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Precision in Prostate Cancer Diagnosis: A Comprehensive Study on Neural Networks

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Abstract

Prostate cancer is a type of cancer that begins in the cells of the prostate in the male reproductive system. The diagnosis of prostate cancer is a crucial aspect of healthcare where precision and efficiency play a pivotal role. This research paper delves into the analysis of deep learning techniques to enhance the accuracy and effectiveness of prostate cancer diagnosis. Advanced convolutional neural network architectures like DenseNet121, MobileNetV2, and EfficientNetB0 are used operationally within this research. It was conducted on Prostate Cancer Grade Assessment (PANDA) dataset Training models individually with the dataset and getting their performances via training plots shows that DenseNet121 overtakes the other two models at an amazing 85.98% accuracy. This result demonstrates the great potential of deep learning for the improvement of diagnostic accuracy, in particular within the scenario of prostate cancer. The research offers a large amount of insight into this implementation of state-of-the-art neural network architectures on medical image classification that helps to improvements in diagnostic accuracy and treatment for prostate cancer patients.

Keywords: Prostate Cancer Diagnosis, DenseNet121, MobileNetV2, EfficientNetB0, Medical Imaging.

1 Introduction

PROSTATE cancer is one of the most common and serious health threats, so there is an intent to look for improved methods of diagnostics. The existing approaches to diagnostics are very often challenged regarding the accuracy of the information, which can lead either to overtreatment or timely intervention. Better diagnosis is desperately needed—more precise, more effective—in order to bring down unwarranted medical procedures and improve patient outcomes. This study intends to assess state-of-the-art neural network architectures, such as DenseNet121, MobileNetV2, and EfficientNetB0. The main objective of research is improving medical diagnostics, eventually enhancing the level of management of cases of prostate cancer.

A lot of research has been done in the field of machine learning and deep learning for improved prediction and diagnosis of prostate cancer. (Bygari et al., 2023; Padmanabhan et al., 2015) used deep learning for prostate cancer grading. Srivenkatesh & Muktevi, (2020) pioneered the use of a prediction

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model that uses various algorithms such as Support Vector Machine, Random Forest, and Najson, among others, and logistic regression that placed the model at commendable accuracy between 70% and 90%.

In this research paper, we embark on a very comprehensive study in which the exploration of state-of-the-art neural network architectures will be conducted to increase precision in diagnosing prostate cancer. The idea of proper and timely diagnosis, in this respect, is essential for developing effective strategies of treatment, minimizing unnecessary medical and/or surgical interventions, and, finally, the overall prognosis for a patient (Puri et al., 2013; Muralidharan et al., 2020).

The emergence of advanced technologies and the growing availability of extensive datasets has opened up a new pathway for integrating sophisticated computational techniques into medical diagnostics (Camgözlü et al., 2023; Chatterjee et al., 2024). To be specific, the deep learning models in machine learning have shown very promising capabilities regarding tasks within image analysis and the identification of patterns (Arora et al., 2024). The novelty of work is it is dedicated to checking the functioning of three well-recognized architectures of neural networks, including DenseNet121, MobileNetV2, and EfficientNetB0 on the problem of prostate cancer diagnosis by performing comparative analysis (Jelena et al., 2023; Stevovic et al., 2018; Conti et al., 2017; Alkishri et al., 2023; Ramakrishnan et al., 2019).

Research work has been directed towards the training and validation of these neural network models using a mixed dataset of prostate cancer images (Aram et al., 2015). The dataset contains different ranges of cases, which gives the models a subtle measure of their performance at different levels of disease intensity (Sumiati et al., 2024). We compare the performances of different advanced models to get the best performance model for the neural network architecture so that prostate cancer can be diagnosed accurately (Kutlu et al., 2021).

The research methodology consisted of medical image preprocessing, neural network training, and performance evaluation on the validation dataset. It was also studied how increasing the robustness of the models can be achieved through data augmentation techniques and dynamic learning rate. The research results are supposed to provide with useful information on possible applications of neural networks in the problem of prostate cancer diagnosis to move a further discussion related to new achievements in the field of medical imaging and diagnostics.

With that, we hope that through this comprehensive study, we contribute to the intellectual discourse related to the integration of cutting-edge technologies in healthcare with a focus on precision improvements in diagnosis related to prostate cancer. This study will have a positive impact on clinical practice in terms of providing an accurate and less costly means to detect and classify cases of prostate cancer.

2 Related Work

Prostate cancer poses an enormous global challenge with an appreciable incidence-to-mortality ratio as the second most diagnosed cancer in men. Considering these complexities and errors associated with conventional grading by pathologists, it is necessary for an accurate grading that forms the bedrock of individualized exactitude in the choice of strategies of treatment.

Barlow et al., (2019) were focused on predicting high-risk prostate cancer, and with respect to the limitations of the PSA screening test, they had an impressive accuracy of 91.5%.

Additionally, Oyewo & Boyinbode, (2020) highlight issues of both accuracy and sensitivity by proposing an innovative ensemble model that uses a Support Vector Machine, Decision Tree, and

Multilayer Perceptron, and the derived model can have a remarkable value of prediction accuracy of 99.06. A more recent systematic review by Nematollahi et al., (2023) has highlighted the ability of multiparametric magnetic resonance imaging (mpMRI) to diagnose the detection of prostate cancer, exemplifying proficiency by deep learning, random forest, and logistic regression algorithms.

In addition, in another work by Mughal et al., (Iqbal et al., 2021), deep learning approaches such as Residual Net (ResNet-101) and Long Short-Term Memory (LSTM) are compared with conventional classifiers. Their findings further show performance superiority in ResNet-101 and have promise for future efficient detection of prostate cancer. Similarly, the Abbasi et al. (2020) model applied a transfer learning approach using a convolutional neural network (CNN), which, however, was seen to outshine other machine learning classifiers.

Mandal et al., (2021) introduced a deep-learning-based framework for the detection and classification of prostate cancer, showing the potentiality of ML in enhancing diagnostic accuracy.

On the other hand, Mashak et al., (2022) contributed more to the field of prostate cancer classification by using deep learning and MobileNetV2. They outlined a new landscape of ML methodologies applied to boost diagnostic capabilities in prostate cancer.

Tolkach et al., (2020) deployed the NASNetLarge architecture and reported 97.3% accuracy for the detection of tumors with an enhancement in Gleason grading. This definitely shows the importance of deep learning in prostate cancer pathology. Pipeline for prostate cancer diagnosis: The state-of-the-art pipeline proposed by Gavade et al., (2023) for the prostate cancer diagnosis task is implemented by proving that the joint employment of the U-Net and LSTM architectures is viable for segmenting and classifying tasks with the mpMRI images.

Araujo et al., (2023) contributed to this diagnosis-model landscape with a linear SVM model and achieved remarkable accuracy (86.8%) along with sensitivity (88.2%) and specificity (85.3%) in predicting the presence of prostate cancer. Mewada and Sharma, (2023) boldly put a point across machine learning applications in the analysis of MRI images, introducing a model that had histogram equalization, the fuzzy C means algorithm for segmentation, and KNN for classification with the objective of achieving better accuracy and specificity in the diagnosis of prostate cancer.

Ren et al., (2019) explored statistical modeling of survival models from feature quantification on histopathological images of prostate cancer. These methods, based on diverse textures and convolutional neural network-based feature extraction, establish correlations between image features and patient outcomes.

In addition, the deep learning approaches have remained pivotal to the Gleason grading, promising state-of-art to the betterment of the severity assignment of the prostate cancer problem Chavda & Degadwala, (2023). Singh et al., (2024) introduced a novel technique with the use of a 3D convolutional neural network in the detection of prostate cancer from MRI images. His approach distinguished itself in the joint detection of epithelium and the Gleason Score, hence underlying high specificity (85%), accuracy (87%), and sensitivity (89%).

This study by Erak et al., (2023) developed deep learning algorithms for predicting molecular subtypes of prostate tumors using histopathologic images. The authors developed a transformer-based hierarchical architecture trained on whole-slide images, which achieved high accuracy in the identification of ERG fusions and PTEN deletions. The efficiency of such algorithms based on vision transformers was robust across different patient cohorts, thus indicating the possible creation of a universal screening tool for revealing genomic alterations in prostate cancer.

Molla et al., (2023), in their study, have covered the application of machine learning algorithms in the prognosis of prostate cancer. They looked at different methods, including support vector machine, random forest, Naïve Bayes, k-nearest neighbor, logistic regression, and others. Among them, logistic regression achieved the best accuracy (86.21%), so it shows promise in being used for the prediction of prostate cancer.

Lee et al., (2023) presented the application of machine learning based on texture and deep learning based on images for the detection of TZPCa. They went further to display the complementation in the application of each of these approaches, where the texture-based machine learning is highly specific, and the image-based deep learning is highly sensitive. This dual-method strategy may lead to the enhanced diagnosis and detection of TZPCa. De Vente et al., (2020) proposed that a neural network may be graded using a joint determination of prostate cancer within a parametric MRI. Their 2D U-Net has shown promise in giving features on cancer aggressiveness in conjunction with clinically relevant data, with training on the ProstateX-2 challenge dataset.

Rai's review (2024) provided a thorough examination of these methods, emphasizing their role in enhancing diagnostic accuracy. Mesrabadi & Faez, (2018) proposed the use of Artificial Neural Networks and Deep Learning to improve the early diagnosis of prostate cancer, demonstrating encouraging outcomes. Yoo et al., (2019) introduced a deep convolutional neural network (CNN) for detecting prostate cancer, showcasing the potential of CNNs in this area. For patch aggregation in prostate cancer detection systems, Duran-Lopez et al., (2021) further advanced this field by introducing a Deep neural network model, which contributed to enhancing the efficiency of detection algorithms.

It holds very strong promises of improving with significance the precision and efficiency in detecting prostate cancer based on the large set of medical imaging data fused by machine learning techniques, especially those that involve state-of-the-art deep learning architectures such as DenseNet121, MobileNetV2, and EfficientNetB0. However, the literature available sheds a shining light on the methodologies and algorithms used in this area. Some of the studies report excellent accuracies, while others underline that multiparametric magnetic resonance imaging (mpMRI) and novel deep learning architectures are crucial for diagnostics precision. The next question that therefore arises is this: Which machine learning approach of DenseNet121, MobileNetV2, and EfficientNetB0 works better for assessing the grade of prostate cancer? Second, how does the proposed model compare to those previously used, and does it represent a significant step forward in enhancing the accuracy of diagnosis?

However, despite such advancements in the field of machine learning to make predictions for and diagnose prostate cancer, it has particularly been plagued by issues associated with standardization, reproducibility, and robustness of models across different patient groups. Large variability in methodologies of the existing literature, from traditional algorithms like Support Vector Machines to modern state-of-the-art deep learning architectures, therefore mandates an exhaustive inquiry into their comparative effectiveness.

The literature review would thus be well grounded in the urgency and importance needed in unpeeling the complexities associated with the diagnosis of prostate cancer. The plethora of machine learning models—from ensemble techniques through deep learning architectures—speaks volumes of this landscape of ever-dynamism and change. The results from the various studies presented proved the capabilities of the models presented to overcome the drawbacks associated with the traditional grading methods and PSA screening.

However, there is still a lack of common consensus on what the ideal method is. This study will, therefore, contribute to this discourse by systematically comparing performance across DenseNet121,

MobileNetV2, EfficientNetB0, and ResNet50 in the task of prostate cancer grade assessment. This work contributes toward determining best practices for the application of deep learning in the precise and efficient diagnosis of prostate cancer by offering an insight into the strengths and limitations of each model. That is what precisely is aimed by strategic dataset preparation, preprocessing techniques, and model training—answering which strategy turns out more effective in shaping new advances in diagnostic accuracy and innovative personalized treatment strategies for patients with prostate cancer.

3 Methodology

This section explains the dataset and step-by-step methods implemented for the research. Figure 1. shows the proposed methodology. The following is the explanation for each step.

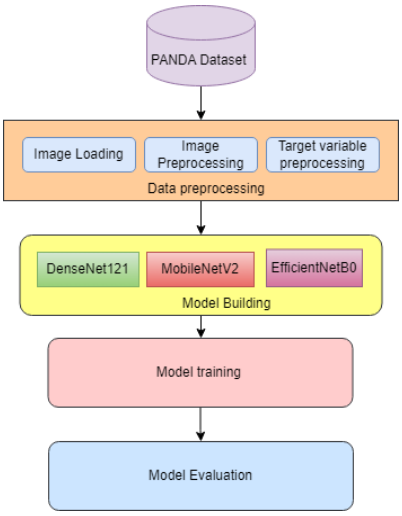

Figure 1: Working of Proposed Methodology

Dataset

The prostate cancer grade assessment (PANDA) dataset is a great tool for studying medical imaging with regard to the prostate tumor pathology issue. It is composed of microscopic high-resolution images of prostate biopsies for the histopathology Gleason and grading system, as well as notes that contain detailed information about these types of prostate cancer diagnosis. This dataset is aimed to provide researchers and developers in deep learning technology for the task of the prostate cancer grade classification with the ability to investigate and amend algorithms to achieve fast and less subjective grading. The PANDA dataset is the example of the multidimensional kind of biopsy images with labels on diverse prostate cancer manifestation aspects, used as a benchmark for diagnostic tools improvement in direction of accuracy increase and the course of our understanding and management of prostate cancer.

Data Preprocessing

Image Loading: The first step in our preprocessing pipeline is through opening medical images using the openslide and rasterio library. The libraries that are selected are those that are compatible in high resolution biopsy image, thus, the unique features of the images remain intact. Using openslide and rasterio allows us to have fast access to the medical imaging data details as well as to the geospatial raster data, which optimizes data to specific medical imaging reconstruction.

Image Preprocessing: The raw medical data are subjected to several preprocessing steps to ensure data integrity and effectiveness for modeling. As a regular rule, resizing the images to a standardized size of 224×224 pixels is important as it assures a consistent dataset and computation within the CNN computational framework is as simple as possible. Thus, this standardization of the computational resources not only saves resources but also sets the ground for an effective model regardless of the differences in image resolution. The conversion of images into NumPy arrays is a pivotal preprocessing step. This transformation facilitates numerical computations, allowing CNN to analyze the pixel-level information within the images. NumPy arrays offer a convenient way to manage the substantial volumes of data found in high-resolution medical images, allowing for easy integration with neural network architectures.

Target Variable Preprocessing: Recognizing the nuanced nature of prostate cancer grading, our research transforms the problem into a multilabel classification task. This decision is motivated by the hierarchical relationship between different cancer grades, a characteristic not adequately captured by traditional single-label classification. The target variable, representing the cancer grade, undergoes a sophisticated preprocessing step to better align with the intricacies of the disease. In our approach, each cancer grade is encoded as a binary label, reflecting the presence or absence of that specific grade. However, we go beyond conventional binary encoding by considering the hierarchical structure of cancer grades. For instance, if a biopsy exhibits grade 4, it is also treated as positive for grades 1, 2, and 3. This modification in target variable representation acknowledges the progression of cancer grades and enables CNN to learn and predict within this hierarchical framework.

Model Building

Three powerful CNN architectures, DenseNet121, MobileNetV2, and EfficientNetB0, are selected for their effectiveness in image classification tasks. DenseNet121 is known for its densely connected layers, MobileNetV2 to enhance both performance and accuracy, while EfficientNetB0 is chosen for its efficiency and performance. Algorithm 1. Shows model algorithm. The selected models are sequentially integrated into the script. For all architectures, a consistent structure is followed, including a global average pooling layer, a dropout layer for regularization, and a final dense layer with sigmoid activation for multilabel classification.

DenseNet121: The key characteristic of this architecture is its convolutional neural network (CNN), which involves a 'dense connectivity pattern' that enables the outgoing nodes within each layer to directly receive inputs from all nodes within the preceding layer. DenseNet121 which was designed to solve the vanishing gradient problem while improving the feature reuse technique consists of dense blocks with several densely connected layers within the blocks, so that information can flow and gradients can be reused. Having 121 layers leads to a compromise between the model depth and computation efficiency. The DenseNet121 model is really advanced for image classification, especially in the field of medical imaging, where the layer's ability to examine from the bottom up and learning the great layers brings the better accuracy.

MobileNetV2: MobileNetV2 which is a deep convolutional neural network (CNN) that follows the principle of being lightweight in the sense of being effective and efficient on mobile and edge devices. It is about the modification of the well-known MobileNet's model to make some alterations to the response time and precision or the accuracy of an image. MobileNetV2 engages the very important conditional statement convolution in which one parameter substitutes for the other, which leads to the significant reduction in its counting and computational requirements while keeping the expressive power.

EfficientNetB0: It is specialized as a CNN architecture, known for its efficiency and high performance in image classification projects. Tan and Le as the makers of EfficientNetB0, proposed the composite scaling technique which ensures that the depth, breadth, and resolution of the network are scaled at the same time and in the same way as the computational efficiency and model size are maximized. Such mechanism allows for a balance of model complexity and computational expenses which makes EfficientNetB0 a quite good option for limited computing environments. Enabling EfficientNetB0 to showcase its outright competency among other cutting-edge designs, its performance has been latest across different images classification benchmarks confirming its applicability to fields like medical imaging, such as prostate cancer, and further application to general computational vision.

Model Training

The training phase of Convolutional Neural Networks (CNNs) is important for developing accurate models in prostate cancer grading. This section explores the intricacies of the model training process, focusing on the optimization technique, hyperparameter choices, and the integration of data augmentation to improve the model's generalization capabilities. Following are parameters for training model.

Optimized Adam Algorithm: A fundamental aspect of our model training is the use of the Adam optimizer, a robust algorithm for optimizing stochastic objective functions. Adam integrates Adaptive Moment Estimation (Adam) and Root Mean Square Propagation (RMSprop) to update model parameters efficiently. Tailored for CNNs, Adam adapts to learning rates individually for each parameter, promoting faster convergence and improved model performance.

The learning rate, a critical hyperparameter, is meticulously set at 0.00010409613402110064 for the Adam optimizer. This careful calibration ensures a delicate balance between convergence speed and model stability, preventing overshooting and oscillations during training. This approach facilitates optimal convergence, capturing complex patterns in high-resolution biopsy images.

Epochs and Batch Size: The training process is organized into epochs, each representing a complete pass through the training dataset. The choice of 11 epochs strikes a balance between model complexity and generalization, preventing underfitting or overfitting. A batch size of 15 enhances computational efficiency, with batches representing subsets of the dataset processed together in each iteration. This accelerates training while reducing memory requirements.

Data Augmentation: To diversify the training dataset and improve generalization, a data augmentation generator introduces variability (Hao et al., 2021). Random transformations such as zoom, horizontal flips, and vertical flips simulate real-world scenarios, enhancing the model's resilience to different imaging conditions. This variation improves the model's overall performance.

Model Comparison

EfficientNetB0 is introduced as an additional exploration in optimizing prostate cancer diagnosis. The training progress and mean accuracy values are compared with those of MobileNetV2, DenseNet121, providing a comparative analysis of the 3 architectures.

Algorithm 1: Prostate Cancer Grade Assessment

Input:

- Training dataset (*train_df*)
- Test dataset (*test_df*)
- Image directory for training images (../*input/prostate-cancer-grade-assessment/train_images/)*

- Image directory for test images *(../input/prostate-cancer-grade-assessment/test_images/)*

Output:

- Trained deep learning models (*DenseNet121, MobileNetV2, EfficientNetB0*)
- Model training history and performance metrics

Variables:

- N: Number of training samples
- *x_train:* Matrix to store pre-processed training images
- *y_train:* One-hot encoded target variable for training
- *data_generator:* Image data generator for data augmentation
- *LR:* Learning rate
- *EPOCHS:* Number of training epochs

Algorithm Steps:

1: *N* = size of training dataset (*train_df*)
2: *x_train* = empty matrix of shape (*N, 224, 224, 3*) for storing pre-processed images
3*: y_train* = one-hot encode(train_df[*'isup_grade'*])
4: Split the training dataset into training and validation sets
5: *data_generator* = create_datagen().flow(*x_train, y_train, batch_size=BATCH_SIZE, seed*=2019)
6: **for** *epoch* in range(*EPOCHS*) **do**
7: **for** *i, image_id* in enumerate(*train_df['image_id']*) **do**
8: *x_train*[i, :, :, :] = preprocess_image(f'../input/prostate-cancer-grade-assessment/train_images/{image_id}.tiff')
9**: end for**
10: Train DenseNet121 model with pre-trained weights using *data_generator*
11: Train MobileNetV2 model with pre-trained weights using *data_generator*
12: Train EfficientNetB0 model with pre-trained weights using *data_generator* and learning rate scheduler
13**: end for**
14: Visualize and analyze training history for each model (*loss and accuracy*)
15: Compare and visualize the final accuracies of DenseNet121, MobileNetV2, and EfficientNetB0 models

Return: Trained deep learning models (*DenseNet121, MobileNetV2, EfficientNetB0*) and associated training histories

4 Result and Discussion

In this study, the dataset under investigation revolves around biopsy images pertinent to the grading of prostate cancer. The dataset encompasses two crucial components: the training dataset and the test dataset. These datasets serve as repositories of vital information essential for the deep learning task at hand. Three pre-trained convolutional neural network (CNN) architectures, namely DenseNet121, MobileNetV2, and EfficientNetB0, were employed for prostate cancer grade classification. Each model underwent training on the pre-processed dataset using a generator with data augmentation. Training occurred over a specified number of epochs with a defined batch size, and the training progress, reflecting changes in loss and accuracy, was monitored. Specifically for EfficientNetB0, a Learning Rate Scheduler was employed, dynamically adjusting the learning rate during training to enhance model convergence and performance, showcasing a thoughtful approach to optimize the training process and achieve better overall results.

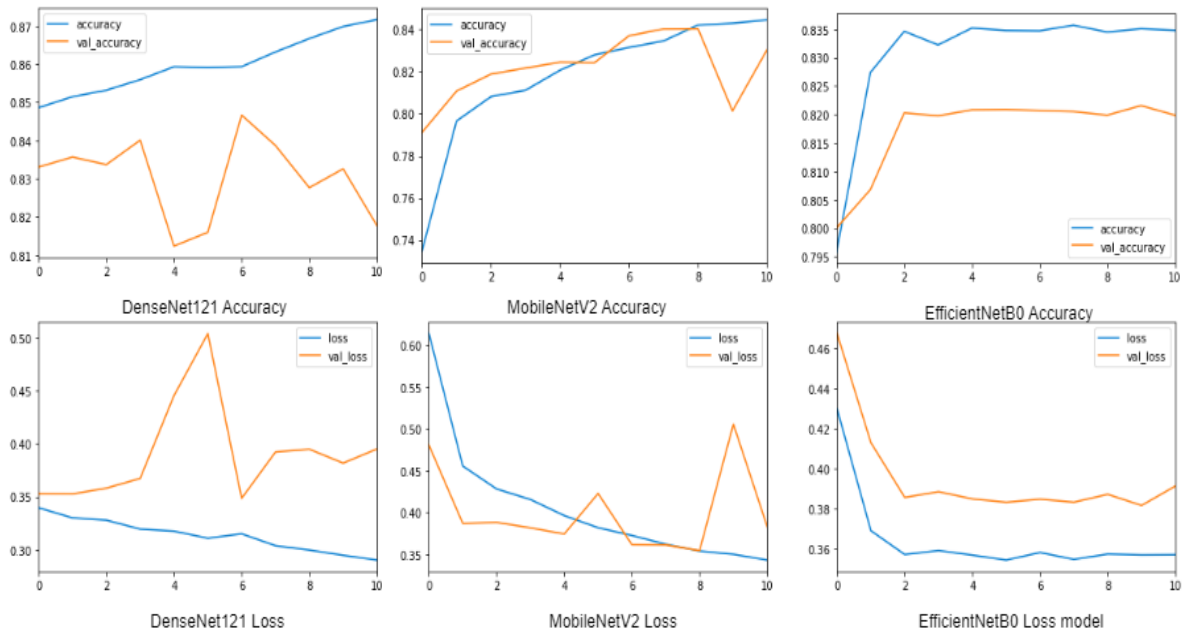

Figure 2: Accuracy and Loss Curve

Figure 2. shows the training plots visually represent the performance of three distinct neural network architectures—DenseNet121, MobileNetV2, and EfficientNetB0—during the training process. Accuracy and loss of training is indicated by blue and that of validation is indicated by orange. These plots consist of two primary curves: one for training and another for validation. The training loss curve shows the degree to which model fits the training data with each epoch. On the contrary, unlike training loss which evaluates its performance on a given training set trying to effectively memorize the given data, validation loss curve assesses how the model is able to generalize from the validation dataset. Also, training accuracy chart is an interpretation of the model's accuracy over the training dataset in terms of epochs, while validation accuracy curve is an interpretation of the model's accuracy on previously unseen new data in the process of training.

These curves reflect on how well the model learns and generalizes its knowledge. The curves here reveal the nature of the trends such as underfitting, overfitting, or convergence. Successfully training the model on the training datasets would yield less values for loss and better results for accuracy on both training and validation datasets, suggesting effective learning and generalization. Deep learning model validation with the training plots not only represents a diagnostic feature but also makes it easier to detect existing impending problems, adjust deep learning model training and achieving desired outcomes.

Table 1: Results of Models Performance

Model	Accuracy%	Val accuracy%
DenseNet	85.9847	83.0363
MobileNet	81.7693	82.1834
Efficient	83.0467	81.7400

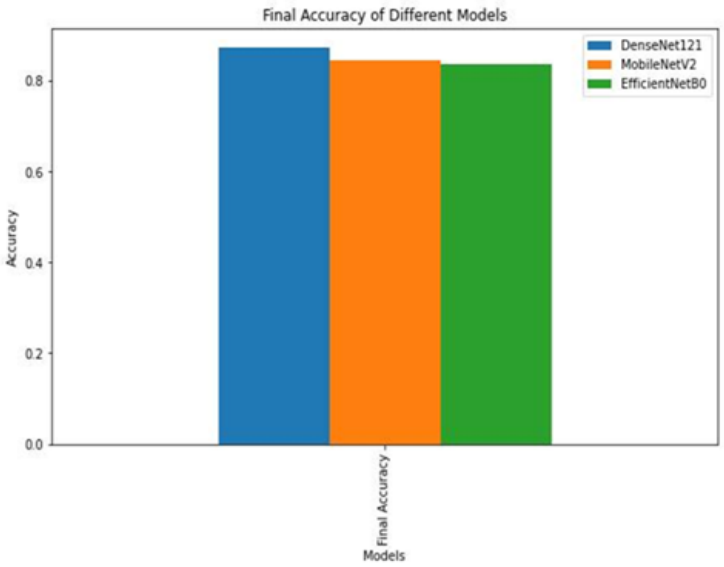

Figure 3: Accuracy Graph of Models

As given in table 1. The model evaluation results indicate varying levels of accuracy and validation accuracy for three distinct convolutional neural network (CNN) architectures: DenseNet121, MobileNetV2, and EfficientNetB0 are some of the examples of various neural networks that have been developed in recent years. DenseNet121 reached up to 85.98% accuracy on our training set that means its efficiency in learning complicated features from prostate patient imaging. Still, validation accuracy reaches the lowest level of 83.04% which is an indication of the model possibly losing its predictive power. With the same accuracy, MobileNetV2 supports 81.77% and similarly gets a validation accuracy of 82.18%, the two perform a balanced equivalent. EfficientNetB0, although endowed with a high level of accuracy of 83.05%, displays an even lower validation accuracy of 81.74%, thus exhibiting some generalization challenges on unseen data. This result draws attention to the necessity of model theory development and setting up, while pointing toward the necessity of looking in details for the opportunities for optimization of the model's generalization. Figure 3. shows model accuracy graph.

5 Discussion

In this section, we share the outcomes of a study that examined the grading of prostate cancer utilizing three distinct convolutional neural network (CNN) architectures: DenseNet121, MobileNetV2, and EfficientNetB0. Table 1 presents details of the accuracy and validation accuracy as well as the number of iterations taken by each model. Figure 2 shows the training plots of the models. In contrast, the accuracy graph is visualized in Figure 3.

Achieving 85.98% accuracy, the DensNet121 network performed the best on the training set, which is evidence of its ability to extract the most difficult features from the prostate cancer images. Nevertheless, the validation accuracy also dropped slightly by to 83.04%, implying possible overfitting, which highlights the paramountcy of model selection that is not far from tuning. MobileNetV2 showed a good performance with a balanced accuracy of 81.77%, followed by a validation accuracy of 82.18%, which illustrates its ability to generalize new data. EfficientNetB0, on the other hand, obtained an accuracy of 83.05%, but its validation accuracy of 81.74% needs to be more competent, thus raising the problem of its generalizability to new data.

The results are thereby proof of the fact that careful model selection and tuning are necessary in the field of prostate cancer diagnostics. The diagnostic devices, including training curves and accuracy graphs, give you an idea of how quick the learning will be and how well it will perform on the new data. Additional studies are required to get a better understanding of the universal nature of the DenseNet121 architecture, especially the overfitting issue.

6 Conclusion

Prostate cancer is a global health burden that needs innovative responses and an accurate diagnosis for better treatment options. This research has stretched the limits of deep learning in prostate cancer diagnosis by testing the capabilities of advanced convolutional neural network architectures like DenseNet121, MobileNetV2, and EfficientNetB0. Proper preparatory work on a comprehensive dataset, which includes the design of multilabel target variables and strategically planned train-validation splits, set a strong foundation for this study. The careful review of training plots brought out strengths as well as areas where there were chances to improve in these models. During training, DenseNet121 revealed an impressive 85.98% accuracy, but a minor dip in validation accuracy (83.04%) may suggest overfitting. MobileNetV2 is another example of a balanced model, with the performance rates being 81.77% and 82.18%, respectively, for accuracy and validation accuracy. By contrast, EfficientNetB0 manages to achieve quite a good result of 83.05% accuracy but suffers from lower validation accuracy (81.74%). These results indicate that proper selection and fine-tuning of models are important for prostate cancer diagnosis. Addressing this issue would require looking further into it so as to understand the meaning of model optimization better. This paper offers critical insights into the field that will significantly boost diagnostic accuracy and personalized treatment approaches among men suffering from prostate cancer. Future directions lie in refining the models to minimize overfitting, exploring ensemble methods, and integrating different datasets to improve generalization. The relevance of interpretability tools and collaboration with physicians must be considered when these models are adopted in real-life clinical settings. Moreover, expanding the scope to include other modalities and incorporating longitudinal patient data could provide a holistic understanding, fostering more accurate predictions and personalized treatment strategies.

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