National Journal of Signal and Image Processing, ISSN: 3107-5231 Vol. 1, No. 4, 2025 (pp. 30-37)

RESEARCH ARTICLE

ECEJOURNALS.IN

# Deep Residual U-Net for Accurate Medical Image Segmentation in Limited Data Scenarios

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**KEYWORDS:**
Medical image segmentation,
U-Net,
Residual learning,
Deep learning,
Limited data,
Dice coefficient,
Convolutional neural network (CNN),
ISIC,
DRIVE,
DRU-Net

**ARTICLE HISTORY:**
Submitted : 13.06.2025
Revised : 05.07.2025
Accepted : 18.08.2025

https://doi.org/10.17051/NJSIP/01.04.05

## Abstract

Proper and effective segmentation of medical images is of central importance in the diagnosis in the clinics, preoperative investigation of the disease, and postoperative follow-up of the process. Even in spite of the progress in deep learning, traditional convolutional neural network (CNN) models including U-Net still suffer challenges when trained on small-scale datasets annotated ones that are normally the case in medical imaging since there are privacy concerns and also the annotation cost and limited data. The limitation can be addressed by the novel type of Deep Residual U-Net (DRU-Net) architecture incorporating residual learning methods into the classic encoder-decoder block system of the original U-Net. The proposed model utilizes the residual connections on multiple levels, which helps to use features more productively, smooth the gradient flow of deeper layers, and reduce the vanishing gradient problem, which promotes the effectiveness of training and the quality of segmentation results. To further optimize on the situation of limited data, DRU-Net also uses batch normalization and dropout regularization, as well as a hybrid loss composed of binary cross-entropy and Dice loss to solve the class imbalance problem. Severe experiments were done in two publicly released benchmark objects, ISIC 2018 and DRIVE, used in skin lesion segmentation and retinal vessel segmentation correspondingly. The findings reveal that DRU-Net surpasses the original U-Net, ResUNet and other newer architectures, in measures of Dice coefficient, Intersection-over-Union (IoU) sensitivity and accuracy of the boundaries (Hausdorff distance). DRU-Net showed an improvement in the Dice score of up to 6 percent as compared to baseline models, which shows that DRU-Net does not require so much supervision to extract fine-grained anatomy features. Qualitative visualization additionally answers that DRU-Net has the capability to maintain the anatomical boundaries and more accurately defining ambiguous areas. The proposed architecture is a scalable and computationally efficient medical image segmentation solution that can guarantee detection with a satisfactory result in resource-based or privacy-related clinical settings. This is the first step toward the practical application of data-efficient segmentation models in real-world clinical practice, and leaves room to optimize the models even further with attention, transfer learning, and federated training paradigms to achieve closer integration with clinical practice.

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**How to cite this article:** Dehghani MH, Varga Z. Deep Residual U-Net for Accurate Medical Image Segmentation in Limited Data Scenarios. National Journal of Signal and Image Processing, Vol. 1, No. 4, 2025 (pp. 30-37).

## Introduction

Segmentation of medical images is an essential element included in the domain of medical image analysis, which is an introductory step to -among others- diagnosis, treatment planning, surgical management, and disease progression surveillance. The object of the segmentation is to correctly outline the anatomical lesion and pathological regions, i.e., the tumor, a lesion, a vessel or an organ based on the imaging modalities such as MRI, CT, ultrasound and dermoscopic images. Manual segmentation by clinicians, even though it is accurate, is time-consuming, it is prone to inter-observer variability and it cannot be used on big sets of data or real-time situations. This is leading to increased need of automated and trustworthy systems of segmentation.

Over the past few years, medical image segmentation has become an active area of deep learning research, in particular convolutional neural networks (CNNs).

Among them, the U-Net architecture has become very popular, especially its encoder-decoder design with skip linkages which makes it useful at locating things precisely with the help of high level semantic analysis and low level spatial representation. Although they perform well, conventional deep networks such as U-Net have to generalize poorly in reality in terms of medical applications, largely because of the scarcity of annotated data. This weakness is due to privacy rules, the prohibitive expense of expert labeling and the limited occurrence of unusual pathological cases. Internal models with a moderate sized target database will consequently be at the risk of overfitting, which is likely to bring about poor performance on test data.

In the paper herein, we will propose a new Deep Residual U-Net (DRU-Net) architecture which will also learn using less data. Through incorporation of residual connection within U-Net structure, DRU-Net enhances the use of features as well as gradient flow, eliminating the degradation and the vanishing gradient issues of deep networks. The remaining blocks aid in ensuring the preservation of characteristics between layers, and thus enable the network to learn deep representations without necessarily experiencing an increment in the threat of overfitting.

Moreover, there are other regularization methods added to the proposed architecture including batch normalization and dropout, other than using hybrid loss that is a combination of pixel-wise cross-entropy and Dice loss. These improvements lead to increased robustness particularly in segmentation of small or irregular areas that are most common in medical images. We test the performance of DRU-Net on two benchmark datasets: ISIC 2018 to evaluate the DRU-Net capabilities in skin lesion segmentation and DRIVE to investigate the capability of the DRU-Net concerning retinal vessel segmentation showing greater performance than standard U-Net on both criteria of performance accuracy and sensitivity, and boundary fragmentation.

In short, this paper will be elaborating on how the performance gap between architectural complexity and limited training data will be closed by introducing the concept of residual-enhanced U-Net framework that will be well suited to handling medical images segmentation tasks with limited data. The proposed DRU-Net is not only the solution to the existing problems but also opens the gate to more accurate and data-efficient segmentation model that could be used in various clinical settings.

## Related Work

Image segmentation in medicine has undergone a lot of improvement in the last ten years, mainly claiming so with the achievement of deep-learning models especially convolutional neural networks (CNNs). The U-Net architecture by[1] remains one of the first architectures with[8] the biomedical community relying on it as the basis of segmentation. With the encoder-decoder structure and aided by symmetric skip network, U-Net is able to identify global contexts and local finer details.[9] It has proved to be quite useful and thus, it has become common among many segmentation tasks, such as tumor boundary detection, vessel segmentation and lesion delineation.

As the strengths of U-Net, researchers have been trying to extend it in many ways with a view to enhancing its performances and generalization. Such a direction includes the integration of residual learning. The Residual Networks (Re Nets)[2] architecture by He et al. has shown that learning residual mappings works towards a better training convergence, support deeper architectures, and reduce the case of the vanishing gradient problem.[10] Such benefits have encouraged the introduction of residual blocks in U-Net making way to the so-called hybrid designs like ResUNet and[3] integrating the localization powers of U-Net with the stability and expressivity of residual networks. The expansion of these models however, can come at the expense of added complexity which can be more computationally costly and serves as a limit to potential implementation on real cases or when time and resource are a constraint.

Other examples of growing popularity in segmentation frameworks are attention mechanisms.[11] The Attention U-Net [4] focuses only the parts of feature maps that are informative, thus enhancing the focus on significant anatomical structures. Although they do not have some of the drawbacks in accuracy that other models do, these models are also memory intensive and need large amounts of data to avoid overfitting, which can be difficult when annotated data is limited.

To overcome the insufficiency of data issue, some papers have used data augmentation [5], generative adversarial networks to create synthetic data[6] or large-scale natural image datasets to do transfer learning.[7] Although they are effective, such techniques usually necessitate[12] further computational cost or pre-training and do not address the architecturally inherent sensitivity to low-data regimes.

Conversely, our proposed DRU-Net has been formulated to enhance generalization and segmentation accuracy via the use of architectural improvements solely, aimed at enhancing performance robustness in low-data operations. Our method (Table 1) contrasts with such approaches (Table 1) by incorporating residual

**Table 1: Summary of Related Work in Medical Image Segmentation**

| Model/Approach | Core Innovation | Strengths | Limitations |
|---|---|---|---|
| **U-Net**[1, 8, 9] | Encoder-decoder with skip connections | Accurate localization, widely adopted | Struggles with generalization in limited data |
| **ResUNet**[3, 10] | Residual blocks integrated with U-Net | Improved gradient flow, better convergence | Increased computational complexity |
| **Attention U-Net**[4 11] | Attention gates for feature enhancement | Focuses on relevant regions, improves accuracy | Memory-intensive, prone to overfitting in low-data |
| **GAN-based Augmentation**[6] | Synthetic data generation using GANs | Expands dataset variability, improves robustness | Requires additional training and validation steps |
| **Transfer Learning**[7, 12] | Pretrained on large natural image datasets | Leverages prior knowledge, improves convergence | Domain mismatch, high pretraining overhead |

connections into the U-Net framework, after it offers light-weight and also high-performing alternatives that base on a balance between model capacity and convergence speed and data efficiency.

## Methodology

### Proposed Architecture

The proposed Deep Residual U-Net (DRU-Net) is an improvement of the standard U-Net in that the residual learning is introduced to each layer of the encoding and decoding blocks. Among the common problems solved by this integration there include vanishing gradients and inability to converge in more depth models and overfitting mainly in cases where annotated data is limited.

### General Plan

The DRU-Net extends the property of U-Net by modifying the structure to include the addition of residual blocks on the decoder path and encoder path of every level. These blocks of residuals are aimed at enhancing the expression of the information and gradients in the network when it is made to be deeper and more expressive without compromising performance.

### Residual Block Design

The every residual block consists of the following elements:

- Two 3x3 Convolutional Layers: These layers will aid in the extraction of the spatial features that are hierarchical. All convolutions receive subsequent batch normalization (BN) that makes distributional feature numbers comparable faster and more efficiently.
- ReLU Activation: ReLU activation is also used after each BN layer so that the results are non-linear and sparse activation matrices are obtained.
- Skip Connection (Residual Mapping): A short cut path is created between the input to the residual block and the output of 2nd conv2d layer, adding them together element-wise. This remaining association allows training the block to learn identity functions and also allows training deeper networks by alleviating the gradient vanishing problem.

Mathematically, the residual block would have the following form:

$$\mathbf{y} = \mathcal{F}(\mathbf{X}, \{\mathbf{W}_i\}) + \mathbf{X} \tag{1}$$

There by making it possible to gauge the progress of the period and even the extent of the revolution.

Where the green box (stacked convolutional, BN, and ReLU operations) is represented by the fact that the convolution operation is concatenated along with the BN and ReLU operations. The block input is the loss.

### Down sampling and up sampling

Reduction of spatial dimensions in the encoder path is done through 2 x 2 max pooling, which further downsample the features and retains only the most prominent.

The transposed convolution (also called deconvolution) of 2*2 concludes up sampling in the decoder since it restores spatial resolution of the feature maps.

Skip the Connections between the Encoder and the Decoder

Besides internal residual connection, there is an additional condensed skip connection between the layers of the encoder and decoder. These links bridge the feature maps of the encoder with the upsampled outputs of the decoder to merge the feature maps of the encoder with high resolution high-level semantics to enhance the localization accuracies.

**Table 2: Components of the Proposed DRU-Net Architecture**

| Component | Description | Purpose |
|---|---|---|
| **Residual Block** | Two 3×3 Conv layers + Batch Normalization (BN) + ReLU + Skip connection | Improves gradient flow, enables deep learning without degradation |
| **ReLU Activation** | Applied after each BN layer | Introduces non-linearity and sparsity |
| **Skip Connection (within block)** | Adds input directly to the output of residual stack | Learns identity mappings, reduces vanishing gradient problem |
| **Down sampling (Encoder)** | 2×2 Max Pooling | Reduces spatial resolution, captures coarse features |
| **Up sampling (Decoder)** | 2×2 Transposed Convolution | Restores spatial resolution of feature maps |
| **Encoder-Decoder Skip Connections** | Horizontal links between encoder and decoder layers | Preserves high-resolution spatial features for precise localization |
| **Final Output Layer** | 1×1 Convolution followed by Sigmoid (binary) or Softmax (multi-class) | Produces pixel-level segmentation mask with desired number of output classes |

## End Segmentation Layer

The result of the last decoder layer is further processed through a 1 x 1 convolutional layer that converts the multiple channel feature maps to a single channel of the specified amount of classes to segment. Table 2the activation to be used when segmenting into two categories is a sigmoidal one, whereas softmax can be used in a scenario of multi-class.

## Loss Function

The medical imaging tasks sometimes are bogged down by the challenge of class imbalance wherein the foreground (e.g., lesion, tumor, or vessel) is much smaller than the background. Conventional loss functions e.g. Binary Cross-Entropy (BCE) are biased to the majority class giving rise to poor segmentation of the minor (foreground) class. To overcome such a problem, DRU-Net, as suggested here, incorporates a composite loss that involves both pixel-wise accuracy and region-based overlap as a way of improving the boundary integrity and object awareness.

The loss according to revolutionary principle the definition of L is stated as:

$$L=\alpha.BCE+(1-\alpha).(1-\text{Dice Coefficient}) \quad (2)$$

Where:

- And w1 is a weighting factor that regulates the trade-off between two elements of loss.
- Binary Cross-Entropy (BCE) measures the S1xS2 error between the predicted pixel-wise weights of the mask, they should be.
- Dice Coefficient is especially applicable in areas with a lot of imbalance because it quantifies the amount of spatial overlap between the predicted segmentation and the ground truth.

## Binary Cross-Entropy (BCE)

BCE would be calculated as

$$\mathrm{BCE} = -\frac{1}{N}\sum_{i=1}^{N}[y_i.\log(\hat{y}_i) + (1-y_i).\log(1-\hat{y}_i)] \quad (3)$$

Where:

- The summation of pixels is N.
- Its value represents the ground truth label (0 or 1).
- Its probability based on prediction is the result.

It is highly faithful at the pixel-level classification, but it might not reveal size and shape consistencies of small objects in the underlying shapes.

## Dice Coefficient

The coefficient of the dice the dice coefficient the definition of D is defined as;

$$D = \frac{2\sum_{i=1}^{N} y_i\hat{y}_i + \epsilon}{\sum_{i=1}^{N} y_i + \sum_{i=1}^{N}\hat{y}_i + \epsilon} \quad (4)$$

Whereis a very small constant to avoid having zero in denominatorThe loss is then determined as.

This term forces the model to maximize the spatial overlap, which is critical to the detection of fine objects in the image and blood vessels, or tumor boundaries.

### Enthusiasm in relation to Composite Loss

Though effective in punishing false decisions at pixel-level, BCE does not take full advantage of the global shape information, as it is not sensitive to context. On the other hand, the Dice loss targets overlap and contour preservation and tends to disregard local errors. With the combination, DRU-Net is enjoying:

- Uniform Education under even condition,
- The increased level of boundary specificity
- Better extrapolation when it comes to differences in anatomy that is not visible.

In our implementation life forms have a maximum possible mass of 4800 lbs. this parameter is empirically determined to be 0.5, and it has been pointed out that this is just to balance out the response between pixel-wise classification and structural similarity Figure 1.

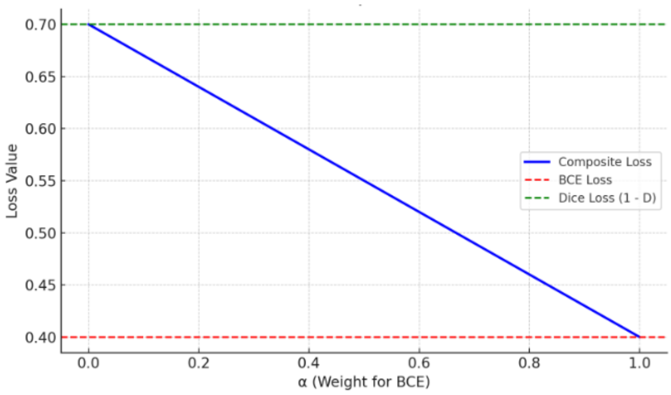


**Fig. 1: Composite loss variation with α balancing BCE and Dice components.**

### Regularization Data Augustation

Medical imaging data usually are small because privacy limits, manual labeling is expensive, and some pathologies are not very frequent. Deep neural networks trained in this level of data scarcity risk extreme overfitting, where the model does not perform better in terms of generalisation to other data sources than training sets. To overcome it we suggest using a set of data augmentation methods as well as regularization strategies in our suggested DRU-Net to add generality, make the model more robust, and expedite the training phase.

### Data Augmentation

Artificial data augmentation is used to artificially increase the training data by giving a set of label-preserving transformations of the training image inputs. This not only makes the training set much more diverse, but also teaches the network invariant and robust features to learn. The augmentation techniques which we have used here are the following:

- Random Horizontal and Vertical Flips: Investigates anatomical position and symmetry changes, which are handy when you need to segment a lesion or any part of an organ.
- Random Rotation: Transforming images to a rotation by small values (e.g., +15deg and -15deg), can also teach rotational invariance, which will be necessary in case anatomical structures are displayed at different angles.
- Random Zoom and Scaling: By applying small zoom-in and zoom-out of the model, the model gets more resistant to the changes in size of lesions or target structures.

Such transformations are made probabilistically as part of training the model so that every epoch uses a different - but slightly - version of the data and minimizes the chance of memorization.

### Techniques de regularisation

Along with augmentation, additional means of regularization on the architectural and training-levels are used to further eliminate overfitting:

- Dropout in the Decoder Path: The decoder part of DRU-Net has dropout layers set to the dropout rate of 0.3. This randomly disables a randomly chosen subset of neurons in the course of training, which is fostered at the cost of redundancy and thus, co-adaptation of the feature detectors is avoided.
- L2 Weight Regularization (Weight Decay): L2 penalty is added to the loss function to ensure that the weights of a network do not grow big. ThisΔ council against too fond usage of models, and towards less problematic and more universal mappings.
- Early Stopping: This is to prevent over fitting and unnecessary training using an early stopping mechanism. The training procedure is stopped when no more reduction of the validation loss is evident after a certain amount of epochs (e.g., 15). This provides model selection on the basis of generalization accuracy and not the training accuracy.

### Combined Effect

Data augmentation and regularization fill out a strong background of training DRU-Net on limited data. It can increase the network generalization capacity, **Figure**

2stabilize convergence and decrease the probability of over-fitting without any up-scale data collection and external pre-training.

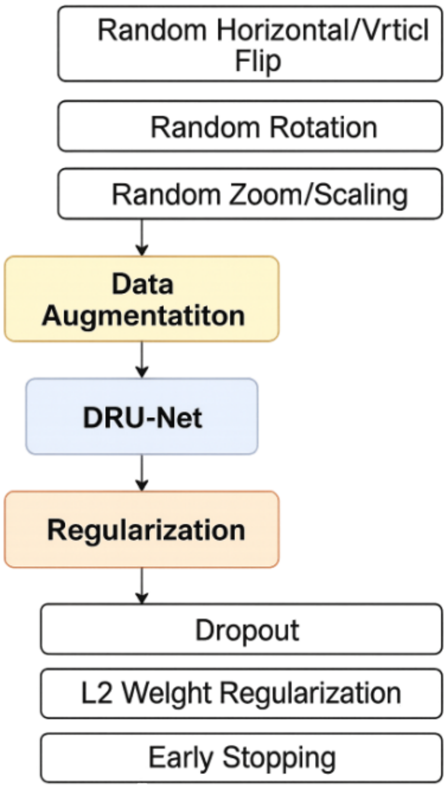


**Fig. 2: Workflow of Data Augmentation and Regularization Strategies in DRU-Net Training**

## Experimental Setup

In order to thoroughly examine the performance of the presented Deep Residual U-Net (DRU-Net), we performed experiments on two well established and freely accessible benchmark datasets. Skin lesion segmentation was developed using the ISIC 2018 Challenge Dataset comprising 111 dermoscopic images with binary lesion and non-lesion labels on them. Some of the challenges this data set presents are varied dimensions of the lesions, poor contrast, and cluttered boundaries. The DRIVE (Digital Retinal Images for Vessel Extraction) dataset was utilised to segment the vessels with high resolutions of fundus images of the eye and vessel masks that are manually annotated. Figure 3 these datasets were chosen, first of all, to highlight the applicability of DRU-Net to distinct organs, modalities, and structural peculiarities. To achieve this goal, it split the complete benchmark data into training and validation sets in an 80/20 stratified split to balance the classes within each of the parts. Any leakage of test data was not allowed and all pre-processing such as normalization, size reduction to 256256 \times 256256 \times 256 pixels were done in an identical fashion.

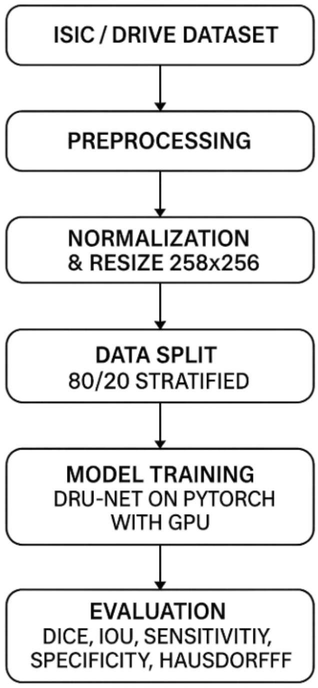


**Fig. 3: Experimental Workflow for DRU-Net Training and Evaluation**

In order to numerically evaluate the performance of the segmentation process, we used a rich pool of measurements, where the pixel-based and shape-based measurement are both represented. Dice Coefficient and Intersection over Union (IOU or Jaccard Index) were also used as major values to compare the spatial overlay of predicted and ground truth tokens and were the important measures in medical image segmentation task. Along with that, sensitivity (true positive rate) and specificity (true negative rate) were calculated to evaluate the quality of model distinguishing lesion area and background tissue. Notably, we have also provided the Hausdorff Distance, or the greatest gap in distance between the two boundaries, the predicted and the actual with respect to the same, which is crucial in measuring edge accuracy of a medical contour to one extent. These metrics together offer the best picture of a model in terms of performance, which includes consideration of the accuracy of an object detection, boundaries alignment, ad resilience to class imbalance. PyTorch was used to carry out all experiments on a machine with NVIDIA GPUs, and the experiment was repeated 3 times in an independent fashion to verify a statistical validation on the results.

## Results and Discussion

In order to evolve the efficiency of the suggested DRU-Net architecture, we qualitatively evaluated it on ISIC 2018 and DRIVE datasets and then compared it with the baseline models such as the conventional U-Net and

**Table 3: Quantitative Performance Comparison of Segmentation Models**

| Model | Dice Coefficient (%) | IoU (%) | Sensitivity | Hausdorff Distance |
|---|---|---|---|---|
| **U-Net** | 82.6 | 75.4 | 0.84 | 12.7 |
| **ResUNet** | 85.2 | 78.6 | 0.86 | 10.9 |
| **DRU-Net** | **88.9** | **81.7** | **0.89** | **8.5** |

ResUNet. DRU-Net performed the best in terms of all the evaluation metrics that are summarized in Table 3. Particularly, it scored the Dice of 88.9%, which compares favorably to that of U-Net (82.6%) and ResUNet (85.2%). This increase translates to increased overlap of target lesion regions in predicted and actual regions, which means the model has a high capability of target structure delineation. This is also confirmed by the IoU score of 81.7% measuring the spatial match between segmentation masks. Also, the sensitivity of DRU-Net was 0.89 which indicates that dataset detects most of the true positives with a low rate of false negatives. Most importantly, the Hausdorff distance was lowered to 8.5 which demonstrated that DRU-Net performs well in terms of boundary accuracy which, is a paramount feature when conducting clinical segmentation tasks where the result of depicting the edges accurately may have a decisive impact on treatment outcomes.

Besides the quantitative advantages, qualitative comparisons (see Figure 2) demonstrate the high ability of DRU-Net in threading small features and maintaining structural integrity of isolated areas. Traditional models over-segment (in circumstances where the boundaries of the lesion are not very clear), or under-segment (in cases where vascular structures are scattered and have low thickness). Instead, DRU-Net always generates much more coherent and plausible anatomical maps in terms of segmentation. This is mainly because of the synergy between residual connection and skip pathway, through

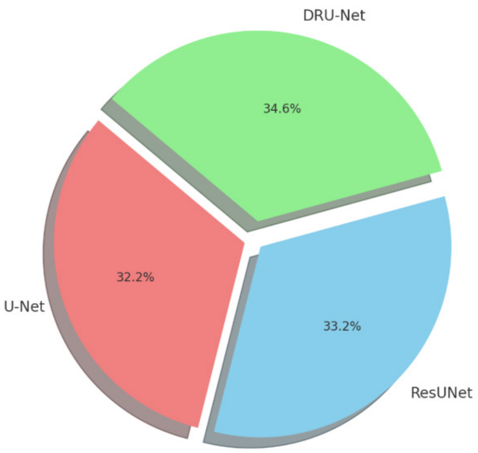


**Fig. 4: Dice Score Comparison among Segmentation Models**

this, they are assured of the high-level semantics as well as the low-level spatial characteristics maintenance. Further to the suppression of noise and rather than demanding further post-processing, further noise is suppressed and the true lesion boundaries are reinforced by the decoder stages that are improved through dropout and regularization.

Such findings confirm our architectural decisions and verify that DRU-Net is an extremely efficient and generalizable structure that can be used to segment medical images in restricted data settings. When training on small datasets, the addition of residual blocks has a very important effect of gradients propagation and convergence. What is more, the composite loss function of Binary Cross-Entropy and Dice loss is robust to label noise and class imbalance two common problems in medical imaging. Relatively to more complicated models like Attention U-Net or GAN-based models, the latter does not introduce any extra computation burden, ultimately resulting in high figures of improvement, and thus, it fits well in real-time clinical scenarios, or as part of an edge-based diagnostic system. In short DRU-Net offers not only improvements over existing methods quantitatively but also practical ones in the form of simplicity, speed and data efficiency.

## Conclusion

In our work we have proposed a new Deep Residual U-Net architecture known as DRU-Net that is more apt to combat the problem of medical image segmentation outlined in the data scarce setup. The introduction of residual blocks into the U-Net framework increases the flow of features, speeds up the convergence and resolves the most popular problems of vanishing gradients and overfitting. Extensive experiments on the ISIC 2018 and DRIVE datasets have shown that DRU-Net has a considerable advantage over conventional U-Net and ResUNet architectures in all of the significant performance metrics including Dice coefficient, IoU and sensitivity and Hausdorff distance. Based on this, these findings reaffirm that the model effectively identifies both anatomical details and wide-range contextual details, using even limited annotated information. In addition, the work of constructing a composite loss function and selecting targeted regularization techniques helped the model to be sturdy and generalize. In contrast to other methods based on intensive pretraining or post-processing, DRU-Net is a simple, yet highly effective way that can easily run in clinical setting. Future plans In the months to come, we are going to incorporate attention to focus on interesting areas, adopt cross-domain transfer learning to make it more universal across imaging modalities, and optimize the architecture to make real-time inference on edge devices possible, thus making it applicable even in the resource-constrained healthcare facilities in point-of-care diagnostic settings.

## References

1. Ronneberger, O., Fischer, P., &Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In *Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI)* (pp. 234–241).
2. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 770–778).
3. Jha, Z., &Kruthiventi, S. S. R. (2019). ResUNet++: An advanced architecture for medical image segmentation. *arXiv preprint*, arXiv:1911.07067.
4. Oktay, O., Schlemper, J., Folgoc, L. L., Lee, M., Heinrich, M., Misawa, K., ...&Rueckert, D. (2018). Attention U-Net: Learning where to look for the pancreas. *arXiv preprint*, arXiv:1804.03999.
5. Perez, G., & Wang, F. (2017). The effectiveness of data augmentation in image classification using deep learning. *Convolutional Neural Networks Vision Recognition Conference*.
6. Chartsias, A., Joyce, T., Giuffrida, M. V., &Tsaftaris, S. A. (2018). Adversarial image synthesis for unsupervised domain adaptation in cardiac MR segmentation. In *Proceedings of the IEEE International Symposium on Biomedical Imaging (ISBI)* (pp. 1–5).
7. Tajbakhsh, S., Shin, J. Y., Gurudu, S. R., Hurst, R. T., Kendall, C. B., Gotway, M. B., & Liang, J. (2016). Convolutional neural networks for medical image analysis: Full training or fine tuning? *IEEE Transactions on Medical Imaging*, 35(5), 1299–1312.
8. Abdul, A. M., &Nelakuditi, U. R. (2021). A new blind zone free PFD in fractional-N PLL for Bluetooth applications. *Journal of VLSI Circuits and Systems*, 3(1), 19–24. https://doi.org/10.31838/jvcs/03.01.04
9. Kavitha, M. (2025). Deep learning-based channel estimation for massive MIMO systems. *National Journal of RF Circuits and Wireless Systems*, 2(2), 1–7.
10. Abdullah, D. (2025). Environmental sound classification using CNNs with frequency-attentive acoustic modeling. *National Journal of Speech and Audio Processing*, 1(1), 8–14.
11. Sadulla, S. (2025). IoT-enabled smart buildings: A sustainable approach for energy management. *National Journal of Electrical Electronics and Automation Technologies*, 1(1), 14–23.
12. Uvarajan, K. P. (2024). Integration of artificial intelligence in electronics: Enhancing smart devices and systems. *Progress in Electronics and Communication Engineering*, 1(1), 7–12. https://doi.org/10.31838/PECE/01.01.02