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Using deep learning to diagnose retinal diseases through medical image analysis

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ABSTRACT

The scientific article focuses on the application of deep learning through simple U-Net, attention U-Net, residual U-Net, and residual attention U-Net models for diagnosing retinal diseases based on medical image analysis. The work includes a thorough analysis of each model's ability to detect retinal pathologies, taking into account their unique characteristics such as attention mechanisms and residual connections. The obtained experimental results confirm the high accuracy and reliability of the proposed models, emphasizing their potential as effective tools for automated diagnosis of retinal diseases based on medical images. This approach opens up new prospects for improving diagnostic procedures and increasing the efficiency of medical practice. The authors of the article propose an innovative method that can significantly facilitate the process of identifying retinal diseases, which is critical for early diagnosis and timely treatment. The results of the study support the prospect of using these models in clinical practice, highlighting their ability to accurately analyze medical images and improve the quality of eye health care.

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1. INTRODUCTION

Modern technologies in medical imaging and deep learning continue to revolutionize the diagnosis and treatment of retinal diseases. Diseases of this important part of the eye require accurate and timely diagnosis for effective management and prevention of potential complications. This study examines the application of advanced deep learning methods such as simple U-Net [1]–[3], attention U-Net [4]–[6], residual U-Net [7]–[9] and residual attention U-Net [10]–[12] to improve the diagnosis of retinal diseases through medical image analysis [13], [14]. The combination of the high resolution of modern medical images and the power of deep learning opens up new prospects in the field of automated diagnosis of eye diseases [15], [16]. This work provides an extensive analysis of the effectiveness of the above-mentioned deep learning models in the task of identifying and classifying various retinal pathologies. The findings promise significant contributions to improving diagnostic methods, providing more accurate and rapid means of detecting retinal diseases and thus improving the quality of medical care in this area. The medical field is faced with a constant increase in the complexity and diversity of retinal diseases, requiring more accurate and innovative diagnostic methods. Traditional medical image processing methods [17], [18] are often limited by their ability to detect fine details and recognize complex patterns [19], highlighting the need to integrate advanced deep learning technologies. The simple U-Net, attention U-Net, residual U-Net and residual attention U-Net models are promising tools that can not only cope with the complexity of the diagnostic task [20] but also provide interpretable results, which is a key aspect in clinical practice. One of the significant achievements of this study is the systematic comparison of the performance of various deep learning models in diagnosing retinal diseases. Analysis of the advantages and limitations of each model allows us to identify their features and optimize their use in specific clinical scenarios. This approach allows us to move from a theoretical consideration of the effectiveness of models to their practical application, which is an important step towards personalized and targeted medical diagnostics.

Yoo *et al.* [21] propose the use of few-shot learning (FSL) using generative adversarial networks (GANs) to improve the applicability of deep learning (DL) in diagnosing rare retinal diseases based on optical coherence tomography (OCT). Using four large, data-rich classes and five rare disease classes with a limited number of samples, the authors trained inception version 3 (InceptionV3) on an expanded training dataset, generating synthetic images of the pathological states of each rare disease. The proposed deep learning model showed significant improvement in the diagnostic accuracy of rare retinal diseases compared to traditional deep learning models such as Siamese network and prototypical network. Increasing diagnostic accuracy for rare diseases could help doctors avoid missing rare cases, reducing diagnostic delays and the burden on patients.

Abed *et al.* [22] review the importance of early detection of two common retinal diseases: age-related macular degeneration (AMD) and diabetic macular edema (DME). The authors focus on the use of optical coherence tomography (OCT) technology and deep learning for retinal image classification. Models such as visual geometry group 16 (VGG-16), MobileNet, residual networks 50 (ResNet-50), inception version 3 (InceptionV3), and extreme inception (Xception) are used to improve diagnostics and provide fast and reliable analytics in large studies. The best model, ResNet-50, achieves 96.21% accuracy on test data, which can greatly help doctors diagnose retinal diseases. Goutam *et al.* [23] provides an extensive study of deep learning strategies used to diagnose five major eye diseases: diabetic retinopathy, glaucoma, age-related macular degeneration, cataracts, and retinopathy of prematurity. The article covers all stages of the deep learning implementation process, including the datasets used, evaluation metrics, image preprocessing methods, and deep learning models. An overview of the different strategies for each of the five retinal diseases discussed is presented. In conclusion, the article highlights eight main areas of research in the field of diagnosing eye diseases, and also indicates key challenges and prospects for the scientific community.

Yang *et al.* [24] proposes a large vessel segmentation method using deep neural networks with a fully convolutional structure for the analysis of coronary X-ray angiographies. Using data from 3,302 diseased large vessels in 2,042 patients, deep neural networks accurately identified and segmented vessels in X-ray angiography images. The average F1-score was 0.917, and 93.7% of the images exhibited a high F1-score greater than 0.8. The method was successfully applied to an external dataset with different image characteristics. The proposed approach allows segmentation of large vessels in real time with minimal image preprocessing. This technology can automate the analysis of coronary angiographies and facilitate the use of quantitative coronary angiography (QCA)-based diagnostic methods. Sorrentino *et al.* [25] discusses the use of artificial intelligence (AI) to improve the efficiency and accuracy of diagnosis of retinal diseases, which are affecting an increasing number of patients worldwide due to the aging population. The authors propose the use of advanced technologies with built-in artificial intelligence algorithms to assist ophthalmologists in clinical tasks and create new biomarkers. Particular emphasis is placed on optical coherence tomography (OCT) for early detection, qualitative localization, and quantitative measurement of abnormalities and pathological features of macular and neurodegenerative diseases. The article reviews progress in the diagnosis of diabetic retinopathy, age-related macular degeneration, and retinopathy of prematurity, suggesting a key role for highly automated systems in screening, early diagnosis, and individualized therapy.

Finally, the results of this study provide a basis for further technological improvements in medical education and practice. They can be used to train medical specialists and develop integrated decision support systems, which helps improve the efficiency and accessibility of diagnosing retinal diseases. Taken together, this study represents a significant contribution to the field of deep learning in medical diagnostics and opens new perspectives for improving eye health care.

2. METHOD

In recent years, with the development of deep learning technologies, the application of artificial intelligence in medical diagnosis and treatment has expanded significantly. This is especially true in the field of retinal image analysis, where accurate and rapid identification of blood vessels is critical for the diagnosis and monitoring of diseases such as diabetic retinopathy, age-related macular degeneration and glaucoma. Deep learning methods based on convolutional neural network (CNN) architectures provide a powerful tool for image segmentation, allowing the identification of retinal blood vessels with high accuracy. Among the variety of CNN architectures, modifications of U-Net, an architecture originally developed for biomedical segmentation tasks, have attracted special attention. Simple U-Net, attention U-Net, residual U-Net, and residual attention U-Net are various iterations and improvements to the basic U-Net architecture, each introducing its own unique features to improve training efficiency and segmentation accuracy. Simple U-Net is a starting point, presenting a basic U-Net structure with alternating convolutional and pooling layers, followed by upsampling layers. It is a simple but powerful model for solving segmentation problems as shown in Figure 1.

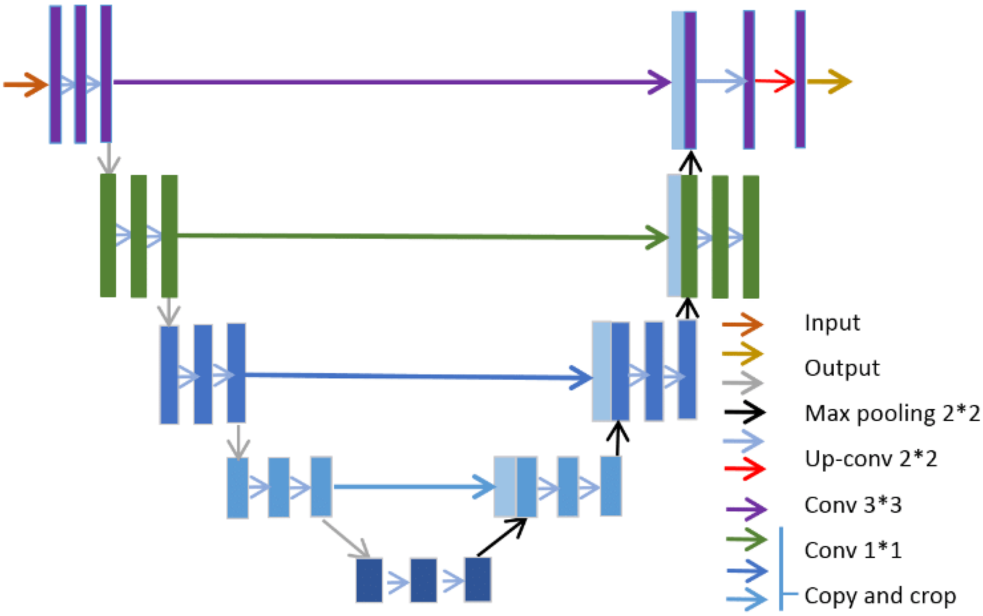


Figure 1. Simple U-Net architecture

Simple U-Net is an adaptation of the U-Net architecture, originally designed for biomedical image segmentation tasks. The main feature of U-Net is its U-shaped structure, combining a compressive path (convolutional part) and an expansion path (de-convolutional part). The compressive path contains repeating blocks with two convolutions, ReLU activation, and a max-pooling layer that allows feature extraction and deepening. The expansion path restores the image dimension by upsampling, convolution, and concatenation with the output of the compression path. Skip-connections connect the layers of both paths, conveying contextual information and improving geometric detail. Training simple U-Net on blood vessel segmentation data showed a decrease in losses and an increase in accuracy and IoU coefficient on the training set. Fluctuations in metrics across the validation set highlight the need for hyperparameter tuning and the possible use of regularization. An important aspect is the choice of a loss function, possibly combining cross-entropy and IoU, as well as an optimizer such as Adam or stochastic gradient descent (SGD). Simple U-Net, despite its relative simplicity, effectively copes with medical image segmentation tasks thanks to accurate localization and classification of objects.

Attention U-Net introduces an additional attention component that allows the model to more accurately focus on relevant regions of the image, thereby improving segmentation accuracy. The attention U-Net architecture as shown in Figure 2 retains the core principles of U-Net, including a symmetric structure with contraction and expansion paths, and the use of skip-connections to transfer feature information between corresponding layers. However, the key difference is the integration of attention blocks into skip-connections, which allows the model to more effectively learn to recognize and highlight important features in an image.

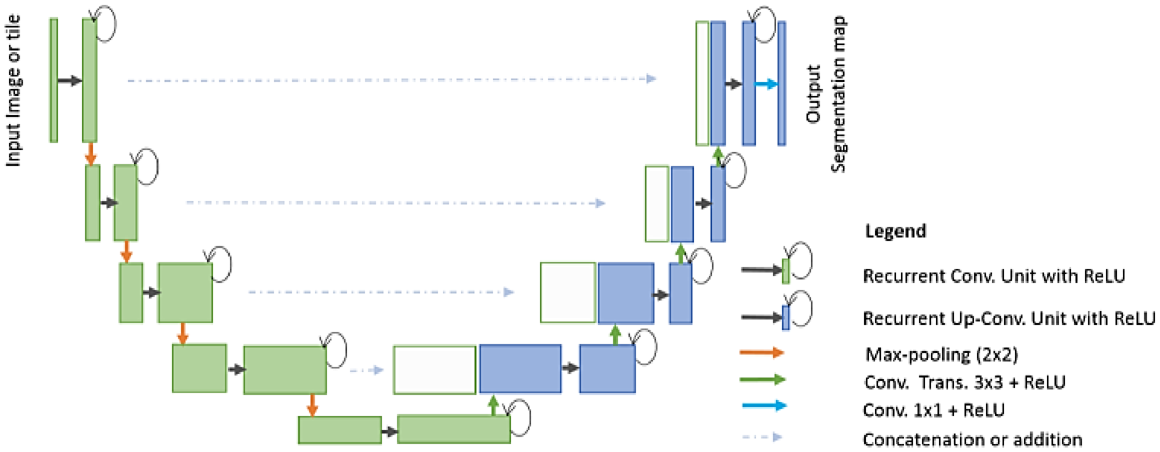


Figure 2. Attention U-Net architecture

The attention U-Net architecture uses attention blocks to weight features across skip-connections, improving the accuracy and quality of segmentation. The attention mechanism allows the network to effectively focus attention on significant areas of the image. By training on retinal blood vessel segmentation data, a significant improvement in accuracy was achieved compared to the baseline U-Net model. The dynamics of learning are reflected in a decrease in the loss function, an increase in accuracy and IoU coefficient. Traditional methods of data augmentation, regularization, and hyperparameter optimization were used. The attention U-Net architecture represents a significant improvement on the standard U-Net model, highlighting the effectiveness of the attention mechanism in medical image analysis tasks, especially in highlighting retinal blood vessels with high accuracy.

The residual U-Net architecture embeds residual blocks into the U-Net structure, allowing deeper networks to be trained efficiently, improving the generalization ability of the model. The integration of residual blocks based on the ResNet concept promotes efficient gradient propagation and vanishing gradient reduction. This improvement greatly improves the quality of segmentation, especially when solving problems that require deep analysis of medical images, such as the retina. Residual attention U-Net represents a further improvement by combining the benefits of residual units and attention mechanisms. This hybrid architecture not only enables efficient training on the deep layers of the network, but also focuses on key regions of the image, resulting in even higher segmentation accuracy. Training residual attention U-Net on the task of retinal blood vessel segmentation confirms its ability to achieve outstanding results, making it a powerful tool for medical diagnostics and image analysis.

3. RESULTS AND DISCUSSION

The structured analysis of the retina (STARE) project includes a set of 20 retinal images intended for the development and testing of vessel segmentation algorithms. Each image is accompanied by manually labeled vessel networks by two different annotators, which serves as a reference for segmentation tasks. This dataset is widely used in medical imaging research, especially to improve techniques for accurately identifying blood vessels in the retina. The training dynamics for each of the retinal blood vessel segmentation methods based on different U-Net architectures present interesting observations based on changes in loss, accuracy, and intersection over union (IoU) values for both training and validation samples. Below is an analysis of the learning dynamics for each method based on the first five epochs.

To analyze emotions in text, you need to represent the words in a numerical format that a machine-learning model Figure 3(a) shows the loss of the attention U-Net model during training. The initial value of the cost function is -0.1112, indicating a significant discrepancy between the model predictions and the true symptoms. However, during training, we observe a gradual decrease in the cost function, reaching -0.2464 at the 150th epoch. This trend indicates that the model performs better at the segmentation task by reducing the difference between the predicted and actual data in each epoch. The accuracy of the model shown in Figure 3(b) also shows a positive trend. Starting from an initial accuracy value of 0.4102, we see a steady increase, indicating that the model's ability to correctly classify image pixels is increasing. At the end of training, the model achieves an accuracy of 0.8752, which shows its effectiveness in recognizing reticular veins. The IoU coefficient as shown in Figure 3(c) also confirms the improvement in model performance, starting from 0.1112 to 0.2464. This result shows that the predicted segmented regions resemble real regions, which is important in medical segmentation tasks.

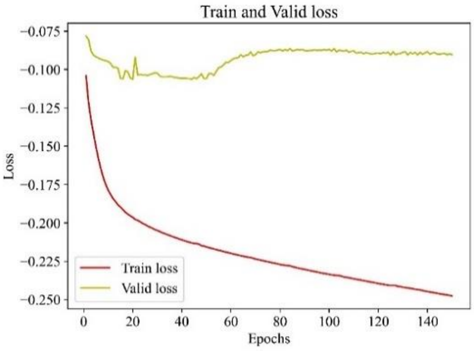
Training of the residual attention U-Net model shows positive dynamics similar to attention U-Net. In both samples, a steady decrease in losses is observed as shown in Figure 4(a), indicating the effectiveness of training. The accuracy on the training set as shown in Figure 4(b) systematically increases, reaching high values, which confirms the effectiveness of integrating residual and attention mechanisms to improve segmentation. The IoU metric Figure 4(c) also shows an improvement, confirming the high quality of segmentation achieved by this method. These results highlight the effectiveness of the combined residual attention U-Net approach in training on the segmentation task, providing high accuracy and quality of object selection in images.

Analysis of the training of the residual U-Net model reveals positive trends. The loss values as shown in Figure 5(a) systematically decrease, especially on the training set, indicating successful model training. Accuracy on the training set Figure 5(b) shows improvement, but fluctuations in accuracy on the validation set require additional attention and possible adjustment of model parameters for robust learning. The gradual increase in the IoU coefficient as shown in Figure 5(c) indicates the good segmentation ability of the model. These results highlight the successful training of the residual U-Net model and indicate the need for additional tuning to improve training stability and accuracy on the validation set.

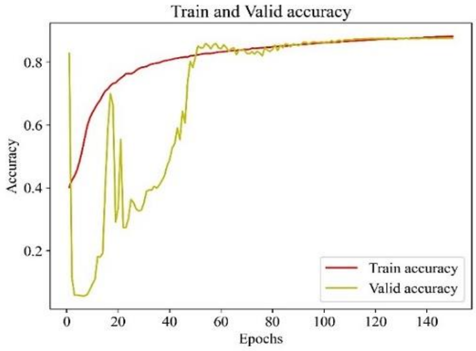
The training process of the simple U-Net model reflects a positive trend, where the loss values as shown Figure 6(a) systematically decrease, indicating successful training. The accuracy on the training set Figure 6(b) shows an increase, but there is some fluctuation on the validation set, which may highlight the need for further optimization of the model to improve its generalization ability. An increase in the IoU coefficient as shown Figure 6(c) indicates increased segmentation efficiency by the model. These results highlight the successful training of simple U-Net, but highlight the potential need for additional tuning to improve stability and accuracy on the validation set. Figure 6(a) shows the training process of the simple U-Net model, which reflects the positive dynamics of losses during model training. It can be seen from the graph that the loss function decreases rapidly at the beginning of training, indicating that the model's performance improves quickly. Starting from -0.1144 in the first epoch, the cost function reaches -0.2467 by the 150th epoch, which shows a significant deepening of the model's segmentation ability during the training process. In addition to the loss function, the accuracy of the model improves over time. Figure 6(b) shows the dynamics of model training accuracy. Initially, the accuracy is 0.4213, which is a relatively low value, but as the epochs progress, the accuracy increases, reaching 0.8753 by epoch 150. This model shows improvement in recognizing vasculature in training images. The IoU ratio as shown Figure 6(c), a key metric for segmentation tasks, is also improved. When running IoU, the coefficient is 0.1144, which means low segmentation accuracy. However, at the end of training it reaches a value of 0.2467, which indicates a significant improvement in the quality of segmentation of the model.

Across all four evaluated architectures, namely attention U-Net, residual attention U-Net, residual U-Net, and simple U-Net, a consistent and positive trend in learning dynamics is observed. Each architecture displays a noteworthy reduction in loss values, a notable improvement in accuracy metrics, and an increase in IoU, highlighting their efficacy in addressing medical image segmentation tasks. This collective evidence underscores the robust performance and potential applicability of these architectures in enhancing the precision and reliability of segmentation processes of medical imaging as shown Figure 7. Figure 7(a) demonstrates the performance of the residual attention U-Net, which illustrates a significant reduction in loss values and improvement in segmentation accuracy. Figure 7(b) presents the results from the result attention architecture, highlighting its effectiveness in improving IoU metrics. Figure 7(c) showcases the ResU-Net, which also shows positive trends in accuracy and IoU, emphasizing its robust performance in medical image segmentation. Lastly, Figure 7(d) displays the simple U-Net, which, despite its simplicity, exhibits a consistent reduction in loss values and notable improvements in segmentation accuracy.

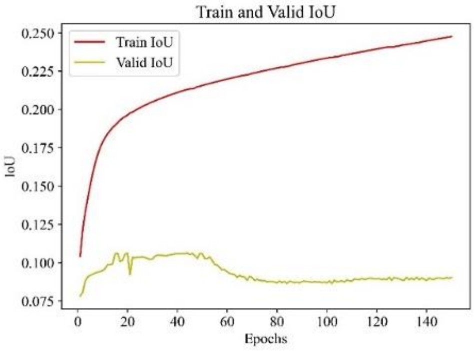
Attention U-Net and residual attention U-Net excel in the integration of attention mechanisms and residual connections, resulting in improved segmentation quality. However, the observed fluctuations in values in the validation sets of some models highlight the importance of additional analysis and possibly adjustments of hyperparameters to combat overfitting and achieve higher generalization power. Overall, these results highlight the importance of not only selecting the optimal architecture, but also carefully tuning model parameters to achieve high accuracy and stability on validation data.



(a)

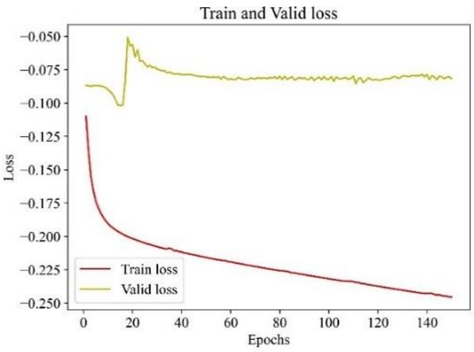


(b)

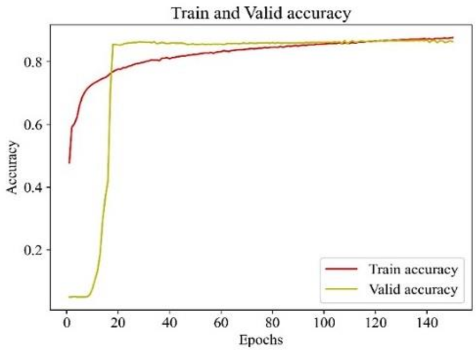


(c)

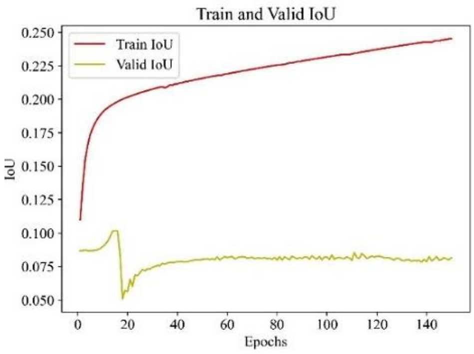
Figure 3. Training result using the attention U-Net method (a) loss values, (b) accuracy value, and (c) IoU indicator



(a)



(b)



(c)

Figure 4. Residual attention U-Net training result (a) loss values, (b) accuracy value, and (c) IoU indicator

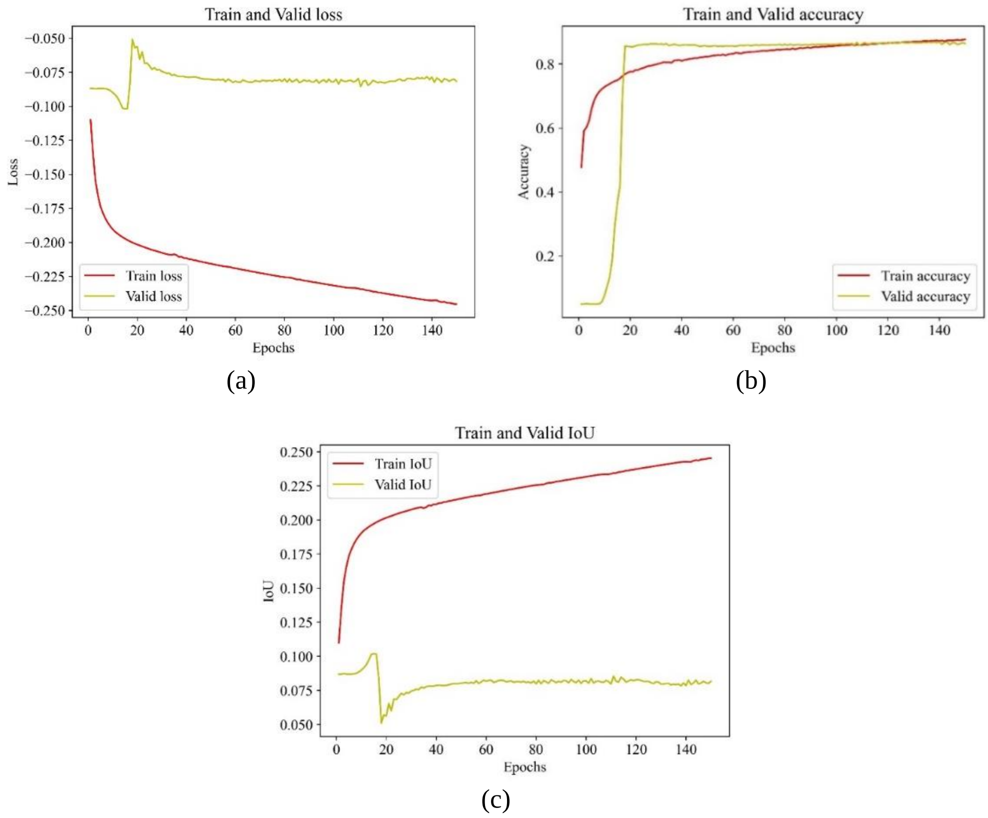


Figure 5. Residual U-Net training result (a) loss values, (b) accuracy value, and (c) IoU indicator

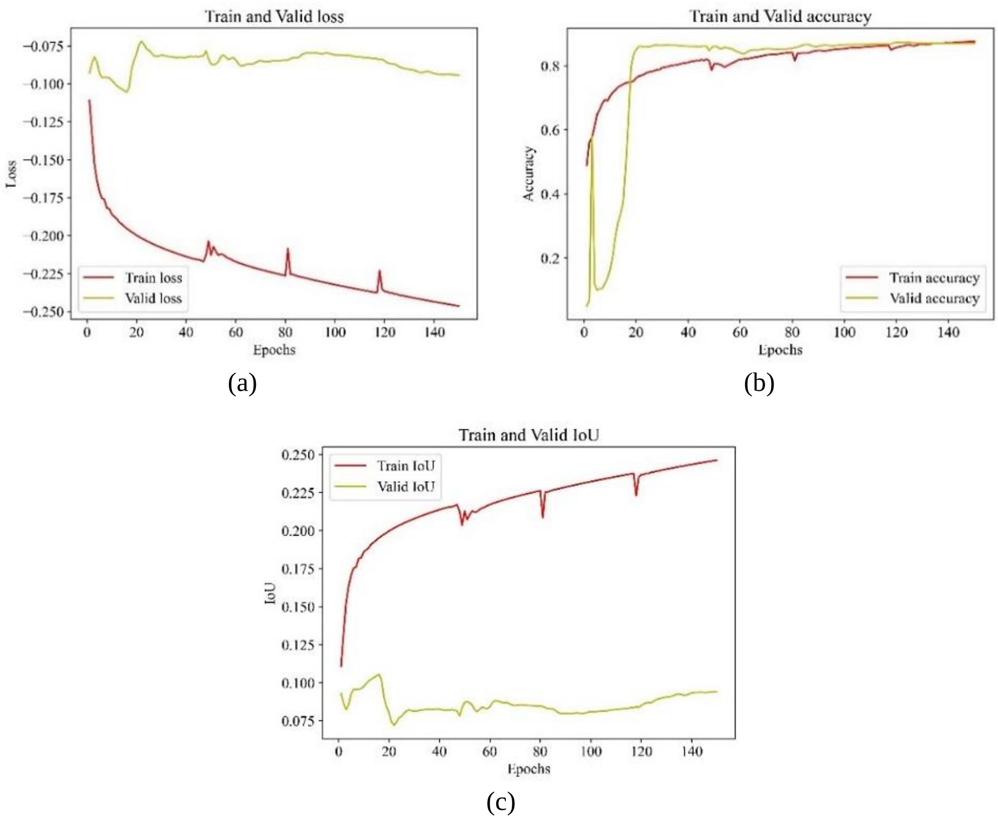


Figure 6. Training result using the simple U-Net method (a) loss values, (b) accuracy value, and (c) IoU indicator

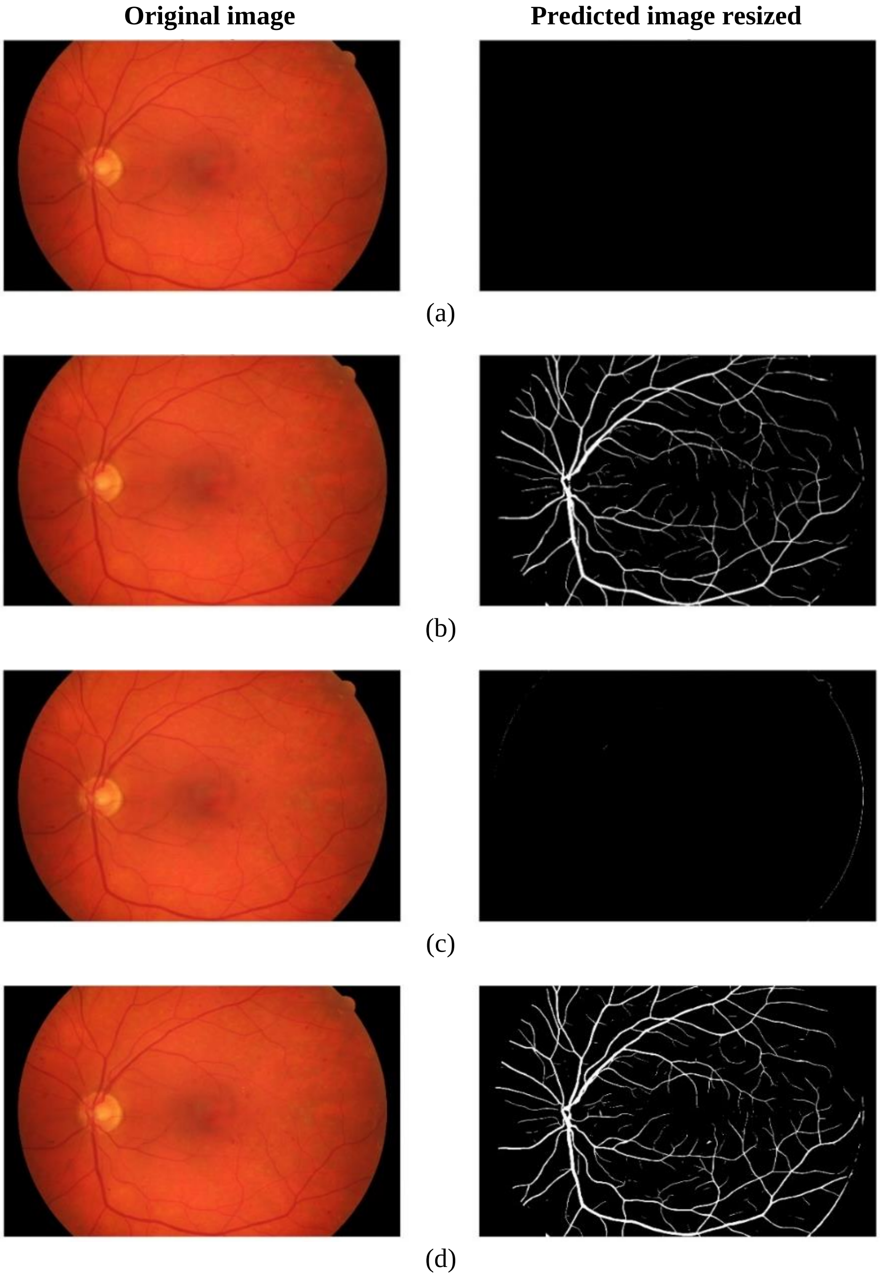


Figure 7. Machine learning results (a) residual attention U-Net, (b) result attention, (c) residual U-Net, and (d) simple U-Net

4. CONCLUSION

In conclusion, our research focuses on analyzing the emotional content of text using various machine learning and deep learning techniques. We strictly separate text data into training, validation, and test sets, thereby providing a robust basis for training and evaluating models. The data preprocessing process, which includes text normalization, tokenization, and vectorization using pre-trained embeddings, is a key step that improves text representation before training models. During the experiments, we compared the performance of different machine-learning models. Multinomial naive bayes achieved an accuracy of 0.84, demonstrating its potential for text classification despite its limitations in handling complex data dependencies. The multilayer perceptron model with parameters 100 and 100, alpha = 0.01 achieved an accuracy of 0.89, highlighting its ability to learn from complex text data and adapt to different emotional expressions. The support vector machine achieved an accuracy of 0.87, indicating its effectiveness in separating text data based on sentiment.

An important result was the superiority of the long short-term memory based deep neural network, including embedding layers and three bidirectional long short-term memory layers. This model achieved an outstanding accuracy of 0.9299 on the validation dataset and 0.9245 on the test dataset, outperforming traditional machine learning models. This highlights the potential of deep learning to analyze emotions in text. In general, the results of our study confirm the effectiveness of using various methods for analyzing emotions in text. The proposed research methodology represents an important contribution to the field of natural language analysis and machine learning, opening new possibilities for creating more accurate and adaptive sentiment analysis systems in different contexts. The conclusion of this study highlights the relevance of applying deep learning, in particular long short-term memory-based models, to emotion classification tasks in text, providing valuable directions for future developments in this area.

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