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# Kidney Segmentations Using CNN models

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## ABSTRACT

For medical diagnostic tests, kidney segmentation from high-volume imagery is an important major. Since 3D medical images need a lot of Graphics Processing Unit memory, slices and patches are used for training and inference in traditional neural network variant architectures, which necessarily slows down contextual learning. In this research, Mobile Net and Efficient Net Convolutional Neural Network (CNN) models were trained for segmenting human kidney images generated from The Human Biomolecular Atlas Program (HuBMAP). The purpose of this work is to evaluate the effectiveness of different strategies for Glomeruli identification in order to solve the issue. The high size images were decoded to be fitted and trained in the models first, then the CNN models were trained. The CNN models result show that the Efficient Net has the highest accuracy rate with 99.49 %, and Mobile Net with 99.33 %.

**Keywords:** medical image, image processing, deep learning

## 1 Introduction

The Human Biomolecular Atlas Program (HuBMAP) is a major initiative aimed at accelerating the creation of a framework for mapping the human body down to single cells [1]. Identifying medically important Functional Tissue Units (FTUs) within whole slide microscopy pictures of human tissues is one component of this larger goal. Once these FTUs have been identified, data on their size, shape, number, and location within tissue samples can be used to aid in the construction of a spatially accurate and semantically explicit model of the human body.

An FTU is a “three-dimensional block of cells centered on a capillary, such that each cell in this block is within diffusion distance of every other cell in this block,” according to the definition. In 2013, Bernard de Bono and his colleagues coined the term "functional tissue unit," which they defined as "a three-dimensional block of cells centered around a capillary, such that each cell in this block is within diffusion distance of every other cell in this block". The glomerulus in the outer layer of kidney tissue known as the cortex, which has an area of around 800 mm2 and an average depth of about 9 mm in humans, is an example of an FTU.

Glomeruli are capillaries that aid in the filtering of waste materials from the bloodstream. The diameter

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of normal glomeruli ranges from 100 to 350 m, with a generally spherical form. Parietal epithelial cells form Bowman's capsule, podocytes cover the outer layer of the filtration barrier, fenestrated endothelial cells are coated with a glycolipid and glycoprotein matrix called glycocalyx and are in direct contact with blood, and mesangial cells occupy the space between the capillary blood vessel loops and are stained by the cobalt blue dye.

Image segmentation is a typical technique in digital picture processing and analysis that divides an image into several portions or areas, frequently based on the pixels' attributes [2]. Separating the foreground from the background, or clustering pixels based on color or shape similarity, are examples of image segmentation. The detection and labeling of pixels in an image or voxels in a 3D volume that represent a tumor in a patient's brain or other organs is a common use of image segmentation in medical imaging. Pathologists use Hematoxylin and Eosin (H&E) to stain body tissue during cancer diagnosis to distinguish between tissue types. They next utilize clustering, an image segmentation technique, to identify the different tissue types in their photos. Clustering is a technique for separating things in a scene into groups. The K-means clustering algorithm finds separations that keep objects within each cluster as near together as possible while keeping them as far apart as feasible from items in other clusters. The uses for picture segmentation are fairly varied. From the autonomous car driving [3] to medical diagnosis [4, 5], the requirement of the task of image segmentation is everywhere. The goal of renal glomeruli segmentation is to precisely delineate the kidney's outline, which is important for computer-aided diagnostics and subsequent radiation treatments. Kidney segmentation is typically a time-consuming and unclear task for radiologists because to the low contrast and vast slices of pictures. As a result, it motivates researchers to develop a more efficient auxiliary automatic kidney segmentation model.

Image segmentation, which is used to separate various anatomical features in medical images like X-ray, MRI, and CT scans, is an essential task in medical image processing [6, 7]. For precise diagnosis, treatment planning, and tracking of illness development, medical image segmentation is essential. For instance, segmenting tumors in MRI images can assist radiologists in precisely assessing the size and location of the tumor, which is crucial for choosing the most appropriate course of therapy. Identifying blood veins, organs, bones, and other structures in medical imaging is another usage for image segmentation. Medical image segmentation is utilized for surgical planning and simulation, radiation planning, and image-guided interventions in addition to diagnosis and treatment planning. Medical picture segmentation accuracy is critical to optimal patient outcomes, making it a fundamental part of contemporary medical practice.

Kidney segmentation is an essential task in medical image analysis that aims to extract relevant structures and tissues from kidney images [8, 9]. The accurate identification of glomeruli in human kidney tissue images is particularly important for the diagnosis and treatment of kidney-related diseases such as glomerulonephritis. In recent years, convolutional neural network (CNN) models have been extensively used for medical image segmentation tasks due to their high accuracy and efficiency. This paper presents a study on the effectiveness of various CNN models for kidney segmentation, with a specific focus on identifying regions with glomeruli in human kidney tissue images. The study aims to provide insights into the performance of Mobile-Net and Efficient-Net models for this task, with the ultimate goal of improving the accuracy of kidney segmentation for clinical applications. The article is organized as follows: following section is a discussion of existing approaches for kidney segmentation. Section 2 explains the methodology; dataset and CNN models. Section 3 presents the experiment study. The results are given in Section 4. Discussion is presented in Section 5. Conclusion are presented in the final Section, as well as avenues for further research.

## Related works

This section reviews previously glomeruli detection methods using machine learning, deep learning and CNN models.

Susan et al. used machine learning to develop a high-throughput method to automatically identify and collect quantitative data from glomeruli [10]. Their method involved little human involvement between processes and generates measurable data that is free of bias. The approach was simple to apply and does not require substantial image analysis knowledge. This study emphasizes the validation of the classifier and feature scores in mice, demonstrating the utility of using this method in murine research. Preliminary results show that following training on relevant data, the approach may be applied to data sets from many species, allowing for rapid glomerular recognition and quantitative measurements of glomerular characteristics.

Jaime et al. used CNN to automate Glomerulus categorization and detection from digitized kidney slide segments [11]. They trained the CNN using the publicly available pre-trained AlexNet model and adjust it to the system using Glomerulus and Non-Glomerulus regions derived from training slides. The method's results show that it is suited for correct Glomerulus identification in Whole Slide Images (WSI), with a high level of robustness and a low rate of false positive and false negative detections.

John et al. used a machine learning image classification method to construct a glomerular localization pipeline for trichrome-stained kidney sections to speed up and optimize the process [12]. The algorithm's training and test datasets included 74 and 13 complete renal sections, totaling approximately 28,000 glomeruli manually located. The performance achieved an average precision and recall of 96.94 percent and 96.79 percent, respectively.

Shruti et al. constructed CNN for properly identifying and segmenting glomeruli [13]. Cropped photos were used as training data for CNN, and the appropriate labels were used as output. An image processing procedure was created using this model to scan the test images and segment the GS glomeruli. No glomerular images could be distinguished from NPS and GS images with high accuracy using the CNN model (performance on test data: accuracy: 92.67 percent 2.02 percent and Kappa: 0.8681 0.0392). The CNN multilabel classifier-based segmentation model correctly identified the GS glomeruli in the test data (matthews correlation coefficient = 0.628).

Nicola et al. described a Computer-Aided Diagnosis (CAD) system for assessing worldwide glomerulosclerosis [14]. They looked examined approaches like SegNet and DeepLab v3+ that are based on Semantic Segmentation networks. In terms of pixel-level performance, they achieved mean F-scores higher than 0.81 and Weighted Intersection over Union (IoU) higher than 0.97 for both SegNet and Deeplab v3+ approaches. In terms of object detection level performance, they achieved best F-scores of 0.924 for non-sclerotic glomeruli and 0.730 for sclerotic glomeruli.

Gloria et al. used CNN to detect glomeruli using Whole Slide Imaging (WSI), semantic segmentation [15]. For pixel-level segmentation, a comparison of U-Net and SegNet CNNs is made for both a two and three class problem, namely; non-glomerular and glomerular structures and non-glomerular normal glomerular and sclerotic structures. The CNN classification used the two-class semantic segmentation result to separate glomerular regions into normal and global sclerosed glomeruli. On a dataset of 47 WSIs from human kidney sections stained with Periodic Acid Schiff, several approaches were examined (PAS). The best method for two-class segmentation was SegNet, which was followed by a fine-tuned AlexNet network to characterize the glomeruli. This procedure of segmentation and classification using sequential CNNs (SegNet-AlexNet) yielded 98.16 percent accuracy.

Previous methods detected glomeruli using different machine and deep learning techniques where the accuracy performances were between 70 % and 98 %. The performance still needs to be improved through applying and using new data and CNN models. The study’s use of DL, which is frequently employed in the medical field for prediction and diagnosis, is what provides it its significance.

# 2 Research Methodology

The segmentation problem in this context refers to the identification of glomeruli within a large dataset of images obtained using various imaging techniques, including light and electron microscopy. The process involves the detection of glomerular structures and their segmentation from the background to obtain a clear and accurate representation of the glomeruli. To address this challenge, the present study utilized a dataset of renal images obtained from different sources, including public repositories and in-house data collection. The dataset was curated to ensure that it contained a diverse set of images with varying levels of complexity and noise.

To detect glomeruli within the dataset, convolutional neural network (CNN) models were employed, which have been proven to be highly effective in image segmentation tasks. The models were trained using the dataset and evaluated based on their performance metrics, including accuracy, precision, and recall. The study utilized several state-of-the-art CNN architectures, including of Mobile-Net and Efficient-Net, to establish the best model for glomerular segmentation. These models were chosen due to their robustness and ability to capture complex features in the images, making them ideal for the segmentation problem. Figure 1 illustrates the flow chart of the study, which includes the dataset preparation, model training, and evaluation. The results obtained from the study demonstrate the effectiveness of the proposed approach in accurately detecting and segmenting glomeruli from the renal images. The present study utilized CNN models and a curated dataset to address this challenge and establish the best model for glomerular segmentation. The results obtained demonstrate the effectiveness of the proposed approach, which has significant implications for the diagnosis and treatment of kidney diseases.

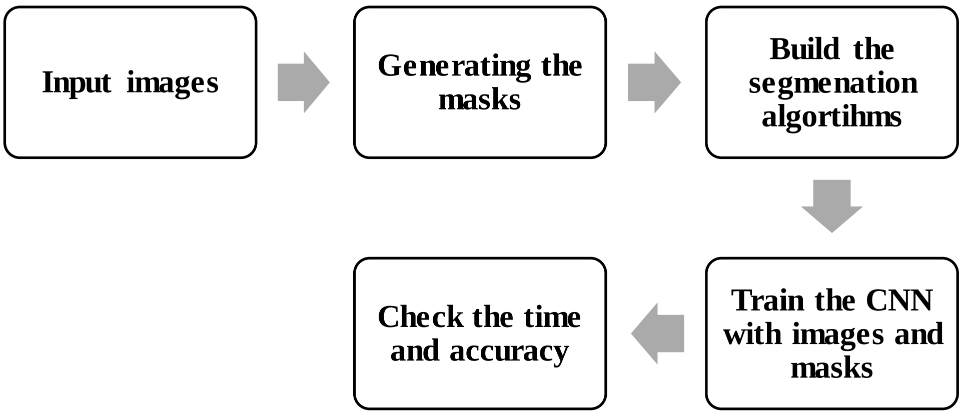


**Figure 1:** Study Flowchart

## 2.1 Dataset

The TIFF files in the data set contain 15 training and 5 test photos (see Figure 2) [16]. Histology tissue slices of the kidney are stained (with Periodic acid Schiff stain). The training images include a mask that specifies the areas of interest, which may be accessed in both unencoded JSON and run length encoded (RLE) form from a CSV file, which holds a series of data in a single value. Additional information, such as demographic data, is also available for each photograph. 11 fresh frozen and 9 Formalin Fixed Paraffin Embedded (FFPE) PAS kidney images were used in this HuBMAP hackathon. All 20 tissue samples include Glomeruli FTU annotations; some will be shared for training, while others will be used to judge submissions. Each human kidney contains around 600,000 glomeruli. Normal glomeruli have a diameter of 100-350m and are approximately spherical in shape.

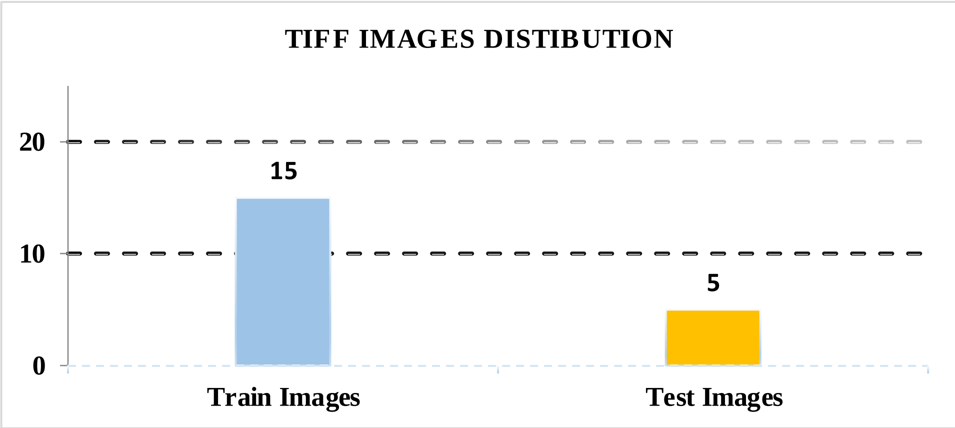


**Figure 2:** TIFF image distribution

### 2.2 Segmentation algorithms

Image segmentation is a method of dividing a digital image into distinct sections based on the distinct attributes of pixels in computer vision. It is often a low-level or pixel-level vision task, unlike classification and object identification, because the spatial information of a 65 image is particularly crucial for semantically segmenting various sections. The goal of segmentation is to extract useful data for easy analysis. In this scenario, the image pixels are labeled in such a way that each pixel in the image has the same color, intensity, texture, and other attributes [17, 18]. There is also a sort of segmentation known as panoptic 70 segmentation [19], which is a combination of two fundamental segmentation methods. Figure 3 depicts many forms of segmentation.

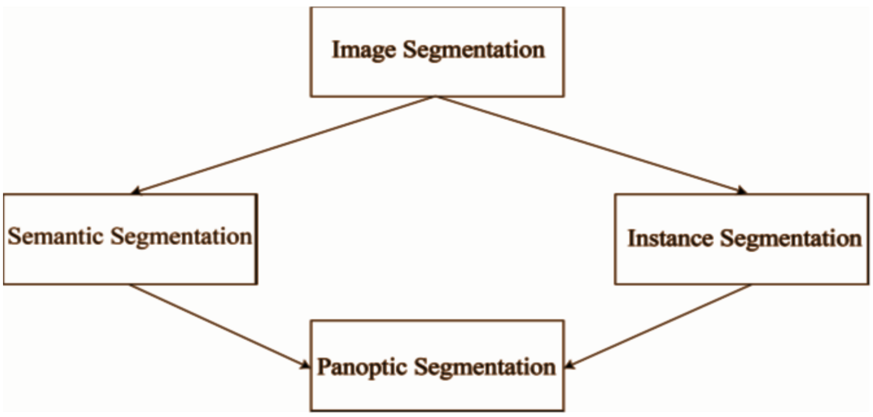


**Figure 3:** Image Segmentiaon

#### 2.2.1 Mobile Net

Mobile Net is an open-source lightweight neural network [20, 21]. In most practical and technical projects, it is necessary to reason in real-time in Inference, which means that a certain set of features of the deep learning model must be met. Mobile Net, the protagonist's protagonist, is a low-cost network with outstanding performance. The Backbone of the UNET, i.e., the characteristic extract network, is a massive VGG16 model. It's possible that many embedded devices aren't moving, preventing the real-time segmentation effect. Mobile net's main concept is depth wise separable convolution (depth separable convolution) It is expected that there is a 3 x 3 convolution layer with a 16-channel input and 32-channel output. The needed parameter is $16 \times 32 \times 3 \times 3 = 4608$. A 32 3× 3-size convolutional nucleus will traverse each of the 16 channels, eventually obtaining the requisite 32 output channels. The application depth can be split, and 16 feature maps are produced by traversing the 16-channel data using 16 $3 \times 3$-size convolutional cores. The 16 feature maps were connected to a 32 1 1 size before the fusion operation, and the required parameters were $16 \times 3 \times 3 + 16 \times 32 \times 1 \times 1 = 656$. The depth wise separable convolution may be shown to lower the model's parameters.

### 2.2.2. Efficient Net

Convolutional Neural Networks (ConvNets) are often built with a fixed resource budget and then scaled up for higher accuracy when more resources become available (see Figure 4) [22, 23]. Efficient Net is a convolutional neural network design and scaling method that uses a compound coefficient to scale all depth/width/resolution dimensions evenly. The Efficient Net scaling method consistently increases network breadth, depth, and resolution with a set of present scaling coefficients, unlike standard technique, which adjusts these factors randomly. B0 Efficient Net architecture is shown in Figure 5.

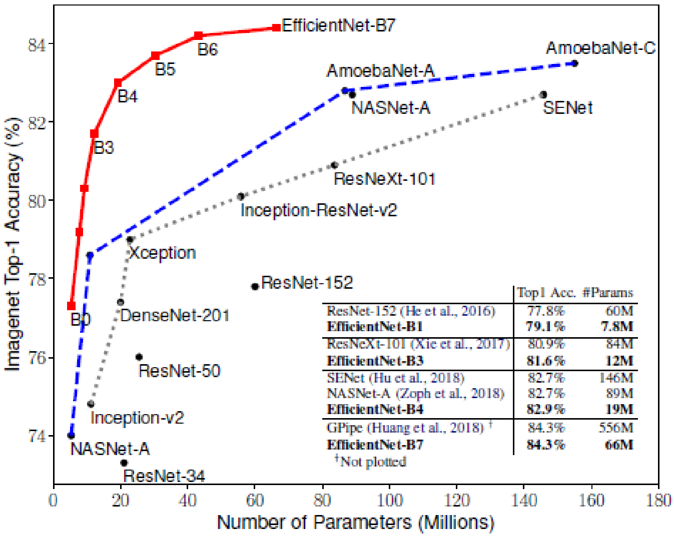


**Figure 4:** Model Size and ImageNet Accuracy [22]

| Stage $i$ | Operator $\hat{\mathcal{F}}_i$ | Resolution $\hat{H}_i \times \hat{W}_i$ | #Channels $\hat{C}_i$ | #Layers $\hat{L}_i$ |
|---|---|---|---|---|
| 1 | Conv3x3 | $224 \times 224$ | 32 | 1 |
| 2 | MBConv1, k3x3 | $112 \times 112$ | 16 | 1 |
| 3 | MBConv6, k3x3 | $112 \times 112$ | 24 | 2 |
| 4 | MBConv6, k5x5 | $56 \times 56$ | 40 | 2 |
| 5 | MBConv6, k3x3 | $28 \times 28$ | 80 | 3 |
| 6 | MBConv6, k5x5 | $14 \times 14$ | 112 | 3 |
| 7 | MBConv6, k5x5 | $14 \times 14$ | 192 | 4 |
| 8 | MBConv6, k3x3 | $7 \times 7$ | 320 | 1 |
| 9 | Conv1x1 & Pooling & FC | $7 \times 7$ | 1280 | 1 |

**Figure 5:** Simple Efficient Net B0 Architecture [22]

## 3 Experiment study

This section presents the results of applying the segmentation algorithms to the kidney images and masks. Before applying the segmentation algorithms, we have to build the masks which contains the important glomeruli features pixels. This section has few parts, started by visualizing the train images and their masks. Then the implementation of the algorithms is given. Last part states the evaluation criteria used for this work and discusses the results.

The experiments were performed using Python programming language and its libraries Keras and TensorFlow. The total number of images was 5987 after decoding. The original images are too big to fit with normal GUP, that's why all the implementations were performed using Kaggle website since it is provide us with 30 hours for using their GUP.

The original images were parted for groups of images, these are the original TIFF images with changing its formats to PNG with their given masks. Few algorithms were written for generating the masks from the encoding data file and read the tiff images and plot them. Figure 5 shows an original kidney image with their corresponding masks.

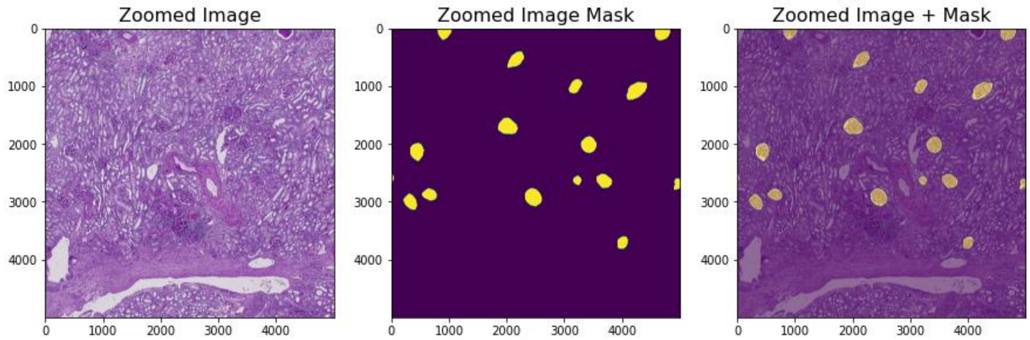


**Figure 6:** Zoomed image and its mask

Since the images sizes were huge, we must divide them into tiles of a specified size, such as 256 x 256, in order to train a deep learning model on them. For example, if the image is 5000 x 5000 pixels, we divide it into 256x256 tiles, divide 5000/256=19.53, and then multiply it by 20 to get a 20x20 grid with 256x256 tiles. Any image is padded to 256x256 pixels. The dataset was spilt to train and validation sets with total of 4789 for training images and 1198 for validation images. The images were resized to 256 *256 dimension. The total batch size was chosen to be 598 (ideal batch size is 128 per core (128*8=1024)) with 25 epochs for both CNN models.

Many image processing applications have used segmentation approaches that have been investigated and implemented. The ability to analyse and compare segmentation approaches is critical. The application developer must select the appropriate tool for implementation. Researchers must also analyse and improve new segmentation algorithms by comparing them to existing approaches in a systematic way.

It is difficult to come up with an evaluation measure for segmentation that considers all of the different types of performance measures needed to achieve the segmentation's goal [24, 25]. To avoid errors in output, segmentation performance is often evaluated using these three sorts of metrics: accuracy, precision, and efficiency. Where accuracy is a metric that indicates how well the segmentation result matches human perception, efficiency is a measure of how much time or effort it takes to segment data and precision refers to the degree to which the same result can be obtained over multiple segmentation sessions. The evaluation metrices of both CNN applied are shown in Figure 6 and 7.

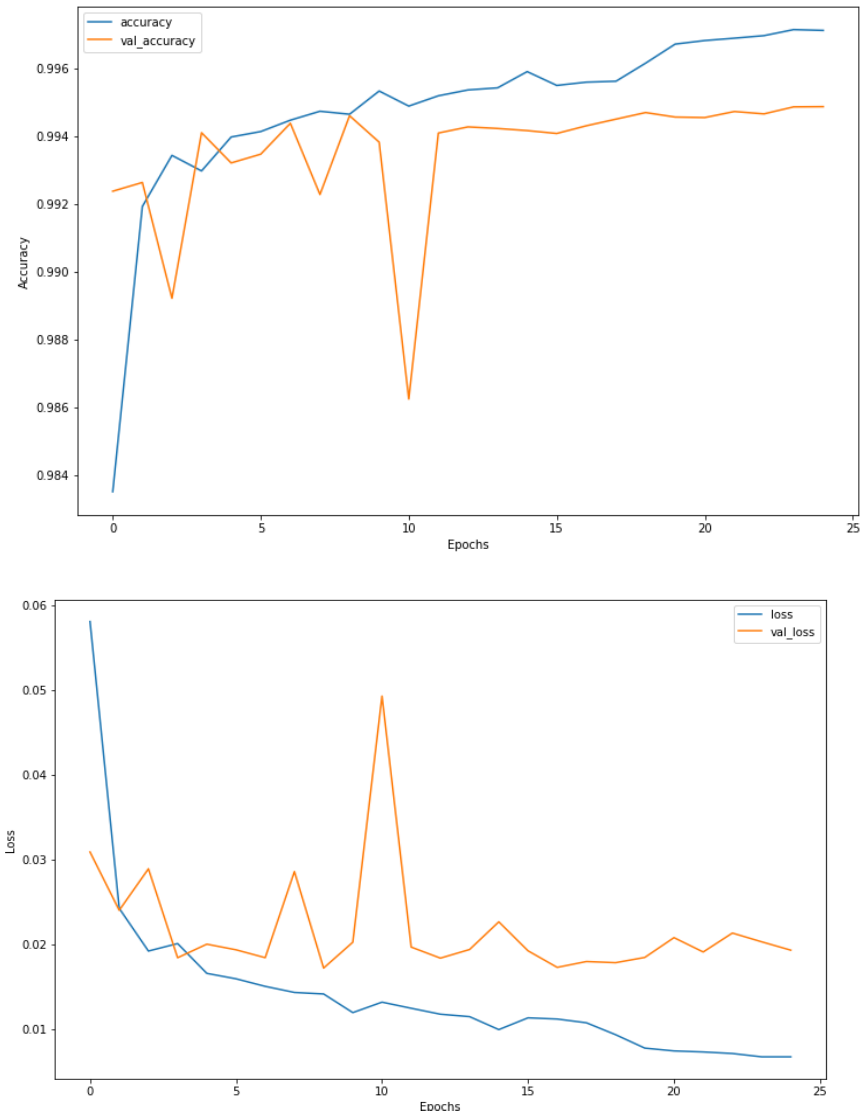


**Figure 7:** Accuracy and validation accuracy for Efficient Net, Loss and validation loss for Efficient Net

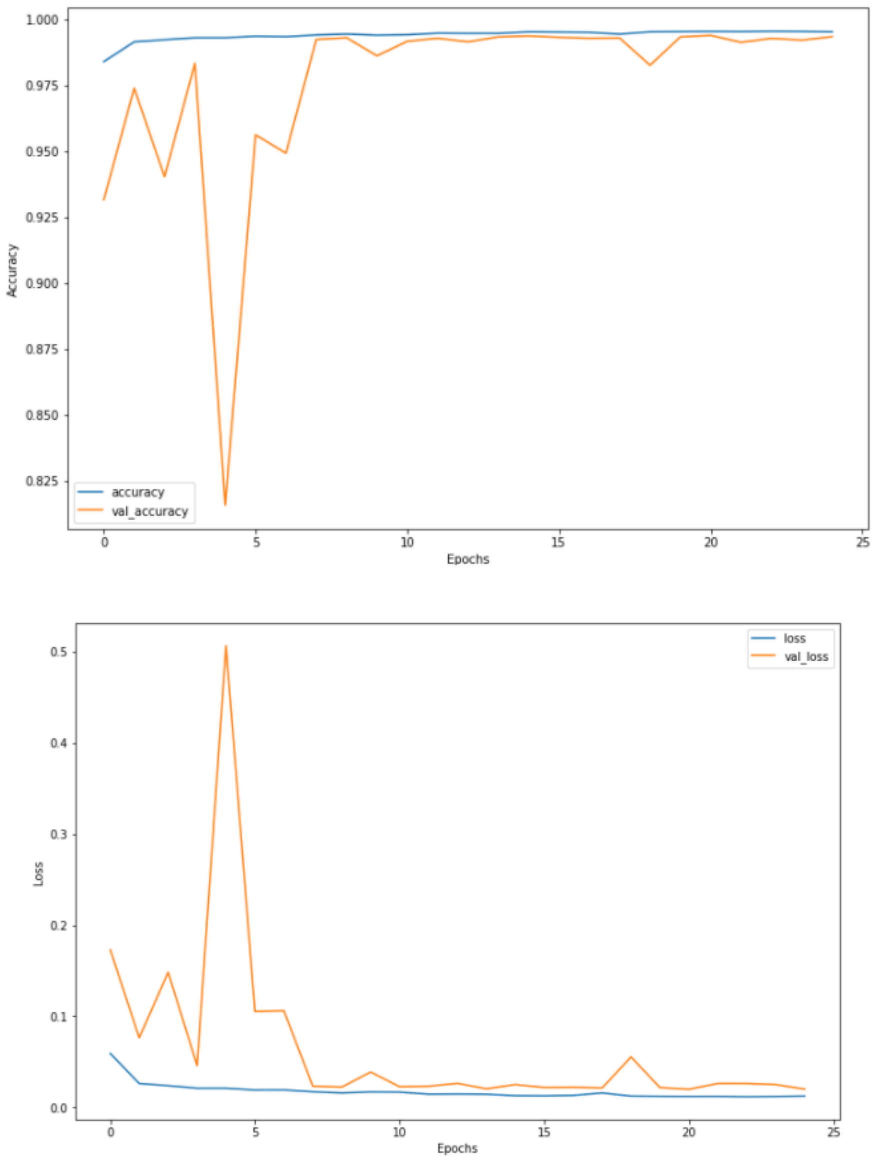


**Figure 8:** Accuracy and validation accuracy for Mobile Net

## 4 Results and Discussion

This section summarizes the result of applied CNN models for Kidney segmentation. Table 1, Table 2, Figure 8 and Figure 9 summarizes the evaluation parameters of segmentation algorithms. Two main parameters were considered in this research: accuracy, efficiency (Time).

**Table 1:** *Segmentation Algorithms Accuracy.*

| Algorithm | Accuracy % |
|---|---|
| Mobile Net | 0.9933 |
| Efficient Net | 0.9949 |

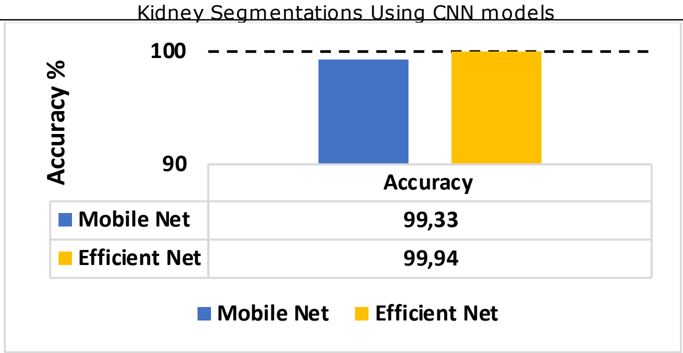


**Figure 8:** Segmentation Algorithms Accuracy

***Table 2:*** *Segmentation Algorithms Efficiency Evaluations.*

| **Algorithm** | **Time (Hour)** |
|---|---|
| Mobile Net | 00:30:24 |
| Efficient Net | 02:02:47 |

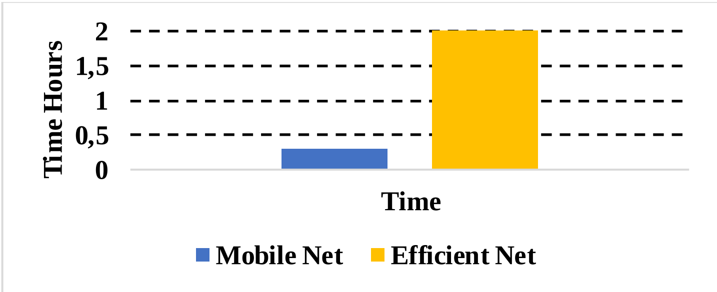


**Figure 9:** Segmentation Algorithms Efficiency Evaluations

Medical image segmentation is a crucial task in medical image analysis that aims to extract relevant anatomical structures from medical images. In recent years, convolutional neural network (CNN) models have been extensively used for medical image segmentation tasks due to their high accuracy and efficiency. The work presented in this paper aims to verify the effectiveness of various segmentation algorithms applied to the HuBAMP human kidney images dataset. This dataset contains 15 tiff images along with their corresponding masks, which were used to evaluate the performance of different segmentation algorithms.

The proposed approach involves a comparative study of two popular CNN models, MobileNet and EfficientNet, on the HuBAMP human kidney images dataset. The images and masks were first decoded into zip files, and the segmentation algorithms were then implemented on the dataset. The results obtained from the study indicate that EfficientNet achieved a higher accuracy of 99.49% with a total runtime of 02:02:47 hours, while MobileNet achieved an accuracy of 99.33% with a runtime of 00:30:00 minutes. The findings of this study demonstrate the potential of CNN models for accurate medical image segmentation, specifically for the HuBAMP human kidney images dataset.

# 5 Conclusions

The task of identifying regions with glomeruli in human kidney tissue images is particularly challenging due to the complex structure of the kidney and the variability in glomerular morphology. In recent years, several studies have shown the potential of CNN models for kidney segmentation tasks. The work presented in this paper aims to verify the effectiveness of various segmentation algorithms applied to the HuBAMP human kidney images dataset, with a specific focus on identifying regions with glomeruli. The study involves a comparative analysis of two popular CNN models, MobileNet and EfficientNet, on the HuBAMP human kidney images dataset. The images and masks were first decoded into zip files, and the segmentation algorithms were then implemented on the dataset. The results obtained from the study indicate that EfficientNet achieved a higher accuracy of 99.49% with a total runtime of 02:02:47 hours, while MobileNet achieved an accuracy of 99.33% with a runtime of 00:30:00 minutes.

The findings of this study demonstrate the potential of CNN models for accurate kidney segmentation, specifically for identifying regions with glomeruli in human kidney tissue images. However, there is still room for improvement, and future work can be extended to apply more CNN models such as VCG, ResNet, and DenseNet. These models may yield better results and provide new insights into kidney segmentation techniques. Moreover, further studies can be conducted to evaluate the effectiveness of these models on larger datasets and to investigate the generalizability of these models to different kidney-related diseases. Overall, this study provides valuable insights into the potential of CNN models for kidney segmentation, which can have significant implications for the diagnosis and treatment of kidney-related diseases.

# 6 Declarations

## 6.1 Authors' Contributions

**Mohammed MANSOUR:** Developing ideas for the research and the article, planning the materials and methods to reach the results, taking responsibility for the experiments, organizing and reporting the data, and writing the manuscript.

**2. Mert Suleyman DEMIRSOY:** Taking responsibility for the literature review during the research.

**3. Mustafa KUTLU:** Taking responsibility for organizing and reporting the data.

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