AUTOMATIC PROSTATE SEGMENTATION

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RECENT AUTOMATIC SEGMENTATION ALGORITHMS OF MRI PROSTATE REGIONS

Recent Automatic Segmentation Algorithms of MRI Prostate Regions: A Review

ZIA KHAN[1], NORASHIKIN YAHYA[1], (Member, IEEE), KHALED ALSAIH[2], MOHAMMED ISAM AL-HIYALI[1], AND FABRICE MERIAUDEAU[3], (Member, IEEE)

[1]Centre for Intelligent Signal and Imaging Research, Electrical and Electronic Engineering Department, Universiti Teknologi PETRONAS, Seri Iskandar 32610, Malaysia

[2]CNRS, IOGS, Université de Lyon, UJM-Saint-Etienne, Laboratoire Hubert Curien, UMR5516, 42023 Saint-Etienne, France

[3]ImViA/IFTIM, Universite Bourgogne Franche-Comté, 21000 Dijon, France

Corresponding author: Norashikin Yahya (norashikin_yahya@utp.edu.my)

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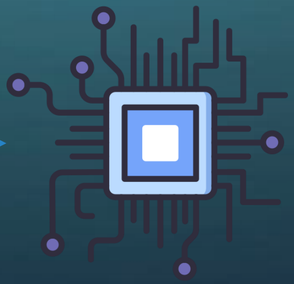
INTRODUCTION AND MOTIVATIONS

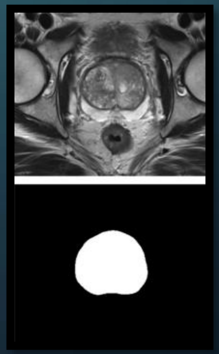
- The incidence of **prostate cancer** is increasing worldwide, especially as the population ages.
- **Early diagnosis**, when cancer is confined to the prostate gland, offers the best chance of treatment and survival.
- Manual segmentation of medical images is **subjective** and **time-consuming**.

INTRODUCTION AND MOTIVATIONS

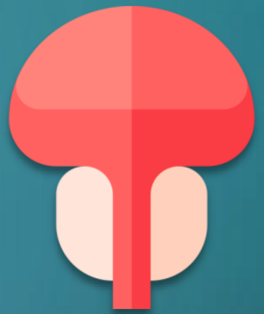
- There is a need to develop **automatic** segmentation algorithms to assist physicians, especially in the absence of radiologists.

- Segmentation of the prostate gland is **complex** due to the variability in shape and different tumour levels in each area.





PROSTATE ANATOMY



- The **prostate** is a glandular organ with four heterogeneous regions:
  - Anterior fibromuscular stroma (no glandular tissue)
  - Transition zone (TZ) (5% glandular tissue)
  - Central zone (CZ) (20% glandular tissue)
  - Peripheral zone (PZ) (70-80% glandular tissue)
- Prostate cancer most frequently develops in the peripheral zone (70-80%), followed by the transition zone (10-20%) and the central zone (5% or less).

PREPROCESSING OF MRI

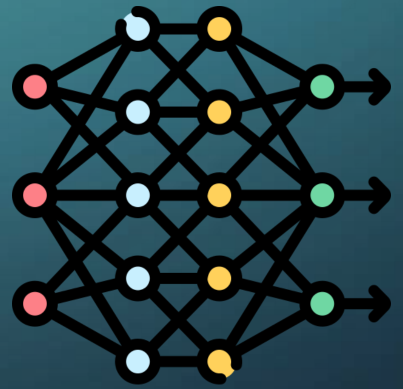
- **Thermal noise** is the main source of noise in MRI images and can be modelled as a Gaussian process.
- **Rician noise** affects the magnitude component of the MRI.
- Noise **reduction** techniques: median filter, bilateral filter, wavelet shrinkage, non-local mean (NLM), BM3D filter.
- The **BM3D** filter offers a good compromise between noise reduction and maintaining image quality.

ML SEGMENTATIONS

- **Atlas-based methods**: use pre-segmented atlases to guide segmentation, with registration methods to align the atlas with the target image.
- **Deformable model-based methods**: use statistical shape models to segment the prostate, adapting them to patient-specific contours.
- **Fuzzy C-Means (FCM)**: unsupervised clustering algorithm for prostate segmentation using multispectral MRI images.

DEEP LEARNING SEGMENTATIONS

- **Convolutional Networks** (CNN) are effective for semantic segmentation, labelling each pixel with the class to which it belongs.
- DL segmentation **techniques** are divided into five classes:
  - Features encoders
  - Upsampling
  - Resolution enhancement
  - Based on regional proposals (RPN)
  - Generative adversarial networks (GAN)



LOSS FUNCTIONS

- **Loss functions** are crucial for the training of neural networks, main loss functions used in prostate MRI segmentation are:
  - **Cross-Entropy**: widely used, calculates the loss for each pixel separately.
  - **Dice Loss**: measures the difference between the predicted and actual segmentation.
  - **Intersection over Union**: similar to Dice Loss, optimises segmentation metrics.

DATASETS AND EVALUATION

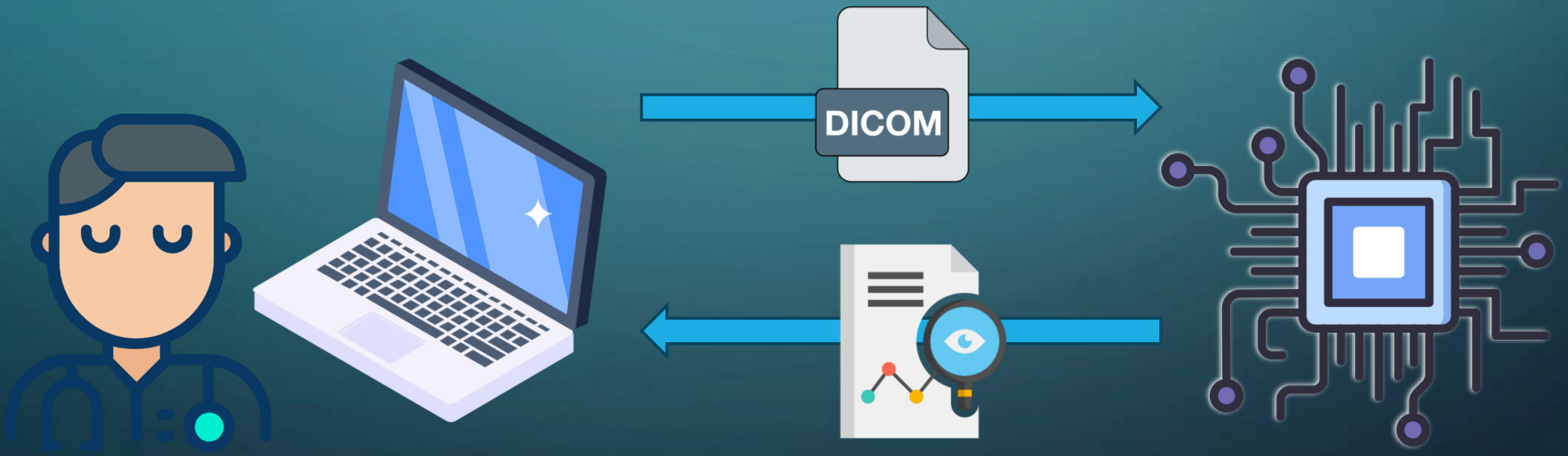
- Public datasets for prostate segmentation: **PROMISE12**, NCI-ISBI 2013, I2CVB, **PROSTATEx**, PROSTATEx-2

EVALUATION METRICS

- **Dice Similarity**
  - The similarity between predicted and manual segmentation.
- **Sensitivity**
  - The ability to correctly identify true positives
- **Specificity**
  - Measures the ability to correctly identify true negatives.
- **Hausdorff Distance**
  - The maximum distance between the boundaries of the segmentations.

OUR PROPOSAL

- Build an **intuitive** platform for doctors to upload their MRI scans and get the most 'accurate' prediction in a **simple** and **efficient** way.



PROBLEM DESCRIPTION

- Given a set of medical images, specifically MRI, we're trying to accurately obtain a **segmentation** of prostate MRI images.

HANDLING DATA TYPES

- **Variability** in MRI scans (different formats, resolutions, noise levels), we also need to handle **non-uniform** data, with differences in intensity levels across scans that requires **normalization**.

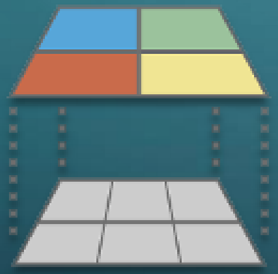
HANDLING DATA TYPES

DICOM	MHD
▪ Standardized storage, transmission, and exchange of medical images in clinical environments. ▪ A single **dcm** file that contains both the image data and extensive metadata.	▪ Used for storing medical images along with metadata in research and deep learning applications. ▪ Consists of a header file (**mhd**) that describes the image properties, and a separate raw binary file (**raw**) that contains the pixel/voxel data.

HANDLING DATA TYPES

- **Preprocessing** pipeline to **standardize** input, this includes several techinques commonly used in **data normalization**:

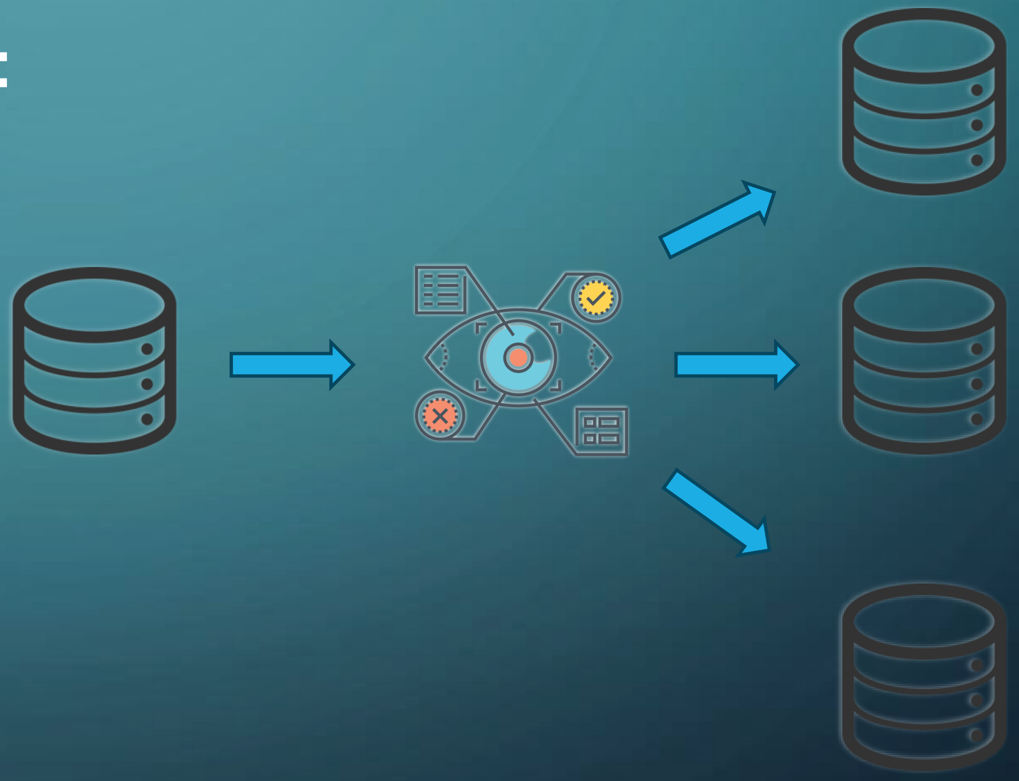
RESAMPLING



NORMALIZATION

HANDLING DATA TYPES

- Data **augmentation** tecniques:
  - Random zoom.
  - Random shift.
  - Elastic Transformation.
  - Adding Gaussian Noise.
  - Random Brightness Contrast.
  - Random Flip and Rotation.



MODEL ARCHITECTURE

- U-Net is a convolutional neural network that was developed for image segmentation.

- The network is based on a fully CNN whose architecture was modified and extended to work with fewer training images and to yield more precise segmentation.

MODEL ARCHITECTURE

- Why **UNet**?
  - Efficient, handles spatial information well.
  - Skip connections help in retaining fine-grained details.

- Training Strategy:
  - **Loss function**: Using Dice Loss with Dice Coefficient as metric alongside accuracy and Mean Intersection over Union.
  - **Optimizer**: Adam with learning rate scheduling.

RESIDUAL U-NET VARIANTS

Spacial Dropout	Attention Gate	Squeeze Excite
▪ Uses skip connections to improve gradient flow and stability. ▪ Regularization via **Spatial Dropout** to enhance generalization.	• Upsampling via transposed convolutions, with attention gates refining the skip connections.	▪ Improves feature representation by adaptively recalibrating channel-wise feature responses.

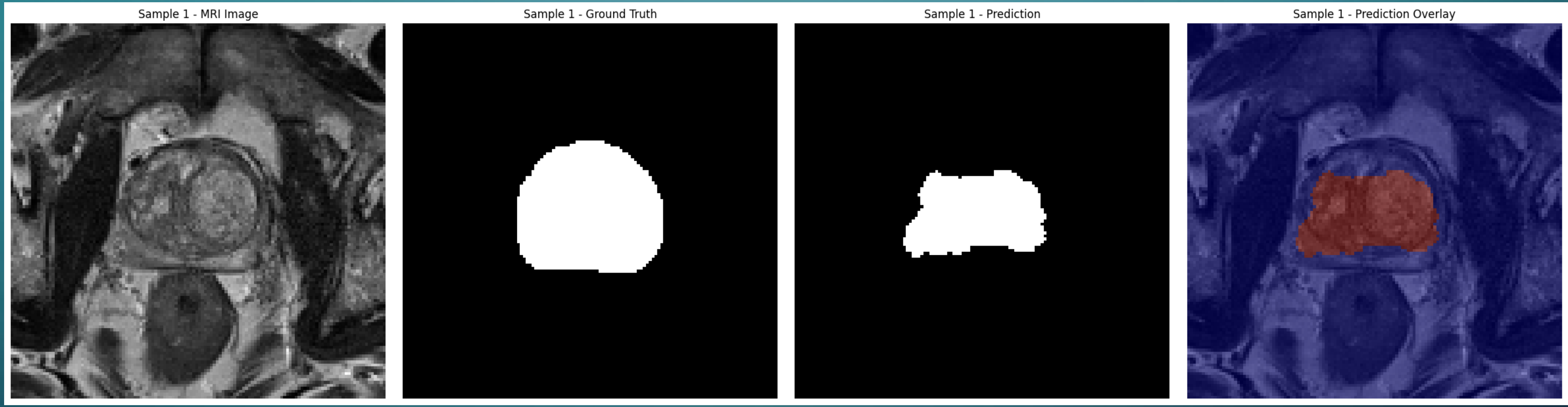
TRAINING PIPELINE

Data Preparation	• Loading data, apply preprocessing.
Models Initialization	• Build the models and compile them.
Callbacks and Optimization	• Various callbacks like Early Stopping, Checkpoint and ReduceLR on Plateau.
Training Execution	• Fit the model and then save the result.

EVALUATION

- **Ensemble Prediction**:
  - Averages outputs from our ensamble for the better result.
- **Evaluation**:
  - Computes Dice Coefficient, Accuracy, and Mean IoU on validation data.
- **Visualization**:
  - Displays MRI images, ground truth, and model predictions for comparison.

EVALUATION


Sample 1 - MRI Image
Sample 1 - Ground Truth
Sample 1 - Prediction
Sample 1 - Prediction Overlay

PLATFORM INTEGRATION

Backend

- Flask API for segmentation prediction.
- Ensemble model inference.
- Handles multiple image uploads, processes, and returns overlays.

Frontend

- React (Vite) Web interface for image upload and visualization.
- Rest API (using axios) to interact with the backend.

DEMO TIME

CONCLUSION AND FUTURE DIRECTIONS

- Working on this type of datasets proved to be challenging, given their non uniformity between each other and this was reflected on the difficulty of training our models. Nonetheless our ensemble proved to be acceptable.

- A possible other approach would be Multi-modal MRI fusion (combining T2W, DW-MRI, and DCE-MRI for better accuracy).

CONCLUSION AND FUTURE DIRECTIONS

- The importance of having a system that is simple and intuitive but that can give doctors all the instruments on performing this kind of tasks in the most efficient way.
- But this is not something that, depending on the kind of task, can be achieved and harmonized as easy as we would want it to be.

THANK YOU