patients and their reports showed that 4125 abnormal transaxial were found from 239 PET abnormal images. Out of these 4125 abnormal transaxial, 3210 were found in the training data set while the remaining is used in the testing process. Almost the same amount of transaxial were randomly included and then allocated in the training and testing process. The sensitivity of the data set showed and confirms the presence of abnormality i.e. 91.2% (criterion of 0.531) while the curve area is found 0.862 (p-value: .00). Statistical results showed about 99% of the loss function and accuracy of the results. The same has been seen 22% in the training 93% in the testing process.



2D-CNN cased-Based

The results reported that 192 were abnormal, 55 were normal and 8 were found indeterminate PET images. The study has used 120 samples data set which includes 60 normal and 60 abnormal cases for training purpose. While the test data set has included 50 PET images i.e. 25 normal images and 25 abnormal images and were distributed on the basis of random sampling. The findings of abnormal images showed that 16, 27, 32, 41 and 47 have lymph node metastasis, local recurrence and distant metastasis respectively. The results showed that the twenty five reflects 3 or more abnormalities i.e. lymph node metastasis and local recurrence. The data analysis was based on the cases found as lymph node metastasis and local recurrence. The sensitivity analysis and specificity of the training data showed about 90.9% & 91.1% respectively (criterion 108.9) and the area curve was found 0.684 (p-value: .00). The results for the accuracy and loss function showed about 99.1% and 0.17% in the training data set while 88.19% and 47.64% for the test data sets.



Discussions

The findings of the study showed that the 2D-CNN slice based approach can be considered as the best technique to detecting abnormal cases for the prostate cancer uptake in the PET images. The same can be generated from the medical reports on the patients included in the data collection process. Majority of the studies have suggested that the PET scans can be the better option for the abnormal cases of prostate cancer (Wang et al., 2017 & Nakagawa et al., 2019). The present work has used DL method to include the large level of data from the patients by including transaxial PET slide by using wide variety of abnormality and normality of the cases. The slice based approach has been used on the different size, shape and also the location of recurrence of PC and also the analysis of lymph nodes and distant metastases. The study has used more heterogeneous method of including PET images as never taken by the previous studies. The present study does not include the clinical variables or CT imaging features. Due to these features, the study has easily detected the abnormal cases i.e. F-fluciclovine uptake in PET images. In the present work, a 2D-CNN slice-based approach had better performance than the case-based approach. The performance of 2D-CNN case-based approach of this study was similar to that of a previous study from our group studying a 2D-CNN model for the characterization of brain lesions on FDG-PET, with a sensitivity, specificity, and AUC of 87.2%, 68.0, and 0.822 (Nobashi et al., 2019). A possible explanation of these results is the differences in the composition of the training dataset and test dataset used on these two approaches. In the case-based approach, normal transaxial slices were part of the abnormal PET images but were labeled as abnormal for the purpose of training a model based on cases. In contrast, in the slice- based approach, transaxial slices labeled as abnormal were meticulously chosen, and only real abnormal transaxial slices were labeled as the abnormal for the purpose of model training.

Our results highlight the importance of curating pertinent training datasets in the DL. In the 2D-CNN case-based approach in this work, a PET image abnormality is determined based on the average score of its 10 transaxial slices with highest probability on test dataset. This means that the distribution of abnormality score is more convergent than just a single transaxial slices, because an abnormal PET image is generally intermingled with normal and abnormal transaxial slices. Consequently, finding a specific cutoff between normal and abnormal group labels is hard. Nevertheless, our 2D-CNN case-based approach showed a good performance. We postulate that the limited scan range of the pelvis helped improve the performance of this DL model; this region was chosen because it is most frequently affected in BCR of PC (Raveenthiran et al.,

2019). There are several limitations to our study. Firstly, as previously mentioned, the number of PET images included is small. DL modeling is data-hungry, and larger datasets are almost always beneficial for the performance of DL models. The clinical use of 18F-fluciclovine PET scan is less frequent than 18F-FDG PET. Specifically, 18F-fluciclovine PET has a narrower clinical indication than 18F-FDG PET, which typically is BCR in PC in the US. Secondly, labeling in this study was based on formal clinical reports. There could be disparities between physician readers (e.g., variation in reader experience); labeling based on these may differ from the actual clinical follow-up or from pathology results. Additionally, this study is based on PET scans acquired at a single institution with a limited number of scanners and possibly patient demographics. We think that these limitations warrant a prospective and multicenter study that ensures heterogeneity of scanners, patients, and readers prior to clinical deployment

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