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Soft Tissue Sarcoma Classification

Hacettepe University Artificial Intelligence Engineering Graduation Project

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Motivation

Diagnostic Challenges:

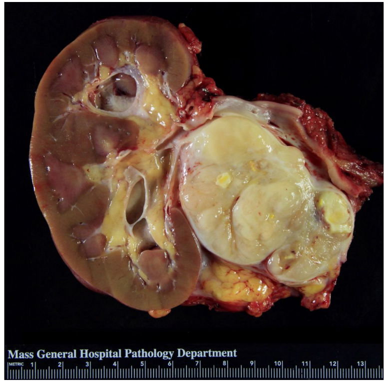
- Over a hundred histological subtypes complicate diagnosis.
- Each subtype has different prognostic and clinical features, leading to potential diagnostic errors.
- Errors can cause significant clinical problems due to varied treatment approaches and prognoses.

Increasing Incidence:

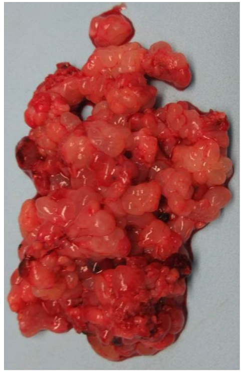
- Although rare, the incidence of STS has steadily increased over the last decade.
- Associated with significant morbidity and mortality.

Incidence and Rarity:

- Sarcomas are rare, but they represent a significant proportion of pediatric cancers worldwide.
- Account for 6-15% of pediatric cancers, 11% of adolescent and young adult cancers, and 1-2% of adult cancers.



Leiomyosarcoma Tissue Specimen



Rhabdomyosarcoma Tissue Specimen

Problem Statements

Clinical Consequences:

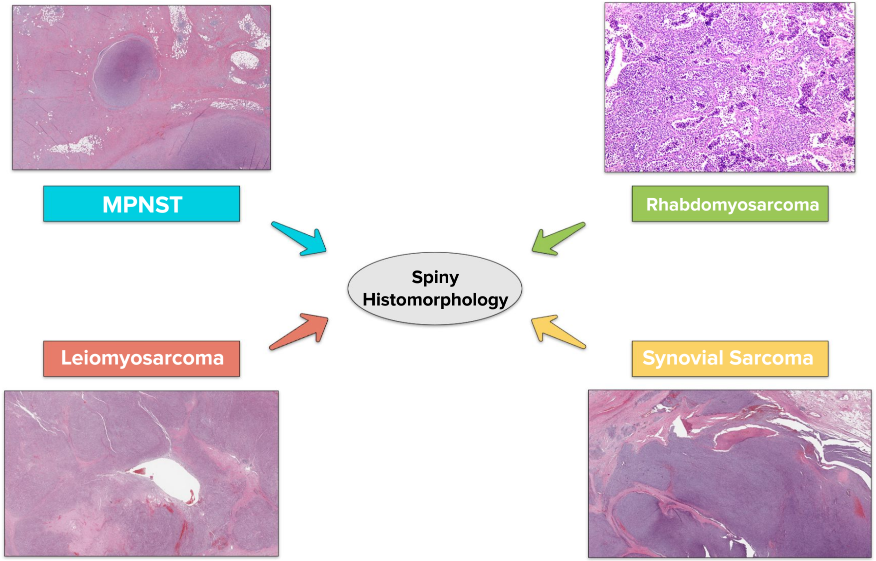
- Diagnostic errors can lead to significant clinical problems.
- Misclassification affects treatment decisions and patient outcomes.

Treatment Variability:

- Different subtypes require different treatment regimens.
- Variations in treatment approaches are associated with different prognoses.

Need for Accuracy:

- Accurate classification is crucial for appropriate treatment.
- Current manual diagnostic processes are time-consuming and prone to error.



Project Objectives

Automated Classification System:

- Develop a deep learning model to classify four STS subtypes: Rhabdomyosarcoma, Leiomyosarcoma, Synovial Sarcoma, and Malignant Peripheral Nerve Sheath Tumors.

Model Evaluation:

- Test and compare pre-trained models: ResNet50V2, VGG19, InceptionV3, EfficientNetV2S.
- Use cross-validation to determine the best-performing model.

Data Utilization:

- Utilize high-resolution Hematoxylin & Eosin-stained images from TCGA-SARC and Istanbul University-Cerrahpaşa archives.

Transfer Learning:

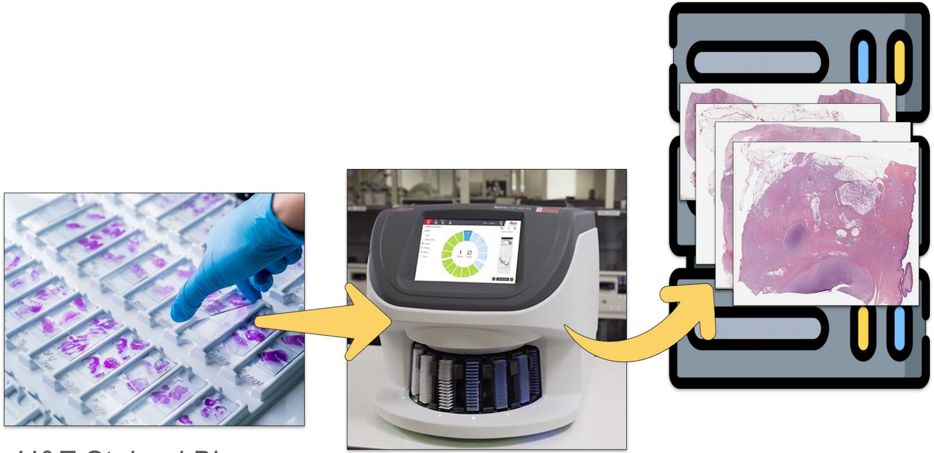
- Employ transfer learning to optimize model inference times while maintaining high-resolution details.

Physical Tissue Samples

Methodology

Dataset Preparation:

- High-resolution Hematoxylin & Eosin-stained images from TCGA-SARC and Istanbul University-Cerrahpaşa archives.
- The samples from the archive of Cerrahpasa medical faculty were scanned with a Leica GT450 model WSI scanner at x40 zoom.



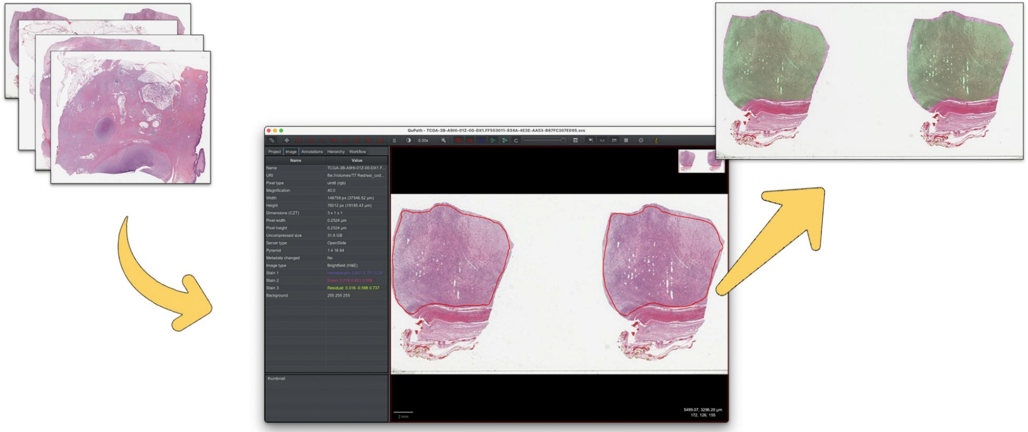
H&E Stained Biopsy Sections

WSI Scanner

Scanned slide images

Methodology

- The scanned samples and samples from the TCGA-SARC dataset were labelled as cancerous tissue samples by expert pathologists at the Department of Pathology, Cerrahpasa Medical Faculty, using the open source QuPath software.



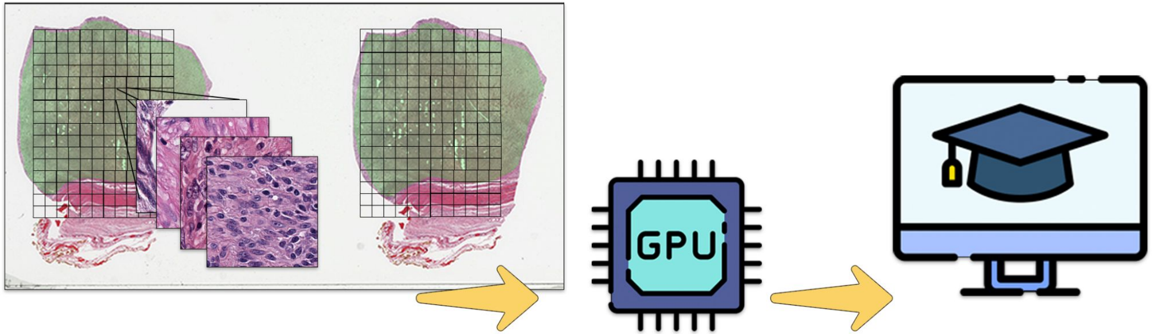
Scanned Slides Images

QuPath

H&E Stained Biopsy Sections

Methodology

- High resolution digital images were divided into 384x384 resolution patches with opeslide, an open source wsi library, to include only the marked areas during the pre-processing phase.



Methodology

Phase One:

- In order to find the most suitable model architecture for the problem, 4 different foundation models were benchmarked on the TCGA-SARC dataset.

TCGA-SAR Dataset

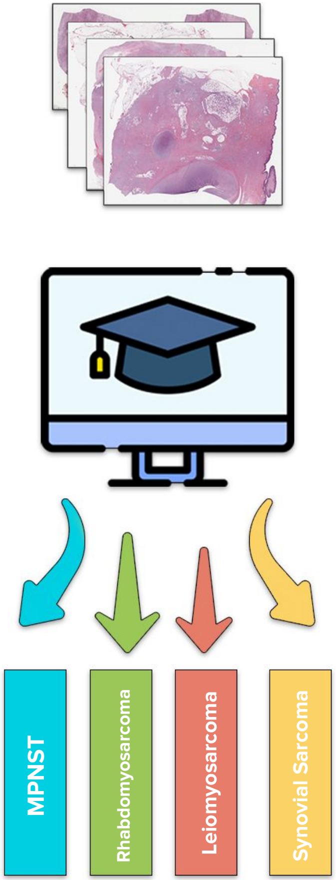
AI Model

Results

Methodology

Phase Two:

- The ResNet50V2 model, which had the best results in the first phase, was fine-tuned with data from the archive of Cerrahpasa Medical Faculty.



Cerrahpasa Dataset

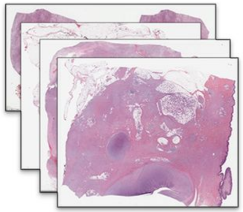
Best Model from Phase One

Results

Methodology

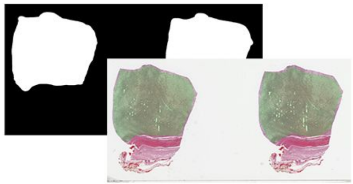
Phase Three:

- A segmentation model was developed for automatic cancerous area detection with masks.



TCGA-SARC and Cerrahpasa Dataset

Segmentation Models



Segmentation Masks

Methodology

Phase Four:

- A method using transfer learning to compensate for the model's loss of information at low resolution was proposed.

Low Zoom Patches from Cerrahpasa Dataset

Trained Model in Phase Two

Results

Results

Model Benchmark:

- ResNet50V2 achieved the highest performance among tested models.
- Average classification accuracy rates: ResNet50V2: 0.49, VGG19: 0.41, EfficientNetV2S: 0.27, InceptionV3: 0.39.

Accuracy Improvement:

- Fine-Tune training and increased fully connected layers improved ResNet50V2 accuracy to 70.16% (cross-validation) and 60% (test set).

Challenges:

- Segmentation masks presented difficulties during the test phase.
- High similarity of tissue samples led to learning challenges for the model.

Results

Transfer Learning Impact:

- Transfer learning optimized inference times while maintaining high-resolution details.
- Despite transfer learning, significant information loss was observed at lower resolutions, affecting accuracy.

Phase Comparisons:

- Phase one identified ResNet50V2 as the best model.
- Phase two improved ResNet50V2 performance by augmenting the network's fully connected layers.

Ön eğitimli görüntü işleme modellerinin yumuşak doku sarkomlarına yönelik sınıflandırma başarımlarının TCGA-SARC veri seti kullanılarak karşılaştırılması

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Özet

TCGA-SARC veri seti kullanılarak gerçekleştirilen araştırmada, yumuşak doku sarkomlarının sınıflandırılmasında ön eğitimli derin öğrenme modellerinin performansları incelenmiştir. Hedef aldığımız yumuşak doku sarkomları, mezenkimal kökenli malign tümörlerin heterojen bir alt grubunu temsil etmektedir. Tanı süreci birbirlerine benzerlikleri sebebi ile oldukça zordur. Güncel derin öğrenme teknolojileri ile yapay zekâ modellerinin patoloji alanındaki potansiyellerinin değerlendirildiği çalışmada, en çok kullanılan dört ön eğitimli model arasından ResNet50V2 modelinin diğerlerine göre daha iyi bir performans sergilediği ortaya koyulmuştur. Bu bulgular, patoloji pratiğini desteklemek ve hastaların tanı ve tedavi süreçlerini iyileştirmek için oluşturulacak yapay zekâ tabanlı yardımcı tanı sistemlerinin temel mimarisinde ResNet50V2 modelinin kullanılabileceğini göstermiştir.

Anahtar Kelimeler: *"Derin Öğrenme", "Sağlıkta Yapay Zekâ", "Yumuşak Doku Sarkomu"*

Discussion

Impact on Diagnostic Process:

- Deep learning models can significantly reduce diagnostic time.
- Automated classification can lighten the workload for pathologists.

Model Robustness:

- Larger datasets needed to further enhance model robustness and reliability.
- Continued data collection and refinement are essential.

Transfer Learning Benefits:

- Effective in maintaining high-resolution details and optimizing inference times.
- Crucial for handling large, high-resolution medical images without significant information loss.

Limitations and Challenges:

- High similarity among tissue samples presents learning challenges.
- Segmentation mask issues indicate the need for improved data preprocessing techniques.

Future Directions

Dataset Expansion:

- Collect and annotate larger datasets to improve model performance and robustness.
- Focus on underrepresented STS subtypes to enhance model generalizability.

Technical Enhancements:

- Overcome limitations to enable the use of entire frames instead of selected samples.
- Improve data preprocessing techniques to address issues with segmentation masks.

Model Optimization:

- Continue refining models to increase accuracy and reduce inference times.
- Explore additional deep learning architectures and techniques.

Research and Publications:

- Prepare and submit findings for peer-reviewed journals.
- Share results at conferences to contribute to the ongoing research in digital pathology.