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Trustseg-Net: Uncertainty-Calibrated Medical Image Segmentation with Boundary-Aware Confidence Estimation

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Abstract- Medical image segmentation plays an important role in computer-aided diagnosis by identifying anatomical structures and pathological regions from medical images. Deep learning models have achieved significant improvements in segmentation accuracy, but they may produce uncertain predictions and inaccurate boundaries, particularly in low-contrast and irregular regions. This study proposes TRUSTSEG-NET, an uncertainty-calibrated medical image segmentation framework with boundary-aware confidence estimation. The proposed framework combines deep learning-based segmentation, boundary-aware learning, uncertainty estimation, and confidence calibration to improve segmentation accuracy and prediction reliability. Medical images are preprocessed using resizing, normalization, and augmentation techniques before model training. The framework generates pixel-level segmentation masks while estimating uncertainty in difficult regions. Performance is evaluated using Dice Similarity Coefficient, Intersection over Union, Precision, Recall, and Boundary F1-Score. The proposed approach provides both segmentation results and confidence information, supporting reliable medical image analysis and computer-aided diagnostic applications.

Keywords— Medical image segmentation, deep learning, uncertainty estimation, confidence calibration, boundary-aware segmentation, medical image analysis, computer-aided diagnosis, trustworthy AI, deep neural networks.

I. INTRODUCTION

Medical imaging techniques such as MRI, CT, ultrasound, X-ray, and dermoscopy are widely used for disease diagnosis and treatment planning. Accurate segmentation of organs, tissues, and pathological regions is important for extracting meaningful clinical information.

Manual segmentation requires significant time and medical expertise. Differences between medical experts can also result in inconsistent annotations. Deep learning provides an effective solution by automatically learning important features and generating pixel-level segmentation masks.

CNN-based architectures such as U-Net have achieved significant success in medical image segmentation. However, existing models may produce incorrect boundaries or highly confident predictions in uncertain regions.

Medical images often contain noise, low contrast, irregular structures, and unclear boundaries. These conditions make accurate segmentation difficult, particularly for small lesions and complex anatomical regions.

Therefore, this research proposes TRUSTSEG-NET, which combines segmentation, boundary-aware learning, uncertainty estimation, and confidence calibration. The main objective is to produce accurate segmentation masks while identifying regions where the model is less reliable.

The proposed framework aims to improve the reliability of medical image segmentation and support trustworthy computer-aided diagnosis.

II. LITERATURE REVIEW

Traditional medical image segmentation methods mainly use thresholding, region growing, clustering, edge detection, and active contour techniques. These methods are useful for simple images but their performance decreases when images contain noise, intensity variations, and unclear boundaries.

U-Net introduced an encoder-decoder architecture with skip connections, allowing the model to preserve spatial information while learning high-level features.

Several U-Net variants have incorporated attention mechanisms, residual connections, dense connections, and multi-scale feature extraction. These improvements have enhanced segmentation performance for different medical imaging applications.

Transformer-based approaches have also been introduced to capture long-range relationships within medical images. Hybrid CNN-transformer architectures combine local feature extraction with global contextual information.

However, high segmentation accuracy does not always indicate reliable predictions. Deep learning models can sometimes produce overconfident predictions for incorrect regions. Therefore, uncertainty estimation and confidence calibration have become important components of trustworthy medical AI.

Boundary-aware approaches have also been developed to improve the segmentation of irregular and weak boundaries. These approaches focus on contour information and boundary-specific learning to reduce boundary errors.

Existing studies generally focus on segmentation accuracy, uncertainty estimation, or boundary improvement separately. TRUSTSEG-NET combines these components into a unified framework to achieve accurate, boundary-aware, and trustworthy medical image segmentation.

III. METHODOLOGY

The proposed methodology consists of the following major stages:

[Dataset Collection]
↓
[Image Preprocessing]
↓
[Dataset Splitting]
↓
[Feature Extraction]
↓
[Segmentation Module]
↓
[Boundary-Aware Module]
↓
[Uncertainty Estimation]
↓
[Confidence Calibration]
↓
[Performance Evaluation]
↓
[Final Segmentation + Confidence + Uncertainty Maps]

1. Dataset Collection

A publicly available medical image segmentation dataset will be used for model development and evaluation. The dataset contains medical images and corresponding ground-truth segmentation masks.

The ground-truth masks will be used as reference annotations for comparing the predicted segmentation results.

The dataset will be carefully organized to ensure that training, validation, and testing images are separated without data leakage.

2. Data Preprocessing

The collected images will be preprocessed to provide consistent input to the proposed model.

The preprocessing steps include:

- Resizing images to a fixed input resolution.
- Normalizing pixel intensity values.
- Removing unwanted artifacts where required.
- Applying data augmentation techniques.
- Converting images and masks into tensors.

Data augmentation techniques such as rotation, horizontal flipping, scaling, cropping, and brightness variation will be applied to improve model generalization.

3. Dataset Splitting

The dataset will be divided into three subsets:

- Training Set – 70%
- Validation Set – 15%
- Testing Set – 15%

The training set will be used for learning model parameters. The validation set will be used for monitoring model performance and selecting suitable model configurations.

4. TRUSTSEG-NET Architecture

TRUSTSEG-NET consists of four major components designed to improve segmentation accuracy and prediction reliability.

Feature Extraction Module

The feature extraction module learns important visual features from the input medical image. These features include edges, textures, shapes, intensity patterns, and anatomical structures.

Segmentation Module

The segmentation module generates a pixel-level probability map and produces the final segmentation mask.

An encoder-decoder architecture with skip connections can be used to preserve both high-level semantic information and fine spatial details.

Boundary-Aware Module

The boundary-aware module focuses on the edges of the target region.

It gives additional importance to boundary regions so that the model can better identify irregular and weak anatomical or pathological boundaries.

Uncertainty and Confidence Module

The uncertainty module identifies regions where the model is less certain about its prediction.

The confidence calibration component provides more reliable confidence values and helps reduce overconfident incorrect predictions.

This allows the system to identify potentially unreliable segmentation regions that may require additional inspection.

Overall Architecture

The overall TRUSTSEG-NET architecture is designed to provide accurate segmentation together with reliable prediction information. The input medical image is first processed through the feature extraction module to identify important spatial and contextual features. The extracted features are then passed to the segmentation module to generate the pixel-level segmentation map.

The boundary-aware module focuses specifically on the boundary regions of the target structure. This helps the network preserve fine details and improve segmentation around irregular or weak boundaries. The uncertainty estimation module identifies regions where the prediction may be unreliable, while the confidence calibration component provides a more meaningful confidence value for the predicted segmentation.

The final system produces three important outputs: the segmentation mask, confidence map, and uncertainty map. These outputs provide both the predicted medical region and additional information about the reliability of the prediction. Therefore, TRUSTSEG-NET is designed not only for accurate segmentation but also for improving the trustworthiness and interpretability of medical AI systems.

5. Model Training

The TRUSTSEG-NET model will be trained using the prepared training dataset.

The proposed training configuration includes:

- Optimizer: Adam
- Learning Rate: 0.0001
- Batch Size: 16 or 32
- Epochs: 30–50
- Activation: Sigmoid
- Loss: Segmentation and Boundary-Aware Loss

Early stopping and model checkpointing will be used to reduce overfitting and preserve the best-performing model.

6 Performance Evaluation

The trained model will be evaluated using the unseen testing dataset.

The performance will be measured using:

- Dice Similarity Coefficient
- Intersection over Union
- Precision
- Recall
- Boundary F1-Score
- Uncertainty and Confidence Measures

Dice and IoU will measure the overlap between the predicted segmentation and ground-truth mask. Precision and recall will measure the correctness and completeness of the segmentation. Boundary F1-Score will evaluate the quality of the predicted boundaries.

7. Workflow

Medical Image Dataset
↓
Image Preprocessing
(Resizing, Normalization, Augmentation)
↓
Dataset Splitting
(Training, Validation, Testing)
↓
TRUSTSEG-NET Feature Extraction
↓
Segmentation Module
↓
Boundary-Aware Module
↓
Uncertainty Estimation
↓
Confidence Calibration
↓
Performance Evaluation
(Dice, IoU, Precision, Recall, Boundary F1-Score)
↓
Reliable Medical Image Segmentation

IV. MEAN OUTPUT

The final output of TRUSTSEG-NET consists of the predicted segmentation mask, confidence map, and uncertainty map for each input medical image. The segmentation mask identifies the target anatomical or pathological region, while the confidence map indicates the reliability of the prediction.

The mean performance is calculated across all test images to obtain an overall representation of the model's segmentation and prediction reliability.

The mean output will include the following measures:

- Mean Dice Score
- Mean IoU
- Mean Precision
- Mean Recall
- Mean Boundary F1-Score
- Mean Confidence Score
- Mean Uncertainty Score

The mean values will be calculated after completing model training and testing. Since the proposed model has not yet been experimentally evaluated, numerical mean values are not assumed or reported. The final output can be represented as:

Input Medical Image → Segmentation Mask + Confidence Map + Uncertainty Map

The segmentation mask provides the predicted region, the confidence map indicates prediction reliability, and the uncertainty map highlights regions requiring additional attention or verification.

1. Output Visualization

The output of TRUSTSEG-NET can be visualized using the original medical image, ground-truth mask, predicted segmentation mask, confidence map, and uncertainty map.

The original image represents the input, while the ground-truth mask provides the reference region. The predicted mask shows the region identified by the proposed model.

The confidence map represents the level of confidence associated with the segmentation prediction. The uncertainty map highlights regions where the model has lower confidence.

Such visualization can help researchers understand the behavior of the segmentation model and identify challenging regions that require further analysis.

2. Mean Performance Interpretation

The mean output provides a comprehensive summary of the model performance across the complete testing dataset. Instead of considering the performance of a single image, the mean values represent the overall segmentation quality of the proposed framework.

A higher mean Dice, IoU, Precision, Recall, and Boundary F1-Score indicates better segmentation and boundary localization, whereas the mean uncertainty and confidence values provide information about the reliability of the model predictions.

The combination of segmentation performance and uncertainty information is important for medical applications because an accurate prediction alone may not always indicate a reliable prediction. TRUSTSEG-NET therefore provides additional confidence and uncertainty information that can help identify difficult regions and support further clinical verification.

Future Work

Advanced Architectures

Future research can investigate Vision Transformers, hybrid CNN-transformer architectures, and other advanced segmentation networks to improve feature extraction and segmentation performance.

Improved Uncertainty Estimation

Advanced Bayesian deep learning, ensemble learning, and probabilistic segmentation techniques can be explored to obtain more reliable uncertainty estimates.

Explainable AI

Explainable AI techniques such as Grad-CAM, attention maps, and uncertainty visualization can be integrated to help medical professionals understand model predictions.

Multi-Modal Medical Imaging

The framework can be extended to different medical imaging modalities such as MRI, CT, ultrasound, X-ray, and dermoscopic images.

Cross-Dataset Validation

Future studies can evaluate the proposed framework using multiple datasets to measure its generalization across different imaging conditions, devices, and patient populations.

Real-Time Deployment

Model compression, quantization, and TensorFlow Lite conversion can be explored for deploying the proposed framework on mobile and edge devices.

Clinical Validation

Large-scale clinical evaluation can be performed to determine the practical usefulness and reliability of the proposed framework in real-world healthcare environments.

V. CONCLUSION

This research proposed TRUSTSEG-NET, an uncertainty-calibrated medical image segmentation framework with boundary-aware confidence estimation.

The framework combines deep learning-based segmentation, boundary-aware learning, uncertainty estimation, and confidence calibration to improve segmentation accuracy and prediction reliability.

The proposed methodology focuses not only on generating accurate segmentation masks but also on identifying uncertain regions and improving boundary localization.

The model will be evaluated using Dice Similarity Coefficient, IoU, Precision, Recall, Boundary F1-Score, and uncertainty-based measures. The mean output will provide an overall representation of segmentation quality, confidence, and uncertainty across the testing dataset.

Since experimental implementation has not yet been completed, numerical performance values are not assumed or reported. The actual mean results will be added after training and evaluating the proposed TRUSTSEG-NET model.

Overall, TRUSTSEG-NET provides a promising approach toward accurate, boundary-aware, uncertainty-calibrated, and trustworthy medical image segmentation. The framework can potentially support medical image analysis, computer-aided diagnosis, and clinical decision-support applications.

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