**Computer Assisted Prostate Cancer Diagnosis - Literature Review**

**Introduction**

Prostate cancer (PCa) is the third leading cause of cancer death in America. However, current diagnostic practices such as digital rectal examination (DRE), prostate-specific antigen (PSA), and transrectal ultrasound (TRUS) underestimate the severity of the cancer in 30% of patients1. The low sensitivity and suboptimal accuracy of traditional PCa classification techniques has lead to a popularity increase in multiparametric magnetic resonance imaging (MPMRI)2. MPMRI is a composite imaging technique consisting of capturing T2-weighted imaging (T2WI), diffusion-weighted imaging (DWI), and apparent diffusion coefficient (ADC) or dynamic-contrast enhanced (DCE) MRI1,2,3. However, diagnostic accuracy is still largely dependent on the skill of the radiologist and is a time consuming task. In response to these issues, researchers have developed several methods that incorporate machine learning (ML) to assist in PCa classification and diagnosis.

**Current Research**

Current research uses supervised learning machine learning (ML) technologies on preprocessed, segmented MPMRI images with cancerous regions registered by experts and confirmed with ground truths determined by professional pathologists2. Performance of ML techniques is measured with K-fold cross validation scores based on a receiver operating characteristic (ROC) area-under-curve (AUC) metric2. AUC scores measure the propensity of an ML algorithm to predict true positives vs. false positives; due to the small (< 100 case) data set size used in many SVM PCa detection studies, the size of each fold’s testing set during cross validation is unity. High AUC scores indicate accurate algorithms.

Kernel-based ML methods such as support vector machines (SVM) are the most popular for PCa classification due to their extreme generalizability2. Modifications to traditional SVM margin maximization techniques4 including probability weighting (p-SVM)5, cost-sensitivity6, Fisher linear discriminant analysis7, fuzzy *c*-means8, and genetic algorithm-based hyperparameter maximization9 generally improve AUC scores. The AUC of SVM MPMRI applications range from 0.83-0.96, with the majority of AUC scores2 below 0.90, which suggests there is still considerable room for improvement2,10,11.

In recent years, several groups8,12,13,14,15 have found high AUC scores using ML technologies other than SVM derivatives. Random forest classification studies have shown AUC as high as 0.923 but with widely variant dataset sizes, ranging between 12 and 347 patients12,13,15. K-nearest neighbors classification16 and convolutional deep-learning networks trained in 3D space also appear promising (AUC 0.84)14.

**Project Direction**

While previous studies have examined the effect of isolated ML algorithms on different datasets for PCa identification or Gleason scale classification, researchers have yet to compare multiple ML technologies on a single, consistent dataset. In this project, we will compare various optimized ML techniques (e.g., random forest, deep learning, SVM) on a single dataset to study the most effective ML techniques for combination with MPMRI.

**Works Cited**

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Breanna’s Sources:

1. *“A Machine Learning Approach to Identify Prostate Cancer Areas in Complex Histological Images” by Salman et. al*
2. *“****Prostate Cancer Diagnosis using Deep Learning with 3D Multiparametric MRI” by Liu et. al***
3. *“Combined unsupervised–supervised classification of multiparametric PET/MRI data: application to prostate cancer” by Gatidis et. al*
4. *“* ***Decision forests for learning prostate cancer probability maps from multiparametric MRI****” by Ehrenberg et. al*
5. *“Detection of Prostate Cancer Based on Multi-Parametric Regional MRI Features” by Tan et. al*

Alex’s Sources:

1. *“Computer-Aided Diagnosis of Prostate Cancer on Multiparametric MRI: A Technical Review” by Wang. et. al*
2. *“Kernel-based Learning from both Qualitative and Quantitative Labels: Application to Prostate Cancer Diagnosis Based on Multiparametric MR Imaging” - Emilie Niaf et. al*
3. *“Prostate Cancer localization with multispectral MRI using cost-sensitive support vector machines and conditional random fields” - Y. Artan et. al.*
4. “Region of interest based prostate tissue characterization using least square support vector machine LS-SVM” by S. Mohamed
5. *“Prostate cancer: Computer-aided diagnosis with multiparametric 3-T MR imaging -- Effect on observer performance” by T. Hambrock et. al.*

Extra:

1. *“Support vector machines” - Hears et. al*
2. *“Detection of prostate cancer by integration of line-scan diffusion, T2-mapping, and T2-weighted magnetic resonance imaging; a multichannel statistical classifier” - Chan et al.*
3. *“Decision support system for localizing prostate cancer based on multiparametric magnetic resonance imaging” - Shah et al.*
4. *“Multiparametric MRI maps for detection and grading of dominant prostate tumors” - Moradi et al.*
5. *“Computerized analysis of prostate lesions in the peripheral zone using dynamic contrast enhanced MRI” - Vos et al.*
6. ***“Prostate cancer characterization on MR images using fractal features” - Litjens et al.***
7. *“Multi-kernel graph embedding for detection; Gleason grading of prostate cancer via MRI/MRS” - P. Tiwari*