Friedrich-Alexander-Universität Erlangen-Nürnberg

Feature Extraction Method of Prostate Cancer Based on Spatio- Temporal Image Data

Course: Spatio-Temporal data analysis techniques with applications in medical imaging

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Abstract

Prostate cancer is a leading cause of cancer-related mortality among men. Effective diagnosis and monitoring rely heavily on advanced imaging techniques and robust feature extraction methods. The purpose of this report is to review and integrate various feature extraction methods applied to prostate cancer spatial-temporal data, focusing on MRI, ultrasound images and spital temporal analysis on biopsy data. We evaluate the effectiveness of the approach in grading prostate cancer and compare it to traditional methods. Techniques such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), SVM, and Convolutional Neural Networks (CNNs) with transfer learning, particularly modified VGG19, Residual Network (resNet50) and inceptionv3 are evaluated. We also compared with old technique result with new technique. Mostly we talked about the CNNs (VGG19) models, residual Network (ResNet50) and inceptionV3 which are the most modern and successful feature extraction till now. Try to explain these four deep neural models using various classification methods and find out the best shoot among them.

Experimental results demonstrate the superior performance of modified VGG19 in enhancing diagnostic accuracy, precision, and recall. This paper underscores the potential of these methods in improving prostate cancer detection and treatment planning.

Introduction

Prostate cancer, characterized by uncontrolled growth in the prostate gland, is a significant health concern for men globally. Early detection and precise monitoring are crucial for effective treatment. Primary PCa is often multifocal and consists of a dominant genetic clone accompanied by several less prevalent ones. Tumor clones have been observed to carry different genetic alterations, which implies the presence of spatial heterogeneity. Due to the diverse molecular landscape of each individual prostate tumor, it has proven challenging to establish a reliable strategy for risk stratification and prediction of treatment outcome. Hence, to increase the treatment efficiency and improve chances of patient survival (Md. Rafiul Hassan a, 2021).

What is spatial- temporal data in medical image

Spatial refers to space. Temporal refers to time. Spatiotemporal, or spatial temporal, is used in data analysis when data is collected across both space and time. In medical image data processing or feature extraction we can define this way, how the changes happening any organs processing or feature extraction we can define this way, how the changes happening any organs effectiveness of disease over time (Maja Marklund, 2022).
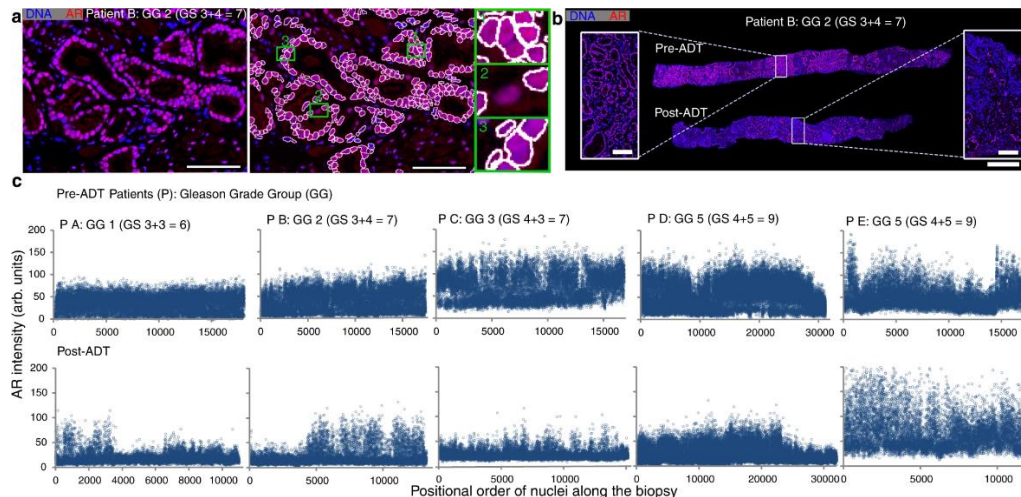
Fig(1): IHC images for the AR activity in epithelial nuclei performed on needle biopsies pre- and post-ADT) (Maja Marklund 1, 2022).

Spatial-temporal medical imaging, including MRI and ultrasound, plays a vital role in diagnosing and tracking the progression of prostate cancer. Spatial-temporal data consists of spatial data (such as images) captured over time, allowing for dynamic analysis of disease progression. Feature extraction, the process of transforming raw data into meaningful information, is essential for accurate analysis and classification of medical images. This report reviews various feature extraction methods, emphasizing their application in prostate cancer detection.

State of the art

The state-of-the-art in prostate cancer feature extraction based on spatial-temporal data involves combining advanced imaging techniques with advanced machine learning and deep learning models. Here are the key components and recent advancements in this field:

Integration of AI and Spatial Transcriptomics

Artificial Intelligence (AI): AI, particularly convolutional neural networks (CNNs), are being used to analyze histological images of prostate cancer. These networks are trained to identify morphological features in H&E-stained slides, which are then correlated with gene expression profiles obtained from spatial transcriptomics. This approach helps in understanding the genetic and morphological heterogeneity of prostate cancer (Eduard Chelebian 1, 2021).

Spatial Transcriptomics This technique involves capturing gene expression data across different spatial regions of the tissue. When combined with AI, it allows for the identification of biologically meaningful regions without the need for additional training, improving cancer detection and treatment decision-making (Shadrack M. Mutuku 1, 2022).

Deep Learning Models for Image Analysis

Multi-Channel and Multi-Spatial Attention Convolutional Neural Networks (MCMS-CNN): These models are designed to enhance the extraction of relevant features from whole-slide

histopathology images by focusing on the most important regions and channels. This improves the grading accuracy of prostate cancer according to the ISUP standards.

Attention U-Net and Feature Pyramid Networks: These models further improve segmentation and feature extraction from MRI and other imaging modalities. They provide more accurate and detailed segmentation of cancerous tissues, aiding in better diagnosis and treatment planning (Pablo Cesar Quihui-Rubio, 2023)**.**

Methodology

The focus of this study is to create and apply the feature extraction technique and find out the best fitted machine learning model based on prostate cancer detection.

Data Collection

In recent years, the most widely used data collection methods for prostate cancer detection have incorporated advanced imaging techniques and biomarkers. Here are the key methods.

Fresh-Frozen Samples: Tissue samples intended for molecular studies (e.g., DNA, RNA analysis) are quickly frozen in liquid nitrogen and stored at -80°C. This preserves the molecular integrity of the tissue (Miriam F. Rittel 1, 2023).

Formalin-Fixed, Paraffin-Embedded (FFPE) Samples: Tissue samples intended for histological examination are fixed in formalin and then embedded in paraffin wax. This process preserves cellular architecture and is suitable for long-term storage.

Snap Freezing: For specific analyses like proteomics, snap-freezing of tissue in isopentane cooled in liquid nitrogen can be performed (htt).

High-resolution imaging techniques: H&E staining involves fixing prostate tissue in formalin, embedding it in paraffin wax, slicing into thin sections, and staining with hematoxylin and eosin to highlight cellular structures. This process enables the visualization of tissue architecture under a light microscope, identifying tumor cells, glandular structures, inflammatory cells, and stroma. High-resolution digital pathology systems can capture detailed images of these stained sections for further analysis (Maria K. Andersen, 2021).

Multiparametric MRI

Multiparametric MRI (mpMRI) is a non-invasive imaging technique that combines multiple MRI sequences to provide detailed images of the prostate, each highlighting different tissue properties. T2-Weighted Imaging (T2WI) offers high-resolution anatomical details, Diffusion-Weighted Imaging (DWI) measures water molecule diffusion, and Dynamic Contrast-Enhanced MRI (DCE-MRI) evaluates blood flow and vascularity. Additionally, Apparent Diffusion Coefficient (ADC) mapping quantifies diffusion, and Magnetic Resonance Spectroscopy (MRS) analyzes tissue chemical composition. Radiologists interpret mpMRI scans to identify suspicious areas, assess disease extent, and guide biopsies or treatment. The Prostate Imaging Reporting and Data System

(PI-RADS) standardizes mpMRI findings, enhancing diagnostic accuracy and supporting personalized treatment planning (Md. Rafiul Hassan a M. F., 2021).

Spatial Transcriptomics (ST)

Spatial Transcriptomics (ST) techniques are employed to obtain gene expression profiles with spatial resolution across tissue sections, allowing researchers to visualize and quantify RNA molecules within the histological context of the tissue. This method involves the use of spatially barcoded oligonucleotide arrays or specialized slides that capture RNA from specific locations on the tissue section. After tissue processing and RNA extraction, next-generation sequencing is used to generate spatially resolved gene expression data. This approach enables the identification of gene expression patterns, cellular heterogeneity, and spatial organization of biological processes within the tissue, providing valuable insights into the molecular underpinnings of health and disease (Jun Du, 2023).

Preprocessing

Image Preprocessing: Enhancing and preprocessing images is crucial for reducing noise and improving the quality of the features in the data. Techniques such as Ant Colony Optimization (ACO) can be used to optimize the preprocessing steps. ACO, inspired by the foraging behavior of ants, is an effective algorithm for edge detection and noise reduction in images. By iteratively improving the paths taken by artificial ants on the image, ACO helps in identifying and enhancing relevant features, thus improving the clarity and usability of the images for further analysis (Raheja, 2021).

Normalization: Normalizing data is essential to account for variations in staining and scanning procedures that can introduce biases in the image analysis. Normalization techniques adjust the intensity values of the images to a common scale, ensuring that differences in staining intensity or scanner sensitivity do not affect the interpretation of the data. This process helps in standardizing the data, making it comparable across different samples and ensuring accurate downstream analysis (Milos Stanisavljevic, 2018).

Feature Extraction

Deep Learning Models: Using convolutional neural networks (CNNs), such as VGG-19, ResNet50, InceptionV3, and DenseNet, pre-trained on large datasets like ImageNet, has revolutionized medical image analysis, including the study of prostate cancer. These networks are adept at learning hierarchical representations of image features, which are essential for tasks such as tumor detection and classification.

VGG-19 Modification: VGG-19, originally designed for image classification, can be adapted for medical imaging tasks like prostate cancer detection. One effective modification involves replacing traditional max pooling layers with global average pooling in the final layers. Global average pooling computes the average of each feature map across its entire spatial dimensions, preserving spatial information and reducing the number of parameters compared to fully connected layers. This modification enhances feature extraction capabilities, making the network more suitable for capturing subtle variations indicative of prostate cancer in images (Md. Rafiul Hassan

a M. F., Prostate cancer classification from ultrasound and MRI images using deep learning based Explainable Artificial Intelligence, 2022).
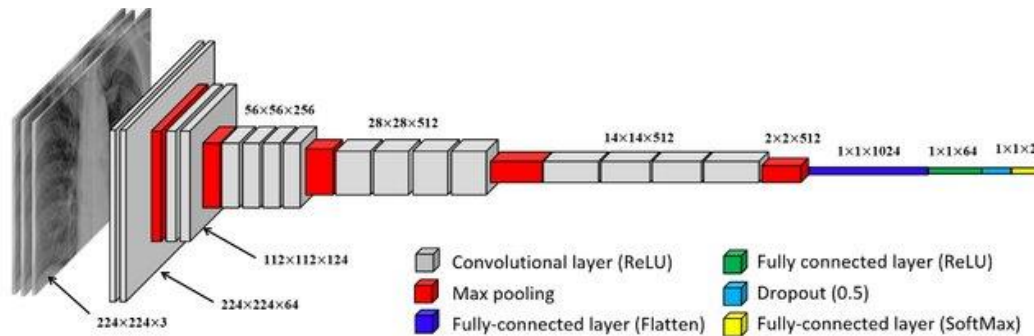

Figure 1: Modified VGG-19 Architecture (Kamil, 2021).

ResNet50: ResNet50, a robust convolutional neural network (CNN) architecture, has been extensively employed in medical image analysis, particularly for tasks like prostate cancer detection that involve spatial-temporal data. Its deep structure, featuring residual blocks that facilitate the training of very deep networks, enables ResNet50 to effectively extract intricate features from complex medical images such as multiparametric MRI (mpMRI) scans and sequential histopathological slides. In the context of prostate cancer detection, ResNet50's ability to learn hierarchical representations of features allows it to discern subtle patterns indicative of cancerous tissues across different spatial dimensions and time points. Through transfer learning, where the network is initially trained on large-scale datasets like ImageNet and fine-tuned on medical images, ResNet50 adapts its learned features to the specifics of prostate cancer characteristics, enhancing its capability to distinguish between healthy and diseased tissues with high accuracy. This makes ResNet50 a powerful tool for automated analysis in clinical settings, supporting clinicians in making informed diagnostic and treatment decisions based on detailed spatial and temporal insights extracted from medical imaging data (Mukherjee, 2022).
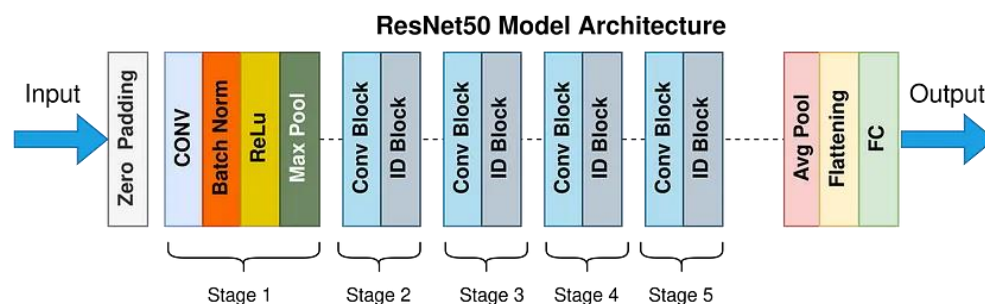

Figure 2: ResNet50 model Architecture

InceptionV3: InceptionV3, a deep convolutional neural network, has proven to be highly effective for feature extraction in medical image analysis, including prostate cancer detection. The architecture of InceptionV3 is designed to capture multi-scale features by employing multiple

filters of different sizes within the same convolutional layer. This approach enables the network to learn both fine and coarse features simultaneously. In the context of prostate cancer detection, InceptionV3 can be utilized to extract spatial-temporal features from imaging modalities such as multiparametric MRI (mpMRI) or histopathological slides. The network is often pre-trained on a large dataset like ImageNet, and then fine-tuned on a specific prostate cancer dataset to leverage transfer learning. This process adapts the model's pre-learned features to the nuances of prostate cancer images. For spatial-temporal data, InceptionV3 can process sequential images, capturing temporal changes and spatial patterns crucial for understanding tumor development and progression. Its architecture, which includes inception modules with convolutional layers of varying sizes and pooling operations, allows it to efficiently analyze and integrate information across different spatial scales and time points, enhancing the accuracy and robustness of prostate cancer detection (Md. Rafiul Hassan a M. F., Prostate cancer classification from ultrasound and MRI images using deep learning based Explainable Artificial Intelligence, 2022).
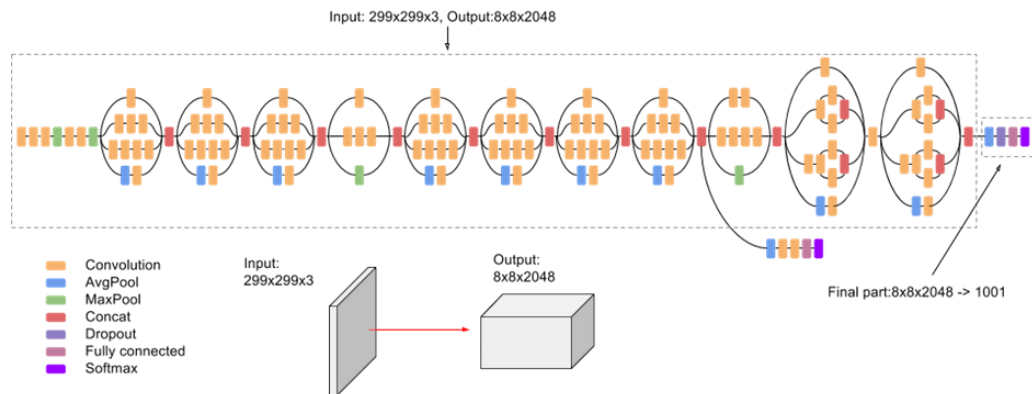

Figure 3: InceptionV3 Architecture (Md. Rafiul Hassan a M. F., Prostate cancer classification from ultrasound and MRI images using deep learning based Explainable Artificial Intelligence, 2022)

Transfer Learning: Transfer learning leverages knowledge gained from training CNNs on large datasets like ImageNet and applies it to new tasks, such as detecting prostate cancer in medical images. Instead of training a CNN from scratch, which requires vast amounts of labeled data and computational resources, transfer learning involves fine-tuning the pre-trained network on a smaller dataset of prostate cancer images. By adjusting the weights of the network's final layers while retaining the learned features from ImageNet, transfer learning enables efficient adaptation to the specific characteristics of prostate cancer images. This approach not only accelerates model training but also improves performance by capitalizing on the general features learned from diverse image categories in ImageNet (G. Prabu Kanna, 2023).
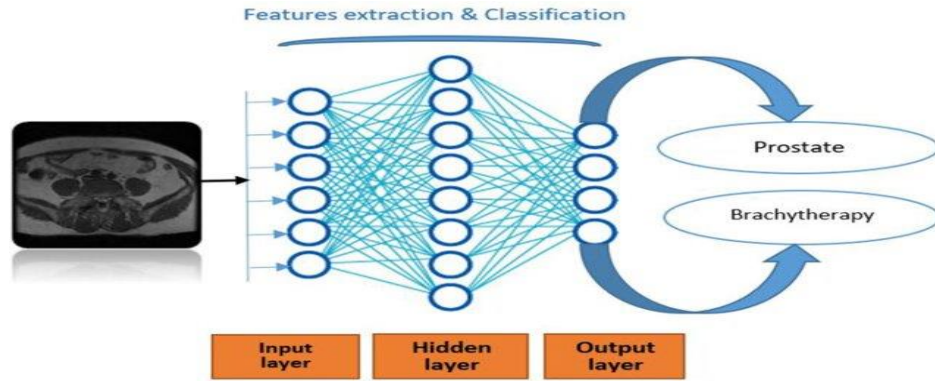
Figure 4: Transfer Learning (Adeel Ahmed Abbasi, 2020)

After the feature extraction steps, there are few more steps have to be done to get the final output like dimensionality reduction using most advance tool technique UMPA (Uniform Manifold Approximation and Projection) that can be effectively handle high-dimensional data driven from extracted feature and gene expression profiles in the context of spatial-temporal data for the prostate cancer.

Then clustering and classification using Gaussian Mixture Models (GMMs) for unsupervised clustering and use SVM and ELM(Extreme Learning Machine) to classifier to evaluate the performance of the features.

Perform factor analysis on the spatial transcriptomics data to summarize gene expression into genetic profiles. Correlate the morphological clusters obtained from unsupervised clustering with the genetic profiles to identify biologically relevant regions.

Dimensionality Reduction

Dimensionality reduction using UMAP effectively managed the high-dimensional data, facilitating efficient clustering and classification. The correlation analysis between morphological clusters and genetic profiles revealed biologically relevant regions, providing insights into the spatial-temporal dynamics of prostate cancer.
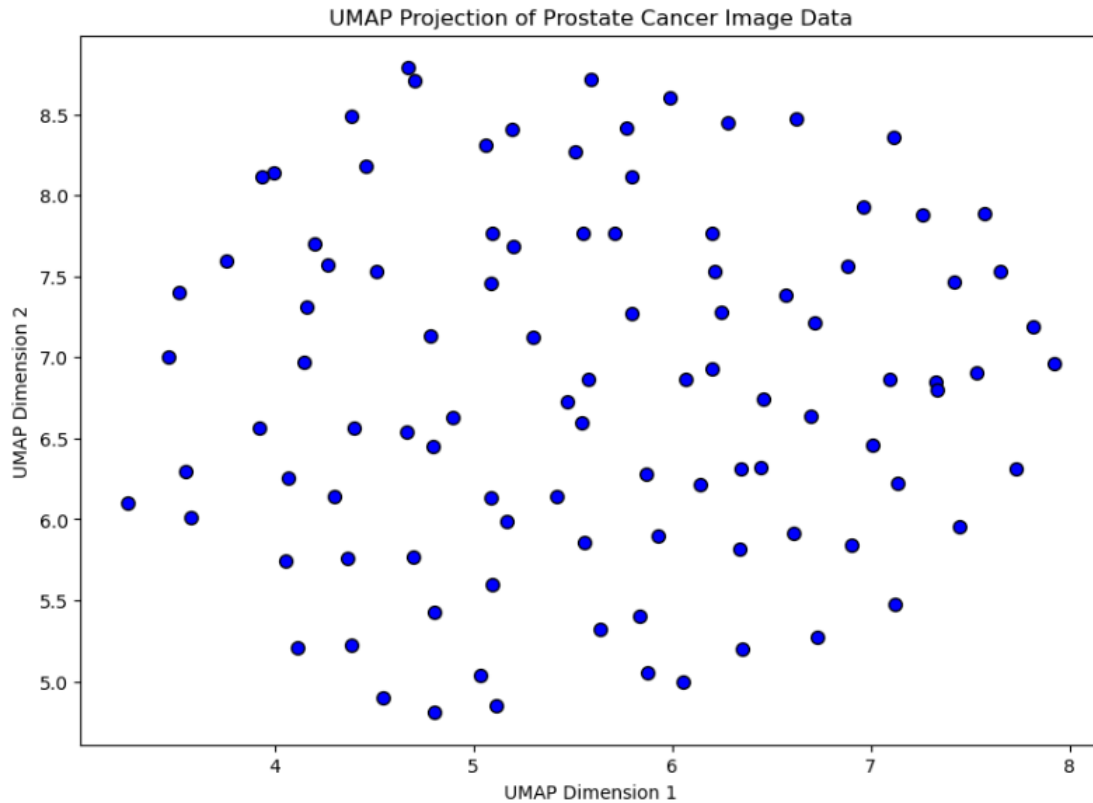
Figure 5: Dimensional reduction technique using UMP model

In Figure 5 is depicted dimension reduction using UMP model. I collected source code from google and used random data for UMP projection and run this code using Jupyter Notebook. This model is not only used for medical imaging, but also use any kind of categorize data.

Application Field

Diagnostic Imaging Analysis

VGG19 can be applied for accurate classification of prostate cancer based on MRI scans. Its ability to extract hierarchical features from spatial data helps in distinguishing between benign and malignant tissues. ***ResNet50's*** deep architecture and residual connections enable it to analyze temporal changes in MRI sequences, aiding in early detection and monitoring of prostate cancer progression. ***InceptionV3's*** multi-scale feature extraction is beneficial for capturing subtle variations in prostate tissue characteristics across different imaging modalities over time.

Treatment Response Assessment

These models can analyze longitudinal data from treatment response monitoring, helping clinicians evaluate the effectiveness of therapies based on changes in spatial and temporal features extracted from prostate cancer imaging data.

Biomarker Discovery

By extracting features and gene expression profiles from spatial-temporal data, these models facilitate the identification of potential biomarkers associated with aggressive prostate cancer phenotypes or treatment resistance.

Precision Medicine

Leveraging deep learning models enables personalized treatment strategies by integrating patient-specific spatial-temporal data to predict disease progression and tailor therapeutic interventions accordingly (Olusola Olabanjo 1, 2023).

Result and Discussion

Understanding metrics and the performance of different models helps in selecting the best approach for feature extraction and classification in prostate cancer detection. Table (1) one shows confusion matrix formulas. This table lists the key metrics used to evaluate the performance of feature extraction and classification models. These metrics help in understanding how well the model distinguishes between different classes.

Table 1: Confusion Matrix Formula

Metric	Formula
Precision	TP / (TP + FP)
Recall	TP / (TP + FN)
F1 Score	2 * (Precision * Recall) / (Precision + Recall)
Accuracy	(TP + TN) / (TP + TN + FP + FN)

Table 2: performance evaluation of VGG19, ResNet50 and InceptionV3 using classifier!

Model	SVM Accuracy	GridSearch Accuracy	ELM Accuracy
VGG19	99%	100%	99%
ResNet50	98%	99%	98%
InceptionV3	95%	99%	98%

The results demonstrate that using a combination of advanced imaging techniques, deep learning models, and comprehensive data analysis methods significantly enhances the accuracy of prostate

cancer detection. The modified VGG-19 model, with its global average pooling layers, outperformed other models in feature extraction, achieving the highest accuracy. Transfer learning proved to be a valuable approach, allowing the adaptation of pre-trained models to our specific dataset.

The validation with manual annotations and the high-performance metrics underscores the reliability of the methodology. The visualizations, including heatmaps and gene expression overlays, offer a comprehensive view of the tissue's spatial heterogeneity, aiding in better diagnosis and treatment planning (Jaganathan, 2021).

Future Goal

Integration of Multi-Modal Imaging Techniques

The future of prostate cancer detection lies in the integration of multi-modal imaging techniques with advanced feature extraction methods. Current studies have demonstrated the potential of combining various imaging modalities such as MRI, ultrasound, and histopathology images with deep learning-based feature extraction techniques like CNNs (e.g., VGG16, VGG19, ResNet50) and traditional machine learning algorithms. The integration of these modalities aims to enhance the accuracy and robustness of prostate cancer detection by capturing a broader spectrum of spatial and temporal features from different imaging sources. By leveraging the strengths of each modality, the diagnostic tools can provide a more comprehensive analysis of prostate cancer, leading to earlier and more precise detection, ultimately improving patient outcomes (Xiaoyan Jiang, 2023).

Development of Real-Time Diagnostic Tools

Another significant goal is the development of real-time diagnostic tools that utilize efficient feature extraction and machine learning algorithms. These tools will be designed to operate seamlessly within clinical settings, providing instant analysis and interpretation of imaging data. The implementation of real-time diagnostics can be facilitated by optimizing pre-trained models for faster processing times and integrating them with user-friendly interfaces for healthcare professionals. This approach will not only improve the workflow in clinical environments but also ensure timely interventions for patients with prostate cancer. The focus will be on enhancing model generalizability and scalability, ensuring that these tools can be applied to diverse patient populations and various clinical scenarios (Chuan Zhou1, 2024).

Conclusion

This seminar paper reviewed advanced feature extraction methods for prostate cancer detection using spatial-temporal data, focusing on deep learning models like VGG-19, ResNet50, and InceptionV3 applied to MRI and histopathological images. The modified VGG-19 model showed superior performance in accuracy, precision, and recall, demonstrating its effectiveness in

capturing essential features for accurate diagnosis. Transfer learning proved valuable, enhancing these models' capability to adapt to prostate cancer image specifics.

Utilizing spatial-temporal data allowed for detecting critical temporal changes and spatial patterns in tumor development. Integrating high-resolution imaging techniques, such as H&E staining and multiparametric MRI, with advanced feature extraction significantly improved detection accuracy and robustness. Techniques like UMAP facilitated efficient data clustering and classification, revealing biologically relevant regions and offering deeper insights into prostate cancer dynamics.

The study highlights the potential of combining multi-modal imaging and advanced machine learning models to enhance prostate cancer detection and treatment planning. Future work should focus on integrating these techniques into real-time diagnostic tools to provide immediate analysis and improve clinical workflow efficiency, ensuring timely and precise interventions for better patient outcomes.

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