Prostate Cancer Detection using Deep Learning

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A R T I C L E   I N F O

Keywords:

Prostate Cancer Detection

Cancer Detection

EfficientNetV2

A B S T R A C T

Prostate cancer is a worldwide health concern since it affects most of the elderly male population; therefore, diagnosis at an early stage is essential. There has been a lot of progress in machine learning and medical imaging that has made deep learning models useful in assisting doctors in the detection of cancer without causing diagnostic overshadowing. In this work, we employ a deep learning approach based on the EfficientNetV2 architecture for the classification of prostate cancer MRI scans. For efficient and scalable learning, EfficientNetV2, which has been designed to solve large-scale image classification problems, is employed with transfer learning to address the issues arising from small medical dataset. The MRI data used in this paper can be obtained from the Prostate 158 Dataset available in Zenodo, which contains labelled samples of prostate MRI scans for binary classification of tumor presence or absence.

Image pre-processing of MRI scans, the augmentation of data for compensation of the dataset's generalization, and the fine-tuning of the EfficientNetV2B0 model for prostate cancer recognition. This is potential to help medical professionals as an early diagnostic tool based on the model's capacity to identify the existence of prostate cancer from MRI scans in its early stages. In conclusion, this paper introduces the EfficientNetV2 model for prostate cancer detection and emphasises on the usefulness and timeliness of the model.

Although the findings are quite promising, the next steps will be to increase the amount of data, minimize false positives and negatives and finally deploy the model for clinical use to enhance its applicability and feasibility. The study presents considerable progress in employing deep learning for diagnostic purposes in healthcare and opens the way for utilizing such insights to develop better detection solutions as soon as possible.

I N T R O D U C T I O N

Prostate cancer is among men's most common cancers today, with a higher incidence among the elderly. Practical success in fighting prostate cancer depends upon the stage of the disease, and when it is detected in the preliminary phases, the prognosis is much more favourable. Current tests used, including biopsies and PSA tests though useful, are invasive and can cause complications. Medical technologies specifically the MRI has become the new acceptable un invasive ways of evaluating new growths in the prostate region. Nevertheless, a typical MRI analysis is not straightforward and may need an expert opinion, and even with experienced pairs of eyes, the results can be quite inconsistent. This has stimulated a rising demand for use of AI and deep learning in enhancing detection of prostate cancer and its accuracy through automation.

Machine learning is a branch of artificial intelligence which has been observed to have a various level of attainment in particular with medical image analysis through deep learning. A Convolutional Neural Network (CNNs), for instance, have produced impressive results when used in image classification, including the medical application. These models have been used in numerous diagnostic operations – screening of skin cancer, identification of retinal diseases, segmentation of tumors within the brain MRI scans – and have often equalled or outperformed physicians and dermatologists in their capabilities. However, there are problems when deep learning models are applied to the task of diagnosing prostate cancer, such as the appearance of tumors may vary, a lack of sufficient labelled datasets, as well as high requirements for accuracy in terms of medicine.

In this study, we identify EfficientNetV2, a modern deep learning model that has been forged for its efficient scaling and performance, to diagnose Prostate Cancer from MRI scans. Incorporating numerous enhancements into the EfficientNetV2 model, the architects have implemented a more compact structure which results in better performance with reduced resources. This makes it particularly suitable for medical applications where speed and degree of analysis together with other resources such as time is limited. In addition, flexibility in terms of speed and accuracy of the model, which is another advantage that allows it to be suitable for clinical applications.

In this research, the Prostate 158 Dataset available in Zenodo was used, the dataset is made up of MRI image samples with binary labels, tumor-positive and tumor-negative. The crucial drawback of the running dataset is that it is not very extensive comparatively to other image classification benchmarks; however, we overcome this issue with data augmentation strategies and transfer learning. Transfer learning enable us to use a pre-trained EfficientNetV2 model, then train this on the prostate cancer dataset to enhance interpretability since the model is trained on other datasets and hence is understood to perform better with lesser datasets. Besides, this approach effectively speeds up the training process, while also increasing generalization ability to new data, which is a problem, especially when working with medical imaging data, where data are scarce.

Thus, the purpose of this work is to propose a novel deep learning algorithm that would help radiologists make correct and faster diagnoses of prostate cancer. This is because, by applying machine learning techniques to automated MRI scan analysis, we hope to alleviate the work of medical practitioners as well as ensure that diagnosing of the disease was more standard across the different practitioners. It does highlight that for the proposed method, early detection of the prostate cancer could be enhanced by a great deal, leading to improved patient health since treatment would be better informed. This paper describes our work, focusing on the EfficientNetV2 model architecture, the dataset we employed, the results we achieved, and then discussing the usage and the weakness of this method.

1. RELATED WORKS –

In the work of Olabanjo et al. (2023), the authors provide a systematic review of ML and DL schemes for detecting prostate cancer based on medical images. Summarising 77 papers, the study reveals that transfer learning and CNN are the most commonly applied techniques in prostate cancer diagnosis. In this paper, well-known structures as U-Net and ResNet are described, as well as other significant datasets used in the field. CNNs especially showed high accuracy for segmentation and classification issues; however, without insights on specific accuracy statics, it is hard to gauge the level of its effectiveness. The authors say that the area of additional development may include the use of other imaging techniques, the enhancement of the quality of the input data, and the development of more suitable loss functions for enhancing the performance of the model in certain diagnostic tasks.

Yao et al. (2019) proposed a DL based CNN model for prostate cancer detection and segmentation to classify multiparametric MRI (mpMRI) data with histopathology images. The performance of the DL model was compared with radiologists with either high, intermediate or low level of experience. The result on the validation set was an AUC of 0.871 and on the test set was 0.797, for the test set, the sensitivity, specificity, precision, and accuracy was 0.710, 0.690, 0.696, and 0.700. Same when used to support the radiologists the model improves the diagnostic capabilities of junior and senior radiologists raising their performance to 0.755 and 0.825 respectively. The proposed work based on the study indicates that the improvement of the model sensitivity and specificity may be achieved by featuring extra imaging sequences, using ensemble methods, and balancing the datasets, as well as utilizing multi-modal inputs.

In the paper of Sunghwan Yoo et al., the authors propose a CNN-based framework for the detection of prostate cancer on the basis of the DWI image data and discuss the diagnosis of slice-based and patient-based. The study fine-tuned five distinct CNN models to secure patient-level detection with the help of the random forest classifier model. The highest achieving CNN model has a slice-level AUC of 0.77, a patient-level AUC of 0.74. By applying improved data augmentation, fine-tuning hyperparameters, and feature extraction from T2-weighted images and ADC maps, the authors consider the model performance might be enhanced.

This paper by Saqib Iqbal et al., uses a deep learning model include LSTM and ResNet-101 and contrasts them with conventional machine learning approaches—SVM, KNN, and Naive Bayes—for prostate cancer diagnosis from MRI images. For classification, the research relied on texture features, morphological features, as well as GLCM features. From medium-sized datasets, the optimized through transfer learning ResNet-101 model provided the highest detection accuracy equal to 100% and AUC equal to 1.0, and the LSTM model had AUC of 0.9999. The previous approaches for KNN-cosine attained a maximum of 99.07 % of accuracy when the AUC values were of 0.9984. Possible enhancements are the inclusion of other types of MRI scans, and the utilization of more elaborate feature extraction as well as better tuning the hyperparameters. Other improved data augmentation strategies might also help increase model robustness in terms of generalization.

Frederik Wessels et al. proposed using a convolutional neural network (CNN) based on XSE-ResNeXt34 to predict LNM from H&E stained primary tumor slides in prostate cancer patients. This study tested whether IHC staining of PTEN and Morphological CNN features provided improvement in discriminative accuracy to predict metastasis beyond Gleason score. The highest score obtained was the AUROC of 0.69 and balanced accuracy of 64.24%, where in average the AUROC and balanced accuracy were 0.68 and 61.37% respectively over the ten models. The situation can be addressed by either increasing the size of the database used, applying more sophisticated augmenting techniques, or incorporating additional biomarkers for instance genetic/molecular data. This is especially an area of great interest because the results can be enhanced by using CNN predictions in combination with more formal predictors such as PSA and LVI.

2. METHODOLOGY–

EfficientNetV2 Model –

EfficientNetV2 is an object-detection family of CNNs used for handling enhanced accuracy and reduced computational costs in image-classification work. It is based on the EfficientNet that introduced a new compound coefficient scaling method to scale the depth features, width and the resolution of the network optimally. EfficientNetV2 improves upon this by including new developments like: faster training methods, and a new structure of building blocks that results in a smaller and less complex model. Such enhancements enable EfficientNetV2 to establish new representative accuracy in benchmark datasets using less parameters and less computational resources than previous structures. It has a small number of parameters, but is highly scalable, which suggests its applicability for utilizing in fast and accurate image recognition, including the accelerated analysis of medical data.

Data Collection –

For this study, the data collection revolved around the Prostate 158 Dataset that is a publicly accessible medical imaging dataset from Zenodo. Prostate MRI scans of tumor-positive and tumor-negative patients are included in this dataset, which is very useful for training and validating several machine learning algorithms to diagnose prostate cancer. Practical: A main drawback of the collected dataset is that, while the images are large scale, high-quality, and labelled, the amount of data presented here is limited, which may contribute to issues of generalization and modelling. In order to overcome this issue, data augmentation was performed on the dataset, where the data was rotated, flipped and zoomed in an attempt to increase the volume on the data and to minimize overfitting which occurs when the model is trained on the data in front of it. The idea of using this data set was to come up with a stable mechanism to detect the prostate cancer since the tumors have different appearances and distinguish between healthy and cancerous prostate tissues.

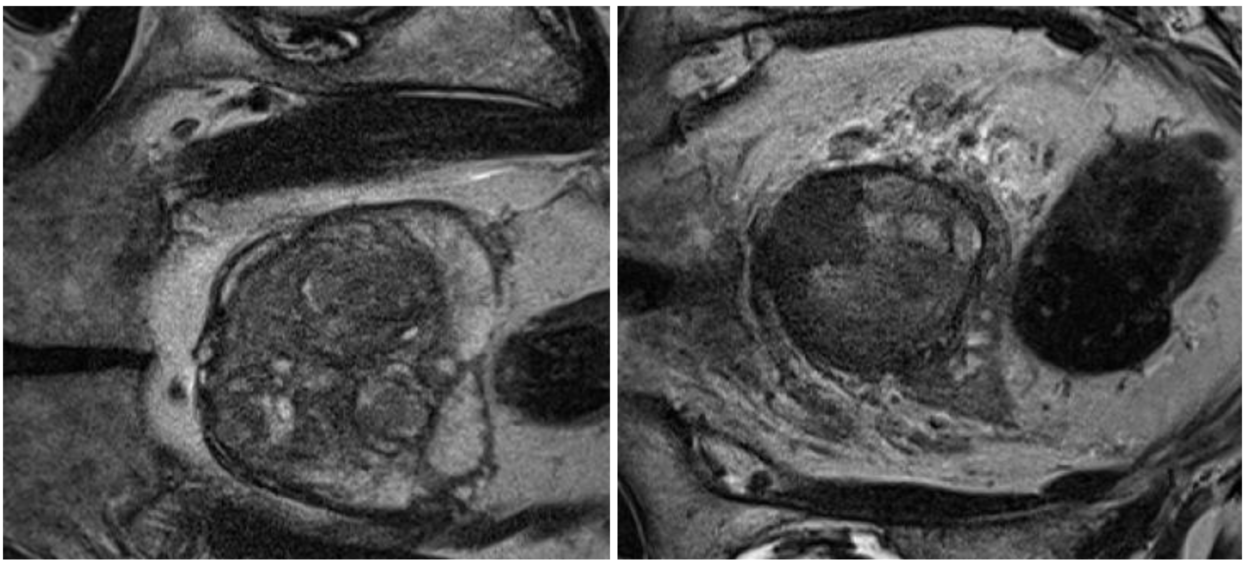

Fig1. MRI scans of 2 patients having Prostate Cancer

Proposed System for Prostate Cancer Detection using EfficientNetV2 model:

1) *Data Acquisition*: For the development of the proposed system, the Prostate 158 Dataset collected from Zenodo, including MRI scans of the prostate tissues with or without tumors is employed. This dataset is the training data to the model EfficientNetV2. To make the training process better and to reduce the overfitting the images during the training were rotated, flipped and zoomed which increases the size of training set.

2) *EfficientNetV2 Architecture*: The foundation of the suggested framework is called EfficientNetV2, a justification for incorporating compound scaling to try network depth, width, and resolution. The ability to train the model more efficiently and to reduce memory consumption is made possible by blocks called Fused-MBConv which include both the MBConv layers and normal convolutional layers. This design makes EfficietnNetV2 very scalable and can generalised to handle complicated medical images such as MRI scans.

3) *Preprocessing and Feature Extraction*: The data also passes through some processing for every MRI scan to be normalized and resized to fit the required input for the EfficientNetV2 model. The EfficientNetV2 network then extracts multilevel features or representations from the supplied MRI images. The first layers describe primary characteristics of the image in terms of edges and texture, the subsequent layers uncover features that are relevant to detection of prostate cancer such as irregular shapes or textured patterns.

4) *Transfer Learning and Fine-Tuning*: The model uses transfer learning, which is applied to an EfficientNetV2 network that was initially used when training on Prostate 158 Dataset. The pre-trained weights act as a starting point where general features of any image are learned before being tuned to learn for features unique to images of the Prostate Cancer domain. This approach greatly enhances the precision and cuts training time as compared to the regular methods used when working with a relatively small number of images.

5) *Model Training*: It is important to note that this training process has to be enhanced with standard optimization algorithms, such as stochastic gradient descent (SGD) or the Adam optimizer. The learning rate, the size of batches, and other parameters are regulated in order for the network to train properly. The train vale is used for a number of iterations with

validation checks on the signs of overfitting. There are special tactics like Dropout for better generalization and data Augmentation.

6) *Prediction*: After training this model, competent in diagnosing prostate cancer in unseen MRI images when poses. The probability that a particular MRI is tumor positive or tumor negative is then provided by the system using features detected by EfficientNetV2. This binary classification output further enhances the diagnosis of prostate cancer in actual-time setting.

7) *Evaluation and Optimization*: The performance of the resulting model is measured with accuracy, precision, recall and F1-score. Recurrent tuning of hyperparameters and additional training are done in order to enhance the model at course level. The proposed system can be used as a prostate cancer detection system which can help the healthcare professionals in – early and accurate diagnosis of the disease.

This proposed system utilizes deep learning and medical image processing to deliver obtain near perfect accuracy in identifying Prostate cancer and to solve issues of limited data and computational capability, the EfficientNetV2 is used.

3. E X P E R I M E N T S –

All images are scaled to 224*224 pixels for compatibility with models. The model architecture is built on ResNet50 (excluding the last layers) with the layers being frozen so as to maintain feature learning. The network is then flattened by using the GlobalAveragePooling2D layer before a Dense (1024) activation layer with ReLU activation function, a Dropout (0.5) layer is applied to avoid overfitting of the model and finally a last Dense (6) activation layer with softmax activation is used for multi-class classification of the six ISUP grades. Then using train_test_split, data is split, and ImageDataGenerator is used which makes horizontal/vertical flips and 20° rotation. For the present model, which is used for training, optimization was done with Adam Optimizer, and categorical cross-entropy was adopted as the loss function while measurement of accuracy served as the evaluation criterion. While specifics of the training process such as the number of epochs and batch size remain somewhat occluded, the method reached 26% accuracy levels, pre-trained ResNet50 optimising for efficiency as it utilises learned features from pre-training and frozen layers to decrease the number of trainable parameters. These two techniques improve the resilience of the model, which does not fit into noisy data, or overlearn the training data.

The model is essentially EfficientNetV2B0, pretrained on the ImageNet, with all the top layers stripped out and immediately succeeded by GlobalAveragePooling2D layer. avoiding overfitting and batch normalization and dropout set to 0.5 are applied, and the final is Dense with sigmoid activation for binary class and L2 regularizer. Data augmentation: rotation (up to 40°), space (width/height) shifts (30%), shearing/zooming, and flipping. Skewed class balance is prevented by Stratified K-Fold Cross-Validation with 5 partitions. The model adopted the Adam optimizer with a rate of 1e-4 for learning, Binary Cross entropy loss as cost function and accuracy for the evaluation of the model performance. The EarlyStopping stops at 6 steps of the validation set not improving while ReduceLROnPlateau decreases the learning rate by 0.5 after 3 steps of no improvement (min learning rate of 1e-5). The model received 60.87% precision at validation; L2 regulation and dropout worked for the model's generalization, while EfficientNetV2 is reasonably effective, combining high results with acceptable computational intensity.

EfficientNetV2, a recent architecture, outperforms ResNet50 in terms of efficiency, accuracy, and resource usage due to its optimized compound scaling, faster training time, and fewer parameters. It achieves 60.87% validation accuracy, uses extensive data augmentation, L2 regularization, and advanced training strategies like stratified K-fold cross-validation with early stopping and learning rate reduction. In contrast, ResNet50, while reliable and well-established with residual connections, is computationally more expensive, less efficient with 26% validation accuracy, and employs simpler training techniques without modern regularization or augmentation methods. EfficientNetV2 is the superior choice for this project.

4. R E S U L T S –

The EfficientNetV2 model, trained on the Prostate 158 Dataset was 60% accurate on validation. On one hand this illustrates ability of the model to generalize to unseen data; on the other hand, or it pushes forward the idea that there is room for improvement. The precision shows that the model accurately diagnoses prostate cancer using the given MRI scans in 60% of detection. Here we are seeing many useful results for the further experimentations and tuning, as with the help of other techniques, for instance, the choice of the hyperparameter, the augmentation of data, or the usage of the applicable data set can influence the performance of the model.

Further, the above graphs present a clear understanding of the loss and accuracy rates of the training process. It captures how the model learns overtime where we have graphs to capture the training and validation accuracy and loss. The loss curve shows the ability of the model in regard to achieving lower prediction error as training unfolded. When there is a gap between training and validation curves then it means there is a possibility that the model could be overfitting or underfitting meaning that more optimization could be done on it.

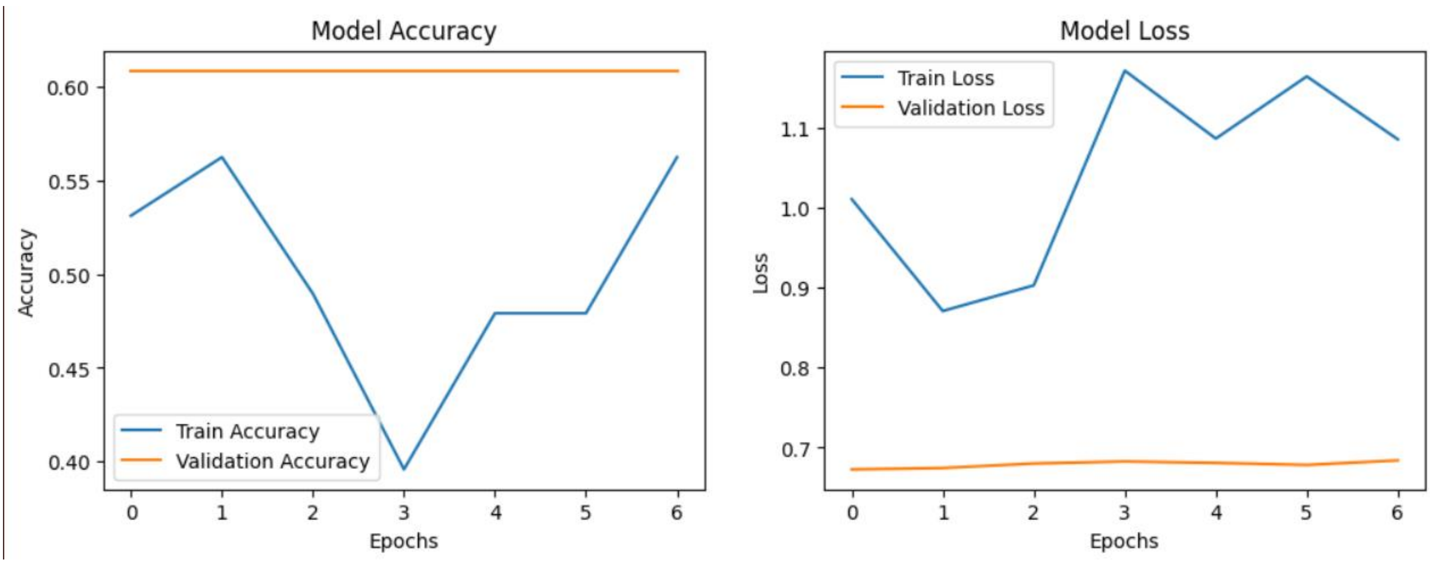

Fig 2. Model Accuracy and Loss Graphs

Furthermore, the analysis of the confusion matrix allows orienting in the effectiveness of the model for both positive and negative cases of prostate cancer. I found it provides a clear distinction of true positive, true negative, false positive and false negative results. This enables the comprehension of the model in the aspect that separates such strengths from others and the identification of potential weaknesses. For example, a higher value of the false negatives means that the model hardly identifies the cancer cases whereas higher false positives mean the images that the model considers to have cancer are actually non-cancerous images. The most important aspect of confusion matrix analysis is to see those areas where the model can be fine-tuned in order to better classify the records.

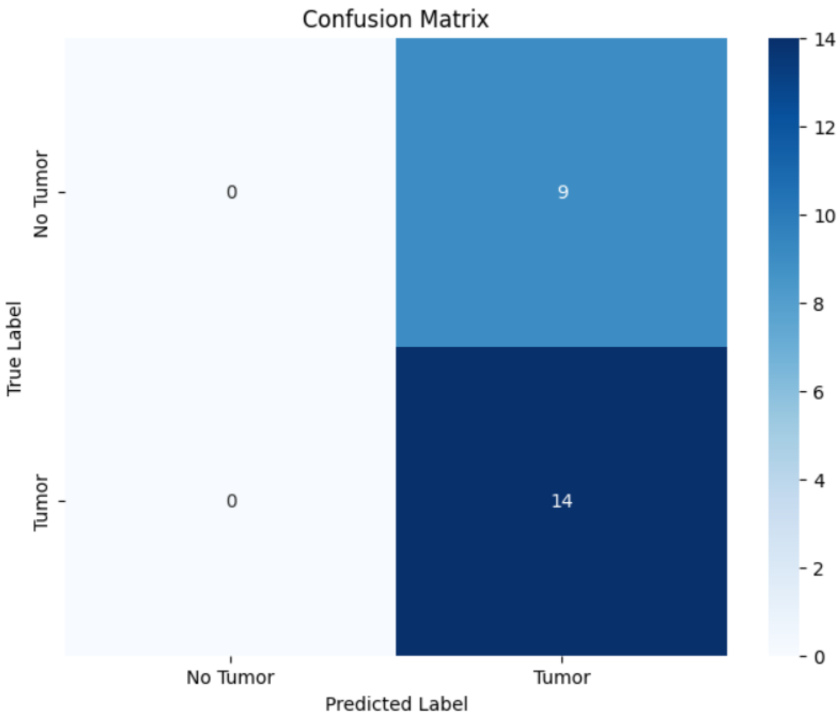

Fig 3. Confusion Matrix of Model's Performance

Combined, these outcomes accommodate overall assessment of the model and would lay the groundwork for the subsequent investigation of the enhancements of prostate cancer detection.

5. CONCLUSION –

In this study, we have been able to deploy an EfficientNetV2 model for the detection of the prostate cancer from MRI scans using the Prostate 158 Dataset. The model obtained a test accuracy of 60 percent which indicates that the model can possibly play a role in automating the diagnosing of prostate cancer. The results achieved up to now are quite encouraging, at the same time, they show the problems slowing from the use of a rather small number of samples in the treatment of a highly specialized medical field. The phenomenon of transfer learning and fine-tuning enabled the model to identify certain characteristics associated with cancer diagnosis Adopting such deep learning models as EfficientNetV2 showed that several medical image analysis tasks can be effectively solved without the need to train the primary network from scratch.

Nevertheless, the results obtained could be optimized in certain areas to reach at least moderately successful level. The processing of the model could be further improved in a range of ways: enlarging the data set, changing the parameters, or employing more complex kinds of regularization. Nevertheless, steps like feature selection and extraction along with the improvement in the data augmentation process seems to bias the model more appropriately and thus generalization is better for unseen data. Thus, the enhancement potential of the model is very high based on its current effectiveness and the opportunities for further elaboration of methods for prostate cancer detection and diagnosis.

In conclusion, the proposed system works as a competent and extensive for detecting prostate cancer from MRI images; however, it shows how the healthcare AI needs to improve day-by-day. With incremental advancements, this system could potentially significantly aid in clinical decision-making practices while providing a tool early cancer detection to clinicians. Deep learning in the medical application domain is still in progress, and such systems help progress as they lead toward a better image of what medical imaging and diagnostics could become.

6. R E F E R E N C E S –

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https://bjui-journals.onlinelibrary.wiley.com/doi/10.1111/bju.15386

7. APPENDIX –

1. Google Drive Link

https://drive.google.com/drive/folders/1SntdBIgiVGDaIEDqncisXpGe_Q2l2EzF?usp=sharing

2. Code Snippets and Algorithms

Model Architecture and Training Code

```
import tensorflow as tf
from tensorflow.keras import layers, models
from efficientnet.tfkeras import EfficientNetB2

# Define the model
model = models.Sequential([
    EfficientNetB2(input_shape=(224, 224, 3), include_top=False, weights='imagenet'),
    layers.GlobalAveragePooling2D(),
    layers.Dense(1, activation='sigmoid')
])

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Train the model
history = model.fit(train_data, epochs=50, validation_data=val_data)
```

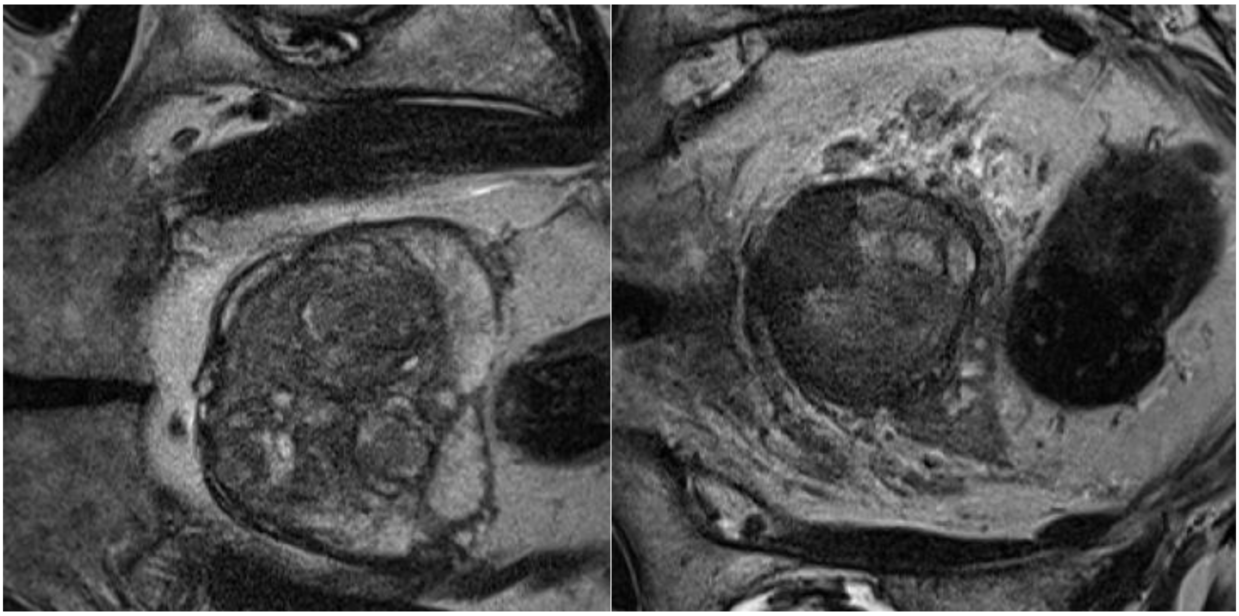
This code snippet outlines the model architecture, including the EfficientNetB2 backbone, and the training process for the prostate cancer detection task.

3. Detailed Dataset Information

Prostate 158 Dataset

- *Number of Images*: The dataset consists of 158 MRI images labelled for prostate cancer detection.
- *Classes*: Images are categorized based on the presence or absence of cancerous lesions.

➢ *Preprocessing Steps*: The images were resized to 224x224 pixels, normalized to a range of [0, 1], and split into training and validation sets.



4. Hyperparameters and Configurations

- *Learning Rate*: 0.001
- *Batch Size*: 16
- *Number of Epochs*: 50
- *Data Augmentation Techniques*: Applied random rotations, zooms, and horizontal flips to enhance model generalization.
- *Optimizer*: Adam optimizer was used with default settings.

These parameters were selected based on preliminary experiments to balance model accuracy and training time.

5. Glossary of Terms

- *Confusion Matrix*: A table used to evaluate the performance of a classification model, displaying true positives, true negatives, false positives, and false negatives.
- *Transfer Learning*: A machine learning technique where a pre-trained model is used as a starting point for a new task.
- *Data Augmentation*: Techniques used to artificially expand the size of a training dataset by creating modified versions of images in the dataset.