Academic Education
 DeepGI: An Automated Approach for Gastrointestinal Tract
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 **Segmentation in MRI International Conference on Social Development

and Intelligent Technology (SDIT2024)

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 **, Dongji Cui³, Xinrui Li⁴, and Xinyu Shen⁵
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 d Approach for Gastrointestinal Tra
 ntation in MRI Scans
 g², Dongji Cui³, Xinrui Li⁴, and Xinyu Shen⁵
 ty of Pittsburgh, Pittsburgh, USA
 Arizona University, Flagstaf **ABSTRACT: Detecting gastrointestinal (GI)**

Segmentation in MRI Scans

Ye Zhang^{1,*}, Yulu Gong², Dongji Cui³, Xinrui Li⁴, and Xinyu S

¹University of Pittsburgh, Pittsburgh, USA

²Northern Arizona University, F

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tract cancers accurately remains essential

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learning model for automated segmentation

of GI regions within MRI scans, featuring

an architectu For improved radiotherapy outcomes. This magnetic resonance
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 **of GI regions within MRI complex GI structures and multival structure of the process that remains

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 of GI regions within MRI scans, featuring intensive and required
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encoder for 2.5D segmentation, and an Edge

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UNet optimized for grayscale images.

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Example Solution that captures includes organs that complex GI structures crucial for treatment

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significant challenge i Gastrointestinal (G1) cancers, encompassing umage classitication an malignancies within the stomach, colon, Although general models list exterm, and small intestine, represent a variants have shown effective is eigenfinica malignancies within the stomach, colon, Although general mectum, and small intestine, represent a variants have shown segmentation, they of the signentation, they of the inationical diversity require- ments. Radiotherapy i rectum, and small intestine, represent a variants have shown
significant challenge in global healthcare due
to their high incidence and complex treatment
require- ments. Radiotherapy is one of the
necessary for accurate
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segmentation precision. Our model

segmentation by providing a streamlined,

high-accuracy solution that captures

includes organs that are

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Leep Learning, MRI

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segmentation by providing a streamlined, the unique anatomy of the

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This se magnetic resonance imaging (MRI) scans, a
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Manual delineation of GI organs is labor-
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inte process that remains predominantly manual.

Manual delineation of GI organs is labor-

intensive and requires significant expertise.

This segmentation pro- cess is also prone to

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intensive and requires significant expertise.
This segmentation pro- cess is also prone to
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clinicians may produce inconsistent
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This segmentation pro- cess is also prone to
inter-operator variability, where different
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trea This segmentation pro- cess is also prone to
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auto mter-operator variability, where different
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automated segmentation ap- proach is essential
to clinicians may produce inconsistent
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to optimize radiotherapy planning and ensure
u segmentations for the same patient, impacting
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includes organs that are highly variable in size,
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the unique anatomy of the GI tract, which
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challenge for automated segmentation mode the unique anatomy of the GI tract, which
includes organs that are highly variable in size,
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challenge for automated segmentation models.
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challenge for automated segmentation models.
Machine learning, particularly deep learning,
has gained prominence in medical imagin shape, and structure, presents a distinct
challenge for automated segmentation models.
Machine learning, particularly deep learning,
has gained prominence in medical imaging due
to its ability to handle complex data patter challenge for automated segmentation models.
Machine learning, particularly deep learning,
has gained prominence in medical imaging due
to its ability to handle complex data patterns.
Convolutional neural networks (CNNs) a Machine learning, particularly deep learning,
has gained prominence in medical imaging due
to its ability to handle complex data patterns.
Convolutional neural networks (CNNs) and
other deep learning architectures have
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to its ability to handle complex data patterns.
Convolutional neural networks (CNNs) and
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image cl to its ability to handle complex data patterns.
Convolutional neural networks (CNNs) and
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image classification and segmentation.
Although gen Convolutional neural networks (CNNs) and
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achieved substantial success in tasks like
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Although general models like U-Net and its
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Although general models like U-Net and its
variants have shown effectiveness in medical
segmentation, achieved substantial success in tasks like
image classification and segmentation.
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variants have shown effectiveness in medical
segmentation, they often struggle to handle the
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Although general models like U-Net and its
variants have shown effectiveness in medical
segmentation, they often struggle to handle the
anatomical diversity and fine structural details Although general models like U-Net and its
variants have shown effectiveness in medical
segmentation, they often struggle to handle the
anatomical diversity and fine structural details
necessary for accurate GI tract segme variants have shown effectiveness in medical
segmentation, they often struggle to handle the
anatomical diversity and fine structural details
necessary for accurate GI tract segmentation.
Moreover, the diversity of MRI sca

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specific aspects of the segmentation task. The

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We develop a hybrid model combining three

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We develop a hybrid model combining three

state-of-the-art architectures: Inception-V4 primary contributions of this work are as

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We develop a hybrid model combining three

state-of-the-art architectures: Inception-V4 for

state-of-the-art architectures: Inceptionfollows Advanced Architecture Integration: **2. Related Work**

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state-of-the-art architectures: Inception-V4 for

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initial organ classification, UNet++ with

diagnosis and treatment,

VGGI9 encoder for 2.5D data processing, and

Edge UNet for p initial organ classitication, UNet⁺⁺ with diagnosis and treatment,

VGG19 encoder for 2.5D data processing, and substantial contributions

Edge UNet for precise grayscale segmentation. This ensemble approach enables the VGG19 encoder for 2.5D data processing, and

Edge UNet for precise grayscale segmentation. This ensemble approaches, par

This ensemble approach enables the model to

capture diverse structural details of the GI foundation Edge UNet for precise grayscale segmentation. approaches, particularly

This ensemble approach enables the model to

conditional details of the GI

organs, providing a more comprehensive which form the basis for our

organ This ensemble approach enables the model to

compenda- tion tasks. This

capture diverse structural details of the GI foundational methodologies

solution than existing single-architecture Kocak et al.1 explored

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Enhanced Data Preprocessing: Recognizing

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the variability in MRI data, we implement a

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spatial and intensity augmentation te Enhanced Data Preprocessing: Recognizing with a focus on enh
the variability in MRI data, we implement a support clinical dec
robust pre- processing pipeline, including
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robust pre- processing pipeline, including

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tailored for GI imaging. Addi- tionally, we

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incorporate a 2.5D pro robust pre- processing pipeline, including
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incorporate a 2.5D processing method that
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silices, offering a richer representation of high detail. Building on

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different practitioners, thus ensuring consistent

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i and effort required by clinicians in integrating adaptive

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integration of deep learning architectures applied a transformer more

segmentation pipeline marks a significant step learning for pedestrian

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segmentation pipeline marks a significant step

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forward in radiotherapy applications.

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Thi tailored for specific tasks within the learning for pedestrian
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reviews recent developments in medical image proposed a two-stage
segmentation with a focus on GI tract imaging. Section ?? outlines the proposed methodo reviews recent developments in medical image

segmentation with a focus on GI tract imaging. Section ?? outlines the proposed methodology, segmentation, wh

including the specific neural network approach.

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especially within gastrointestinal (GI) cancer **2. Related Work**
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The field of medical image segmentation,

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The field of medical image segmentation,
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tailored for GI imaging. Addi- tionally, we

incorporate a 2.5D processing method that

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anatomical context compared to **2. Related Work**
The field of medical image segmentation, especially within gastrointestinal (GI) cancer diagnosis and treatment, has evolved with substantial contributions from deep learning approaches, particularly in The field of medical image segmentation,
especially within gastrointestinal (GI) cancer
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segmenta especially within gastrointestinal (G1) cancer
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substantial contributions from deep learning
approaches, particularly in automating
segmenta- tion tasks. This review covers the
foun diagnosis and treatment, has evolved with
substantial contributions from deep learning
approaches, particularly in automating
segmenta- tion tasks. This review covers the
foundational methodologies and breakthroughs,
which substantial contributions from deep learning
approaches, particularly in automating
segmenta- tion tasks. This review covers the
foundational methodologies and breakthroughs,
which form the basis for our model.
Kocak et al approaches, particularly in automating
segmenta- tion tasks. This review covers the
foundational methodologies and breakthroughs,
which form the basis for our model.
Kocak et al.1 explored the role of deep
learning in medi segmenta- tion tasks. This review covers the
foundational methodologies and breakthroughs,
which form the basis for our model.
Kocak et al.1 explored the role of deep
learning in medical imaging segmentation,
with a focus foundational methodologies and breakthroughs,
which form the basis for our model.
Kocak et al.1 explored the role of deep
learning in medical imaging segmentation,
with a focus on enhanc- ing interpretability to
support cl which form the basis for our model.

Kocak et al.1 explored the role of deep

learning in medical imaging segmentation,

with a focus on enhanc- ing interpretability to

support clinical decision-making. This work

provide Kocak et al.1 explored the role of deep
learning in medical imaging segmentation,
with a focus on enhanc- ing interpretability to
support clinical decision-making. This work
provided foundational insights into the use of
n learning in medical imaging segmentation,
with a focus on enhanc- ing interpretability to
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neural networks in medical imaging. Zhou et
al.2 demonstrated the effectiveness of U-Net
for capturing spatial context, highlighting its
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al.2 demonstrated the effectiveness of U-Net
for capturing spatial context, highlighting its
utility in medical imaging tasks that require
high detail. Building on model efficienc al.2 demonstrated the effectiveness of U-Net
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utility in medical imaging tasks that require
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et al.3 introduced a processor for an for capturing spatial context, highlighting its
utility in medical imaging tasks that require
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high detail. Building on model efficiency, Lu
et al.3 introduced a processor for analyzing
power consumption in data cycles, showcasing
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modeling outcomes. In segmentation tasks,
 et al.3 introduced a processor for analyzing
power consumption in data cycles, showcasing
the importance of preprocessing in reliable
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Edge U-Net was enhanced with Holistically-
Nes power consumption in data cycles, showcasing
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Edge U-Net was enhanced with Holistically-
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Nested Edge Detection (HED),4 focusing on
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Nested Edge Detection (HED),4 focusing on
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in complex structures.
Developments in intelligent systems also
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edge detection for better boundary preservation
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Developments in intelligent systems also
inform medical imaging. Tianbo et al.5
designed a swarm intelligence edge detection for better boundary preservation
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designed a swarm intelligence system
integrating adaptive control and o in complex structures.

Developments in intelligent systems also

inform medical imaging. Tianbo et al.5

designed a swarm intelligence system

integrating adaptive control and object

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inform medical imaging. Tianbo et al.5
designed a swarm intelligence system
integrating adaptive control and object
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systems can enhance robu approach. designed a swarm intelligence system
integrating adaptive control and object
recognition, illustrating how autonomous
systems can enhance robustness. Zhang et al.6
applied a transformer module with evidential
learning for Integrating adaptive control and object
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systems can enhance robustness. Zhang et al.6
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systems can enhance robustness. Zhang et al.6
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applied a transformer module with evidential
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are advantageous for medical imaging. In
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p learning for pedestrian intent prediction,
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are advantageous for medical imaging. In
addressing imbalanced datasets, Chen et al.7
proposed a two-stage classification strategy,
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are advantageous for medical imaging. In
addressing imbalanced datasets, Chen et al.7
proposed a two-stage classification strategy,
improving feature alignment in medical
segm are advantageous for medical imaging. In
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proposed a two-stage classification strategy,
improving feature alignment in medical
segmentation, which inspired our multi-path
approac addressing imbalanced datasets, Chen et al.7
proposed a two-stage classification strategy,
improving feature alignment in medical
segmentation, which inspired our multi-path
approach.
Maccioni et al.8 discussed challenges proposed a two-stage classification strategy,
improving feature alignment in medical
segmentation, which inspired our multi-path
approach.
Maccioni et al.8 discussed challenges in GI
tract segmentation due to anatomical va

Convolutional structure that serves as a reliable
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convolutional structure that serves as a reliable

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In terms of reducing computational CREM Academic Education**
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encoder for image recognition tasks.

In terms of reducing compulational complexity,

Szegedy et al.11 enhanced the Inception model

volatility derivative framew

series, encoder for mage recognition tasks. The employing employeer and it employeer and in the more of seeding complex is excellent series, making it suitable for complex stochastic processes segmentation tasks that demand effici In terms of reducing computational complexity,

Szegedy et al.11 enhanced the Inception model

segmentation tasks that demand efficient

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segmentation tasks that demand efficient

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decoder arc Szegedy et al.11 enhanced the Inception model

sergedy et al.11 enhanced the Inception model

segmentation tasks that demand efficient

processing. SegNet12 introduced an encoder-

insights into model stabili

decoder arch series, making it suitable for complex stochastic processes,
segmentation tasks that demand efficient reliability in financial
decoder architecture that facilitated image en-semble design.
segmentation through efficient do segmentation tasks that demand efficient
processing. SegNet12 introduced an encoder-
decoder architecture that facilitated image
encept and according encept encept encept design.
and up-sampling opera- tions, influencing a processing. SegNet12 introduced an encoder-
decoder architecture that facilitated image
expendition through efficient down-sampling
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and up-sampling opera- tions, influencing
advanc decoder architecture that tacilitated mage

segmentation through efficient down-sampling

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segmentation through efficient down-sampling

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segmentation tasks requiring high-resolution

retention. Expanding beyond biomedical

inaging, Zhang et a and up-sampling opera- tions, influencing

segmentation tasks requiring high-resolution

retention. Expanding beyond biomedical

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imaging, Zhang et al.13 presented a machine

rob segmentation tasks requiring high-resolution

imaging, Zhang et al.13 presented a machine

imaging, Zhang et al.13 presented a machine

imaging, Zhang et al.13 presented a machine

robotics, highlighting precision handling retention. Expanding beyond biomedical builds on these fou

imaging, Zhang et al.13 presented a machine multi-path approacl

vision-based manipulator control system for architectures, target

robotics, highlighting precisi maging, Zhang et al.13 presented a machine multi-path approach

vision-based manipulator control system for architectures, targ

robotics, highlighting precision handling robust ensemble

techniques applicable to segmentat vision-based manipulator control system for

robotics, highlighting precision handling

techniques applicable to segmentation.

In breast cancer detection, Zhang et al.14

advanced binary classification by using novel

poo robotics, highlighting precision handling robust ensemble techniques applicable to segmentation. Zhang et al.14 and efficiency in GI imaging advanced binary classification by using novel
advanced binary classification by u techniques applicable to segmentation.

In breast cancer detection, Zhang et al.14

advanced binary classification by using novel

pooling techniques, enhancing model accuracy.

For face recognition, Liao et al.15 proposed In breast cancer detection, Zhang et al.14 and efficiency in GI imag

advanced binary classification by using novel

For face recognition, Liao et al.15 proposed Cour approach integrates the

Attention Selective Network (A advanced binary classification by using novel
pooling techniques, enhancing model accuracy.
Tor face recognition, Liao et al.15 proposed tour approach integrate
the Attention Selective Network (ASN) to
architectures in
man pooling techniques, enhancing model accuracy.

For face recognition, Liao et al.15 proposed cour approach integrates m

the Attention Selective Network (ASN) to

manage pose variations, a concept that can

manage pose vari For face recognition, Liao et al.15 proposed

the Attention Selective Network (ASN) to

meanage pose variations, a concept that can

focus on clinically significant regions in

segmentation in MRI. By

framework for Bruch'

the Attention Selective Network (ASN) to architectures in a

fiocus on clinically significant regions in

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medical images. Lin16 introduced a

segmentation in MRI.

framework for Bruch's manage pose variations, a concept that can

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medical images. Lin16 introduced a

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framework for Bruch's membrane architectures for a

framework for Bruch's membrane

segmentation in OCT images, supporting

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biomarker track medical images. Lin16 introduced a

segmentation in MRI. By

framework for Bruch's membrane

segmentation in CT images, supporting

biomarker tracking in retinal diseases, which is

model captures both high-

relevant for Tramework for Bruch's membrane architectures for class

segmentation in OCT images, supporting

bromarker tracking in retinal diseases, which is

relevant for improving segmentation in

relevant for improving segmentation segmentation in OCT images, supporting processing, and g
biomarker tracking in retinal diseases, which is model captures b
relevant for improving segmentation in and fine-grained c
diagnostic imaging.
TXiao et al.17 develo biomarker tracking in rethnal diseases, which is

diagnostic imaging.

diagnostic marginal explicit imaging segmentation in

The segmentation.

The segmentation and fine-grained details

graph network, for Alzheimer's diag relevant for improving segmentation in and fine-grained details ne

aliagnostic imaging.

and the al.17 developed dGLCN, a dual-

graph network, for Alzheimer's diagnosis,

demonstrating how graph structures can

enhance s diagnostic imaging.
T Xiao et al.17 developed dGLCN, a dual-
graph network, for Alzheimer's diagnosis,
demonstrating how graph structures can
enhance segmentation interpretability. In the
field of point cloud classificatio T Xiao et al.17 developed dGLCN, a dual-
graph network, for Alzheimer's diagnosis,
demonstrating how graph structures can
enhance segmentation interpretability. In the interdependent path
field of point cloud classificatio graph network, for Alzheimer's diagnosis,
demonstrating how graph structures can
enhance segmentation interpretability. In the interdependent pathwar
field of point cloud classification, Hu et al.18 unique aspect of th
int demonstrating how graph structures can

enhance segmentation interpretability. In the interdependent pathway, ea

field of point cloud classification, Hu et al.18

introduced M-GCN, leveraging multi-scale

introduced M-GCN enhance segmentation interpretability. In the interduced M-GCN elassification, Hu et al.18 unique apect of the segmentation and M-GCN, leveraging multi-scale and gamp inficultions. The practice metallication and Edge U-Net

field of pont cloud classification, Hu et al.18

introduced M-GCN, leveraging multi-scale

llustrated in Figure 1,

fracture fusion, which aligns with our focus on

feature fusion, which aligns with our focus on

alignment Introduced M-GCN, leveraging multi-scale

frashing with our four designed in Figue 1,

frashing with our fours on

fracture fusion, which aligns with our fours on

alignment, a principle adapted in our

alignment, a princi graph convolutional techniques for better
feature fusion, which aligns with our focus on
multi-dimensional data processing. Zeng et and Edge U-Net to achie
al.19 presented a two-phase Alzheimer's segmentation cover- age ad teature tusion, which aligns with our tocus on

multi-dimensional data processing. Zeng et and Edge U-Net

al.19 presented a two-phase Alzheimer's segmentation cov

diagnostic framework, emphasizing feature data types.

al multi-dimensional data processing. Zeng et and Euge to-ivet to ata.

al.19 presented a two-phase Alzheiner's segmentation cover- age

alignment, a principle adapted in our ata types. Classification cover- age

alignment, a al.19 presented a two-phase Alzheimer's segundation cover- a diagnostic framework, emphasizing feature data types
alignostic framework, emphasizing feature and the preprocessing techniques.

In OCT technology, Chen et al.2 diagnostic framework, emphasizing feature

alignment, a principle adapted in our

prepricoressing techniques.

In OCT technology, Chen et al.20 developed

In OCT technology, Chen et al.20 developed

Segmentation applicatio alignment, a principle adapted in our

preprocessing techniques.

In OCT technology, Chen et al.20 developed

Ine first pathway encourage SS-OCT for anterior eye imaging,

architecture, a mode

facilitating detailed imagin

International Conference on Social Development and Intelligent Technology (SDIT2024)

**Trational Conference on Social Development

and Intelligent Technology (SDIT2024)**

directly relevant for segmenting GI tract

organs with complex structures.

Additionally, Wang and Xia23 proposed a

volatility derivativ **rnational Conference on Social Development**
 and Intelligent Technology (SDIT2024)

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volatility derivative and Intelligent Technology (SDIT2024)
directly relevant for segmenting GI tract
organs with complex structures.
Additionally, Wang and Xia23 proposed a
volatility derivative framework, incorporating
stochastic processes, t multi-path approach that components and efficiency directly relevant for segmenting GI tract organs with complex structures.
Additionally, Wang and Xia23 proposed a volatility derivative framework, incorporating stochastic directly relevant for segmenting GI tract
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Additionally, Wang and Xia23 proposed a
volatility derivative framework, incorporating
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volatility derivative framework, incorporating
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reliability in financial analysis, offering
insights into model stability that influenced our
en volatility derivative framework, incorporating
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insights into model stability that influenced our
en-semble design.
These works, while contr Fermantity in Imalican analysis, orientig

insights into model stability that influenced our

em-semble design.

These works, while contributing valuable

advancements, do not fully address the unique

demands of GI tract Insights into model stability that influenced our

en-semble design.

These works, while contributing valuable

advancements, do not fully address the unique

demands of GI tract segmentation. Our study

builds on these fo en-semble design.

These works, while contributing valuable

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builds on these foundations by introducing a

multi-path approach tha These works, while contributing valuable
advancements, do not fully address the unique
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multi-path approach that combines advanced
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advancements, do not tully address the unique
demands of GI tract segmentation. Our study
builds on these foundations by introducing a
multi-path approach that combines advanced
architectures, targeted preprocessing, and
r demands of GI tract segmentation. Our study
builds on these foundations by introducing a
multi-path approach that combines advanced
architectures, targeted preprocessing, and
robust ensemble techniques, specifically
design builds on these foundations by introducing a
multi-path approach that combines advanced
architectures, targeted preprocessing, and
robust ensemble techniques, specifically
designed to enhance segmentation precision
and eff multi-path approach that combines advanced
architectures, targeted preprocessing, and
robust ensemble techniques, specifically
designed to enhance segmentation precision
and efficiency in GI imaging.
3. METHODOLOGY
Our app architectures, targeted preprocessing, and
robust ensemble techniques, specifically
designed to enhance segmentation precision
and efficiency in GI imaging.
3. METHODOLOGY
Our approach integrates multiple deep learning
arc robust ensemble techniques, specifically
designed to enhance segmentation precision
and efficiency in GI imaging.
3. METHODOLOGY
Our approach integrates multiple deep learning
architectures in a synergistic model,
specific segmentation. **3. METHODOLOGY**

Our approach integrates multiple deep learning

architectures in a synergistic model,

specifically designed to address the challenges

associated with gastrointestinal (GI) tract

segmentation in MRI. By **3. METHODOLOGY**

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associated with gastrointestinal (GI) tract

segmentation in MRI. By Our approach integrates multiple deep learning
architectures in a synergistic model,
specifically designed to address the challenges
associated with gastrointestinal (GI) tract
segmentation in MRI. By utilizing distinct
ar architectures in a synergistic model,
specifically designed to address the challenges
associated with gastrointestinal (GI) tract
segmentation in MRI. By utilizing distinct
architectures for classification, 2.5D
processing specifically designed to address the challenges
associated with gastrointestinal (GI) tract
segmentation in MRI. By utilizing distinct
architectures for classification, 2.5D
processing, and grayscale segmentation, our
mode

associated with gastrointestinal (GI) tract
segmentation in MRI. By utilizing distinct
architectures for classification, 2.5D
processing, and grayscale segmentation, our
model captures both high-level classification
and fi segmentation in MRI. By utilizing distinct
architectures for classification, 2.5D
processing, and grayscale segmentation, our
model captures both high-level classification
and fine-grained details necessary for accurate
se architectures for classification, 2.5D
processing, and grayscale segmentation, our
model captures both high-level classification
and fine-grained details necessary for accurate
segmentation.
3.1 Model Architecture Overvie processing, and grayscale segmentation, our
model captures both high-level classification
and fine-grained details necessary for accurate
segmentation.
3.1 Model Architecture Overview
The proposed model comprises three
int model captures both high-level classifica
and fine-grained details necessary for accu
segmentation.
3.1 Model Architecture Overview
The proposed model comprises the
interdependent pathways, each optimized f
unique aspect o and fine-grained details necessary for accurate
segmentation.
3.1 Model Architecture Overview
The proposed model comprises three
interdependent pathways, each optimized for a
unique aspect of the seg-mentation task.
Illust 3.1 Model Architecture Overview

The proposed model comprises three

interdependent pathways, each optimized for a

unique aspect of the seg- mentation task.

Illustrated in Figure 1, the architecture is

designed to lever **3.1 Model Architecture Overview**

The proposed model comprises three

interdependent pathways, each optimized for a

unique aspect of the seg-mentation task.

Illustrated in Figure 1, the architecture is

designed to lev The proposed model comprises three
interdependent pathways, each optimized for a
unique aspect of the seg-mentation task.
Illustrated in Figure 1, the architecture is
designed to leverage the combined strengths of
Inceptio

Classification

interdependent pathways, each optimized for a
unique aspect of the seg-mentation task.
Illustrated in Figure 1, the architecture is
designed to leverage the combined strengths of
Inception-V4, UNet++ with VGG19 encoding,
a unique aspect of the seg- mentation task.
Illustrated in Figure 1, the architecture is
designed to leverage the combined strengths of
Inception-V4, UNet++ with VGG19 encoding,
and Edge U-Net to achieve comprehensive
segmen Illustrated in Figure 1, the architecture is
designed to leverage the combined strengths of
Inception-V4, UNet++ with VGG19 encoding,
and Edge U-Net to achieve comprehensive
segmentation cover- age across various MRI
data designed to leverage the combined strengths of
Inception-V4, UNet++ with VGG19 encoding,
and Edge U-Net to achieve comprehensive
segmentation cover- age across various MRI
data types.
3.1.1Inception-V4 Pathway for Initial
 Inception-V4, UNet++ with VGGI9 encoding,
and Edge U-Net to achieve comprehensive
segmentation cover- age across various MRI
data types.
3.1.1Inception-V4 Pathway for Initial
Classification
The first pathway employs the In and Edge U-Net to achieve comprehensive
segmentation cover- age across various MRI
data types.
3.1.1Inception-V4 Pathway for Initial
Classification
The first pathway employs the Inception-V4
architecture, a model known for segmentation cover- age across various MRI
data types.
3.1.1Inception-V4 Pathway for Initial
Classification
The first pathway employs the Inception-V4
architecture, a model known for efficiently
processing complex image pa data types.

3.1.1Inception-V4 Pathway for Initial

Classification

The first pathway employs the Inception-V4

architecture, a model known for efficiently

processing complex image patterns. In our

segmentation pipeline,

Encoder

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^{Neto} Signer 1. **Overview of Model Architecture**

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^{TVMet}

^{VGG19}

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²⁰¹⁶

 Encoder

For enhanced spatial awareness, the second

Absence traget organs.

For en THE TRISTAND THE CONDITION THE SURFACE OF THE SURFACE ON THE SURFACE ON THE SURFACE OF No Segmentation Mask

Figure 1. Overview of Model Architecture

Figure 1. Overview of Model Architecture

Encoder

For enhanced spatial awareness, the second

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Figure 1. Overview of Model Architecture

Figure 1. Overview of Model Architecture

Encoder

Encoder

For enhanced spatial awareness, the second

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Figure 1. Overview of Model Architecture

Figure 1. Overview of Model Architecture

Encoder

Erocencer

For enhanced spatial awareness, the second

Encoder

For enhanced spatial awareness, the second robustness. 3.1.22.5D UNet++ Pathway with VGG19 3.2.2Intensity

Encoder Images

For enhanced spatial awareness, the second A separate in

consecutive MRI slices to generate a multi-model's sensi

dimensional context. This 2.5D repres Example this conduction in gradient measurement and context the second particular consecutive MRI slices to generate a multi-

consecutive MRI slices to generate a multi-model's sensitivity to

dimensional context. This 2 For enhanced spatial awareness, the second

pathway uses a 2.5D approach by stacking

consecutive MRI slices to generate a multi-

model's sensitivity to

dimensional context. This 2.5D representation

is processed using pathway uses a 2.5D approach by stacking applied to grate consecutive MRI slices to generate a multi-
model's sensitive dimensional context. This 2.5D representation which are crucis is processed using UNet++ with a VGG19

consecutive MRI slices to generate a multi-

model's sensitivity to

dimensional context. This 2.5D representation

is processed using UNet++ with a VGG19

encoder, where the architecture captures contrast, and intensity, dimensional context. This 2.5D representation

is processed using UNet++ with a VGG19

encoder, where the architecture captures contrast, and intensity, creating

incricate anatomical features while preserving that enables Is processed using UNet++ with a VGG19

encoder, where the architecture captures contrast, and intriciate anatomical features while preserving that enables the

essential contextual information. This pathway features in g encoder, where the architecture captures

intricate anatomical features while preserving

that enables the

essential contextual information. This pathway

excels in segmenting regions with complex

intensity adjustm

red Intricate anatomical features while preserving

essential contextual information. This pathway

features in segmenting regions with complex

boundaries, enhancing overall model

boundaries, enhancing overall model

rememb Exertial contextual information. This pathway

intensity adjustments sue

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columinarises,

The third pathway focuses on grayscale image

processing, integrating an Edge U-Net

framework equipped with Holistica excels in segmenting regions with complex

boundaries, enhancing overall model

obustness.

3.1.3Edge U-Net for Grayscale Segmentation

processing, integrating an Edge U-Net

framework equipped with Holistically-Nested

Ed boundaries, enhancing overall model

Tobustness.

The third pathway focuses on grayscale image

The third pathway focuses on grayscale image

processing, integrating an Edge U-Net

framework equipped with Holistically-Nes The third pathod in the produces a unified
The third particle control and the constant and the set of 3.1.3Edge U-Net for Grayscale Segmentation

The third pathway focuses on grayscale image

processing, integrating an Edge U-Net

framework equipped with Holistically-Nested

Edge Detection (HED). This pathway detects

edg The third pathway focuses on grayscale image

processing, integrating an Edge U-Net

framework equipped with Hollistically-Nested

Edge Detection (HED). This pathway detects

edges and contours more effectively in

graysc processing, integrating an Edge U-Net $\frac{1}{200 \times 384 \times 3}$ [Angm

framework equipped with Holistically-Nested

Edge Detection (HED). This pathway detects

edges and contours more effectively in

grayscale data, which sim Tramework equipped with Holistically-Nested

Edge Detection (HED). This pathway detects

edges and contours more effectively in

grayscale data, which simplifies computational

requirements and improves segmentation

accur

Edge Detection (HED). This pathway detects

edges and contours more effectively in

grayscale data, which simplifies computational

requirements and improves segmentation

accuracy for organ boundaries. Grayscale data

is grayscale data, which simplifies compluational
requirements and improves segmentation
accuracy for organ boundaries. Grayscale data
is particularly useful for highlighting edges
without the interference of color informatio requirements and improves segmentation
accuracy for organ boundaries. Grayscale data 3.2.32.5D Image Proc
is particularly useful for highlighting edges
without the interference of color information. In the 2.5D pathway, c

without the interference of color information. In the 2.5D pathway, cons

The outputs from each pathway are aggregated

are stacked to provide the

segmentation map that combines both broad

are stacked to provide the

seg The outputs from each pathway are aggregated

by averaging, which produces a unified

spatial context. This pseud

anatomical context and fine boundary detail.

anatomical context and fine boundary detail.

This ensemble a by averaging, which produces a united

segmentation map that combines both broad

anatomical context and fine boundary detail.

This ensemble approach ensures that each

and This architecture contributes its strengths to t segmentation map that combines both broad

anatomical context and fine boundary detail. Without the computer

This ensemble approach ensures that each

3D model. This

architecture contributes its strengths to the

frail s anatomical context and time boundary detail. Without the computation

segmentation architecture contributes its strengths to the features between slices and

final segmentation result.

3.2 Data Preprocessing the strengths datasets.

1.1 Academic Education

3.2.1Spatial Augmentation Process

The spatial augmentation step standardizes the

resolution of all input images to 320x384

pixels, facilitating consistency in feature

extraction. Augmentation The Schemin Education

The spatial Augmentation Process

The spatial augmentation step standardizes the

resolution of all input images to 320x384

pixels, facilitating consistency in feature

extraction. Augmentation tech **Publishing House**
3.2.1 Spatial Augmentation Process
The spatial augmentation step standardizes the
resolution of all input images to 320x384
pixels, facilitating consistency in feature
extraction. Augmentation techniques **Publishing House**
3.2.1 Spatial Augmentation Process
The spatial augmentation step standardizes the
resolution of all input images to 320x384
pixels, facilitating consistency in feature
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3.2.1 Spatial Augmentation Process
The spatial augmentation step standardizes the
resolution of all input images to 320x384
pixels, facilitat including random rotations, horizontal **Flue Control Control Publishing House**

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3.2.1 Spatial Augmentation Process

The spatial augmentation step standardizes the

resolution of all input images to 320x384

pixels, facilitating consistency in **Academic Education**
3.2.1 Spatial Augmentation Process
The spatial augmentation step standardizes the
resolution of all input images to 320x384
pixels, facilitating consistency in feature
extraction. Augmentation techniqu **Academic Education**
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The spatial Augmentation Process

The spatial augmentation step standardizes the

resolution of all input images to 320x384

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The spatial augmentation step standardizes the

resolution of all input images to 320x384

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The spatial augmentation step standardizes the

resolution of all input images to 320x384

pixels, facilitating consistency in feature
 Publishing House
3.2.1Spatial Augmentation Process
The spatial augmentation step standardizes t
resolution of all input images to 320x3
pixels, facilitating consistency in featu
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includi 3.2.1Spatial Augmentation Process
The spatial augmentation step standardizes the
resolution of all input images to 320x384
pixels, facilitating consistency in feature
extraction. Augmentation techniques,
including random r The spatial augmentation step standardizes the
resolution of all input images to 320x384
pixels, facilitating consistency in feature
extraction. Augmentation techniques,
including random rotations, horizontal
flipping, and resolution of all input images to 320x384
pixels, facilitating consistency in feature
extraction. Augmentation techniques,
including random rotations, horizontal
flipping, and elastic deformations, are applied
to simulate pixels, facilitating consistency in feature
extraction. Augmentation techniques,
including random rotations, horizontal
flipping, and elastic deformations, are applied
to simulate various imaging conditions. These
augmenta

Images

extraction. Augmentation techniques,
including random rotations, horizontal
flipping, and elastic deformations, are applied
to simulate various imaging conditions. These
augmentations expand the training data and
improve t including random rotations, horizontal
flipping, and elastic deformations, are applied
to simulate various imaging conditions. These
augmentations expand the training data and
improve the model's resilience to distortions, flupping, and elastic deformations, are applied
to simulate various imaging conditions. These
augmentations expand the training data and
improve the model's resilience to distortions,
occlusions, and positional variations to simulate various imaging conditions. These
augmentations expand the training data and
improve the model's resilience to distortions,
occlusions, and positional variations in the
target organs.
3.2.2Intensity Augmentatio augmentations expand the training data and
improve the model's resilience to distortions,
occlusions, and positional variations in the
target organs.
3.2.2Intensity Augmentation for Grayscale
Images
A separate intensity a interior and positional variations,

occlusions, and positional variations in the

target organs.

3.2.2Intensity Augmentation for Grayscale

Images

A separate intensity augmentation process is

applied to grayscale imag occlusions, and positional variations in the
target organs.
3.2.2Intensity Augmentation for Grayscale
Images
A separate intensity augmentation process is
applied to grayscale images to enhance the
model's sensitivity to p

Context

accuracy for organ boundaries. Grayscale data 3.2.32.5D Image Processin;

is particularly useful for highlighting edges

wholout the interference of color information.

The outputs from each pathway are aggregated are stac Its particularly useful for highlighting edges

The outext

without the interference of color information.

In the 2.5D pathway, con

by averaging, which produces a unified

segmentation map that combines both broad

segme **Example 1888**

Example 1888 Augmentation

The Textus of Textus Context

In the 2.5D pathway, consecutive MRI slices

are stacked to prov $\begin{tabular}{|c|c|c|c|c|} \hline \multicolumn{1}{|c|}{2.5D image} & \multicolumn{1}{|c|}{\textit{Magnenitation}} & \multicolumn{1}{|c|}{\textit{Magnenitation}} & \multicolumn{1}{|c|}{\textit{2.5D image}} & \multicolumn{1}{|c|}{\textit{Magnenitation}} & \multicolumn{1}{|c|}{\textit{Magnenitation}} & \multicolumn{1}{|c|}{\textit{Magnenitation}} & \multicolumn{1}{|c|}{\textit{Magnenitation}} & \multicolumn{1}{|c|}{\textit{Munge Augmentation}} \\ \hline \hline \hline \$ **Example 18 and 18** France Between Slastic Transform

Figure 2. Data Preprocessing Workflow

3.2.32.5D Image Processing for Enhanced

Context

In the 2.5D pathway, consecutive MRI slices

are stacked to provide the model with added

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Figure 2. Data Preprocessing Workflow
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In the 2.5D pathway, consecutive MRI slices
are stacked to provide the model with added
spatial c Figure 2. Data Preprocessing Workflow
3.2.32.5D Image Processing for Enhanced
Context
In the 2.5D pathway, consecutive MRI slices
are stacked to provide the model with added
spatial context. This pseudo-3D representation
c Figure 2. Data Preprocessing Workflow
3.2.32.5D Image Processing for Enhanced
Context
In the 2.5D pathway, consecutive MRI slices
are stacked to provide the model with added
spatial context. This pseudo-3D representation
 3.2.32.5D Image Processing for Enhanced

Context

In the 2.5D pathway, consecutive MRI slices

are stacked to provide the model with added

spatial context. This pseudo-3D representation

combines depth information across Context
In the 2.5D pathway, consecutive MRI slices
are stacked to provide the model with added
spatial context. This pseudo-3D representation
combines depth information across slices
without the computational demands of a In the 2.5D pathway, consecutive MRI slices
are stacked to provide the model with added
spatial context. This pseudo-3D representation
combines depth information across slices
without the computational demands of a full
3 are stacked to provide the model with added
spatial context. This pseudo-3D representation
combines depth information across slices
without the computational demands of a full
3D model. This technique preserves key
feature spatial context. This pseudo-3D representation
combines depth information across slices
without the computational demands of a full
3D model. This technique preserves key
features between slices and enriches contextual
det combines depth information across slices
without the computational demands of a full
3D model. This technique preserves key
features between slices and enriches contextual
detail, making it particularly effective in
segmen without the computational demands of a full
3D model. This technique preserves key
features between slices and enriches contextual
detail, making it particularly effective in
segmenting the GI tract's layered structures.
F 3D model. This technique preserves key
features between slices and enriches contextual
detail, making it particularly effective in
segmenting the GI tract's layered structures.
Following augmentation, 2.5D images are
input

Example 19 and Architecture

Example 19 and the seales of the seales as illustrated in F

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3.3 Model Architectures

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Figure 4. Edge U-Net Architecture with HED

S.3. Ilnception-V4 for Initial Classification

Inception-V4, developed for complex integr Example the **connections**
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 Connection-V4 for Initial Classification

Integrity, which is critica Figure 4. Edge U-Net Architecture with HED

scales, as illustrated

3.3 Model Architectures

3.3.1Inception-V4 for Initial Classification

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classification tasks, is Figure 4. Edge U-Net Architecture with HED
scales, as illustrated in
scales, as illustrated in
MBConv blocks in Edge
different processing whi
Inception-V4, developed for complex integrity, which is critical
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3.3 Model Architectures
3.3.1Inception-V4 for Initial Classification
Inception-V4, developed for complex integrity, which is
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8.3 Model Architectures

3.3 Mnception-V4 for Initial Classification

Inception-V4, developed for complex

integrity, which is c

classification tasks, is used in our model as the

initial classifi **3.3** Model Architectures

3.3.1Inception-V4 for Initial Classification

Inception-V4, developed for complex

classification tasks, is used in our model as the

initial classification layer. Designed to reduce

computatio 3.3.1Inception-V4 for Initial Classification

Inception-V4, developed for complex

integrity, which is critical

classification tasks, is used in our model as the

initial classification layer. Designed to reduce

computat classification tasks, is used in our model as the delineation.

initial classification layer. Designed to reduce

accuracy, Inception-V4 incorporates various To optimize learnin

filter sizes, batch normalization, and resi mtal classification layer. Designed to reduce

computational load while retaining high

a 3.4 Training and Para

filter sizes, batch normalization, and residual

filter sizes, batch normalization, and residual

efficiently computational load while retaining high

accuracy, Inception-V4 incorporates various

filter sizes, bath normalization, and residual

connections, which together enable it to

efficiently identify large-scale anatomical

e

Segmentation

accuracy, Inception-V4 incorporates various

filter sizes, batch normalization, and residual

connections, which together enable it to

efficiently identify large-scale anatomical

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regi the sizes, batch normalization, and residual

experiencity identifical connections, which together enable it to

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ergions within MRI scans. These design

adjusts the rate th connections, which together enable it to rate of 0.001.

efficiently identify large-scale anatomical

regions within MRI scans. These design

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clements facilitate the preliminary Training is ethicantly identify large-scale anatomical scheduler, couplec
regions within MRI scans. These design adjusts the rate three
lelements facilitate the preliminary Training is conducted
classification that guides subsequent regions within MRI scans. These design

elements facilitate the preliminary Training is conducted

classification that guides subsequent early stopping applied

segmentation processes.

Segmentation architecture combines
 elements facilitate the preliminary Iraning is conducted ove

classification that guides subsequent

segmentation recosses.

3.3.2UNet++ with VGG19 Encoder for 2.5D

Segmentation training efficiency.

Our segmentation arc classitication that guides subsequent early sto

segmentation processes. does not

3.3.2UNet++ with VGG19 Encoder for 2.5D These se

Segmentation architecture combines

UNet++ with a VGG19 encoder to balance

depth and det segmentation processes.

3.3.2UNet++ with VGG19 Encoder for 2.5D

Segmentation

Our segmentation architecture combines

UNet++ with a VGG19 encoder to balance

depth and detail. The VGG19 encoder

depth and detail. The VG 3.3.20Net++ with VGGI9 Encoder for 2.5D

Segmentation

Cour segmentation architecture combines

training eff

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defit a VGGI9 encoder to balance

extracts high-resolution features from the 2.5D

image input, while UNe Segmentation

Our segmentation architecture combines

UNet++ with a VGG19 encoder to balance

depth and detail. The VGG19 encoder

extracts high-resolution features from the 2.5D

extracts high-resolution features from the Our segmentation architecture combines

UNet++ with a VGG19 encoder

depth and detail. The VGG19 encoder

extracts high-resolution features from the 2.5D

image input, while UNet++'s nested skip con-

nections allow for i UNet⁺⁺⁺ with a VGG19 encoder to balance
depth and detail. The VGG19 encoder
depth and detail. The VGG19 encoder
extracts high-resolution features from the 2.5D
in The Dice Coefficient
mage input, while UNet++^x nested s

delineation. **3.4 Training and Parameter Settings**
 3.4 Training and Parameter To scale the model is training that the model with the model is trained in Figure 4. The MBconv blocks in Edge U-Net allow for efficient processing while preserving edge integrity, which is critical for precise GI organ de

WE

We diecture with HED

scales, as illustrated in Figure 4. The

MBconv blocks in Edge U-Net allow for

efficient processing while preserving edge

integrity, which is critical for precise GI organ

delineation.

3.4 Tra **Follow 1.1.**
 reference of the 1.00
 reflicient consists in Edge U-Net allow for

efficient processing while preserving edge

integrity, which is critical for precise GI organ

delineation.
 **3.4 Training and Paramete is a coupled with the Seales, as illustrated in Figure 4. The MBconv blocks in Edge U-Net allow for efficient processing while preserving edge integrity, which is critical for precise GI organ delineation.

3.4 Training** it is set the HED
scales, as illustrated in Figure 4. The
MBconv blocks in Edge U-Net allow for
efficient processing while preserving edge
integrity, which is critical for precise GI organ
delineation.
3.4 Training and Par itecture with HED
scales, as illustrated in Figure 4. The
MBconv blocks in Edge U-Net allow for
efficient processing while preserving edge
integrity, which is critical for precise GI organ
delineation.
3.4 Training and Par scales, as illustrated in Figure 4. The
MBconv blocks in Edge U-Net allow for
efficient processing while preserving edge
integrity, which is critical for precise GI organ
delineation.
3.4 Training and Parameter Settings
To MBconv blocks in Edge U-Net allow for
efficient processing while preserving edge
integrity, which is critical for precise GI organ
delineation.
3.4 Training and Parameter Settings
To optimize learning, the model is trained efficient processing while preserving edge
integrity, which is critical for precise GI organ
delineation.
3.4 Training and Parameter Settings
To optimize learning, the model is trained
with a batch size of 16 and an initia integrity, which is critical for precise GI organ
delineation.
3.4 Training and Parameter Settings
To optimize learning, the model is trained
with a batch size of 16 and an initial learning
rate of 0.001. An adaptive learn **3.4 Training and Parameter Settings**
To optimize learning, the model is trained
with a batch size of 16 and an initial learning
rate of 0.001. An adaptive learning rate
scheduler, coupled with the Adam optimizer,
adjusts 3.4 Training and Parameter Settings

To optimize learning, the model is trained

with a batch size of 16 and an initial learning

rate of 0.001. An adaptive learning rate

scheduler, coupled with the Adam optimizer,

adjus To optimize learning, the model is trained
with a batch size of 16 and an initial learning
rate of 0.001. An adaptive learning rate
scheduler, coupled with the Adam optimizer,
adjusts the rate throughout the training proce with a batch size of 16 and an initial learning
rate of 0.001. An adaptive learning rate
scheduler, coupled with the Adam optimizer,
adjusts the rate throughout the training process.
Training is conducted over 50 epochs, w rate of 0.001. An adaptive learning rate
scheduler, coupled with the Adam optimizer,
adjusts the rate throughout the training process.
Training is conducted over 50 epochs, with
early stopping applied if the validation lo scheduler, coupled with the Adam optimizer,
adjusts the rate throughout the training process.
Training is conducted over 50 epochs, with
early stopping applied if the validation loss
does not improve over 10 consecutive e adjusts the rate throughout the training process.
Training is conducted over 50 epochs, with
early stopping applied if the validation loss
does not improve over 10 consecutive epochs.
These settings balance model performa Training is conducted over 50 epochs, with
early stopping applied if the validation loss
does not improve over 10 consecutive epochs.
These settings balance model performance and
training efficiency.
3.5. **Divise Coeffici**

uation Metrics

• Coefficient (DC)

• Coefficient measures the similarity

predicted and actual segmentations,

g an overlap- based evaluation metric

entation quality. It is computed as:

M and OM represent the predict 2 × ∩ sures the similarity
tual segmentations,
d evaluation metric
is computed as:
the predicted and
ively.
 \times $|PM \cap OM|$
 \times $|M \cap OM|$
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training efficiency.
3.5 **Evaluation Metrics**
3.5.1Dice Coefficient (DC)
The Dice Coefficient measures the similarity
between predicted and actual segmentations,
providing an o training efficiency.

3.5 Evaluation Metrics

3.5.1Dice Coefficient (DC)

The Dice Coefficient measures the similarity

between predicted and actual segmentations,

providing an overlap- based evaluation metric

for segme 3.5 Evaluation Metrics

3.5.1 Dice Coefficient (DC)

The Dice Coefficient measures the similarity

between predicted and actual segmentations,

providing an overlap- based evaluation metric

for segmentation quality. It i **5.5 EVALUATION Metrics**

3.5.1Dice Coefficient (DC)

The Dice Coefficient measures the similarity

between predicted and actual segmentations,

providing an overlap- based evaluation metric

for segmentation quality. It

$$
DC(PM, OM) = \frac{2 \times |PM \cap OM|}{|PM| + |OM|} \#(1)
$$

International Conference on Social Development
and **Intelligent Technology (SDIT2024)**
between the closest points in the predicted and
ground truth masks:
 $HD(PM, OM) = \max\left(\max_{pm,m,om} \min(|pm - om|)\right) \#(2)$
This metric assesses the sp **International Conference on Social Development and Intelligent Technology (SDIT2024)**

ernational Conference on Social Developme
 I Intelligent Technology (SDIT2024)

ween the closest points in the predicted and

und truth masks:
 $HD(PM, OM) = max \left(\max_{pm,om} min (|pm - om|) \right) \#(2)$

is metric assesses the spatial accu **International Conference on Social Development**
 and Intelligent Technology (SDIT2024)

between the closest points in the predicted and

ground truth masks:
 $HD(PM, OM) = max \begin{pmatrix} max min (|pm - om|) \end{pmatrix} # (2)$

This metric assesses th delineation.

International Conference on Social Development
 and Intelligent Technology (SDIT2024)

between the closest points in the predicted and

ground truth masks:
 $HD(PM, OM) = \max\left(\max_{pm,om} \min(|pm - om|)\right) \#(2)$

This metric assesses th **International Conference on Social Development**

and Intelligent Technology (SDIT2024)

between the closest points in the predicted and

ground truth masks:
 $HD(PM, OM) = \max(\max_{p,m,om} \min(|pm - om|)) \#(2)$

This metric assesses the spa **International Conference on Social Development**
 and Intelligent Technology (SDIT2024)

between the closest points in the predicted and

ground truth masks:
 $HD(PM, OM) = max \begin{pmatrix} max \ min (\vert pm - om \vert) \end{pmatrix} \neq (2)$

This metric assesse

$$
Score = 0.4 \times Dice Coefficient + 0.6 \times 3D
$$

Hausdorff Distance (3)

Example 12

Intelligent Technology (SDIT2024)

ween the closest points in the predicted and

und truth masks:
 $HD(PM, OM) = max \left(\max_{pm,om} min (|pm - om|)\right) \#(2)$

or efform

s metric assesses the spatial accuracy of the

mentation, cru between the closest points in the predicted and

ground truth masks:
 $HD(PM, OM) = \max(\max_{m\omega m} \min(|pm - om|)) #(2)$

This metric assesses the spatial accuracy of the

segmentation, crucial for precise anatomical

delineation, crucial f ground truth masks:
 $HD(PM, OM) = \max(\max_{pm0.000} \min(\text{p}m - om)) + (2)$ performance of E

This metric assesses the spatial accuracy of the

segmentation, crucial for precise anatomical

delineation,

3.5.3Composite Score

Combining Dic $HD(PM, OM) = \max \left(\max_{pm,om} \min(|pm - om|)\right) \#(2)$
This metric assesses the spatial accuracy of the
segmentation, crucial for precise anatomical
delineation.
3.5.3Composite Score
Combining Dice Coefficient and 3D Hausdorff
Distance, a c

This metric assesses the spatial accuracy of the
segmentation, crucial for precise anatomical
delineation.
3.5.3Composite Score
Combining Dice Coefficient and 3D Hausdorff
Distance, a composite score evaluates overall
seg This metric assesses the spatial accuracy of the

segmentation, crucial for precise anatomical

delineation

3.5.3Composite Score

Conbining Dice Coefficient and 3D Hausdorff

Distance, a composite score evaluates overall Segmentation, crucial for precise anatomical

delineation.

2.5D Images

2.5D Images

Combining Dice Coefficient and 3D Hausdorff

Distance, a composite score evaluates overall

2.1 Dimage experime

Score = 0.4 × Dice Coef delineation.

3.5.3Composite Score

Combining Dice Coefficient and 3D Hausdorff

Distance, a composite score evaluates overall

Distance, a composite score evaluates overall

Validation scores are precedent

Score = 0.4 × 3.5.3Composite Score

Combining Dice Coefficient and 3D Hausdorff

Distance, a composite score evaluates overall

Segmentation per-formance:

Score = 0.4 × Dice Coefficient + 0.6 × 3D

Table 2: 2.5D Image Segmentation per Combining Dice Coefficient and 3D Hausdorff

Distance, a composite score evaluates overall

Segmentation per-formance:

Score = 0.4 × Dice Coefficient + 0.6 × 3D

Hausdorff Distance

This score provides a balanced view of Distance, a composite score evaluates overall

segmentation per-formance:

Score = 0.4 × Dice Coefficient + 0.6 × 3D

Hausdorff Distance

This score provides a balanced view of model

This score provides a balanced view o segmentation per-formance:

Score = 0.4 × Dice Coefficient + 0.6 ×

Hausdorff Distance

This score provides a balanced view of mo

accuracy and robustness in delineat

complex GI structures.
 4. Experimental Results

Our Hausdorff Distance (3)
This score provides a balanced view of model
accuracy and robustness in delineating
complex GI structures.
4. Experimental Results
Our proposed model was rigorously evaluated
on both grayscale and This score provides a balanced view of model

accuracy and robustness in delineating

complex GI structures.
 4. Experimental Results

On proposed model was rigorously evaluated

on both grayscale ned 2.5D MRI datasets t accuracy and robustness in delineating

scans of the GI tractures.

To all the GI tractures of the GI tractures of the GI tractures of the GI tractions

our proposed model and 2.5D MRI datasets to

sesses its segmentation complex GI structures.

4. **Experimental Results**

Our proposed model was rigorously evaluated

on both grayscale and 2.5D MRI datasets to

achieving a validation

areas its segmentation performance across

different confi

4. Experimental Results

Our proposed model was rigorously evaluated

on both grayscale and 2.5D MRI datasets to

achieving a validation scores

different configuration performance across

different configurations. Resul Our proposed model was rigorously evaluated

on both grayscale and 2.5D MRI datasets to

different configurations. Results for each

different configurations. Results for each

different configurations. Results for each

d or both grayscale and 2.5D MRI datasets to

achieving a validati

assess its segmentation performance across

different configurations. Results for each

model architecture are presented below,

feature extraction consults assess its segmentation performance across
different configurations. Results for each
model architecture are presented below,
highlighting the comparative advantages of
each approach.
4.1 Dataset Description
The dataset model architecture are presented below,

highlighting the comparative advantages of

each approach.
 4.1 Dataset Description
 4.4 Dataset used in this study includes MRI
 5. Conclu

scans of the GI tract, annotated f In the grayscale Images

In the grayscale in this study includes MRI

The dataset used in this study includes MRI

S. Conclusion

S. encoders were tested within the UNet and focused grayscale and sessions of the GI tract, amotated for key regions such as of the GI tract, amotated for key regions such as the GI tract, amotated for key regions and the UNe anatomical structures.
 4.1 Dataset Description

Scans of the GI tract, annotated for key regions

scans of the GI tract, annotated for key regions

This study presents

such as the colon, small intestine, and stomach.
 4.1 Dataset Description

The dataset used in this study includes MRI

scans of the GI tract, annotated for key regions

Such as the colon, small intestine, and stomach.

This study I

such as the colon, small intestine, The dataset used in this study includes MRI

scans of the GI tract, annotated for key regions

such as the colon, small intestine, and stomach.

This study presents

validation sets, was sourced from multiple

in that seg

Such as the colon, small intestine, and stomach.

This dataset, divided into training and

advanced deep

matititions to ensure diversity and robustness
 1.2 Results on Grayscale Images
 1.2 Results on Grayscale Images Is dataset, divided into training and

lidation sets, was sourced from multiple

stitutions to ensure diversity and robustness
 Model evaluation.
 Paramelers and the prayer of the grayscale Images
 Paramelers are cons

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 and Intelligent Technology (SDIT2024)

between the closest points in the predicted and

ground truth masks:
 $HD(PM, OM) = max \begin{pmatrix} max min (|pm - om|) \\ m, om \end{pmatrix} # (2)$

This metric assesse **ence on Social Development**
 nology (SDIT2024)

bints in the predicted and
 $\begin{array}{ll}\n&\text{uncertainty of 0.8} \\
&\text{UNet and UNet} \\
\text{max min } (|pm - om|)\big) \#(2) \\
&\text{performance of edge- focused} \\
&\text{neg of edge- focused} \\
&\text{for precise anatomical} \\
&\text{boundary detection} \\
&\text{ficient and 3D Hausdorff} \\
&\text{in the 2.5D image} \\
&\text{score evaluates overall} \\
&\text{various encoder$ **International Conference on Social Development**

and Intelligent Technology (SDIT2024)

between the closest points in the predicted and

ground truth masks:
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accuracy of 0.84046, outper-forming both

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4.3 Results on 2.5D Images
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4.3 Results on 2.5D Images
In the 2.5D image experiments, UNet++ with
various encoder configurations was evaluated.
Validation scores are presen boundary detection is critical.

4.3 Results on 2.5D Images

In the 2.5D image experiments, UNet++ with

various encoder configurations was evaluated.

Validation scores are presented in Table 2.

Table 2: 2.5D Image Segm **4.3 Results on 2.5D Images**
In the 2.5D image experiments, UNet++ with
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Validation scores are presented in Table 2.
Table 2: 2.5D Image Segmentation Score
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Table 2: 2.5D Image Segmentation Results
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Table 2: 2.5D Image Segmentation Results
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Validation scores are presented in Table 2.

Table 2: 2.5D Image Segmentation Results

Model Encoder Validation Score

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UNet++ Xception 0.7961

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Table 2: 2.5D Image Segmentation Results

Model Encoder Validation Score

UNet++ ResNet50 0.80138

UNet++ Xception 0.7961

UNet++ VGG19 0.84984

For 2.5D images, UNet++ with the **Example 12.1**

UNet++ ResNet50 0.80138

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For 2.5D images, UNet++ with the V

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For 2.5D images, UNet⁺⁺ with the VGG19

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By combining Inception-V4 for initial
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detection capabilities, while UNet++ with $VGG19$ excels in $2.5D$ data processing. bene- fiting from additional depth context in the MRI slices. These complementary strengths support a multi-path approach, advanced deep learning architectures to
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