Penerapan Metode Generative Adversarial Network (GAN) dalam Peningkatan Kinerja Model ResNeSt untuk Mendeteksi Retinal Detachment pada Citra Fundus Retina Mata = Application of Generative Adversarial Networks (GAN) in Improving the Performance of ResNeSt Model for Retinal Detachment Detection in Retinal Fundus Images

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Abstrak

Retinal detachment (RD), atau ablasi retina, adalah kondisi ketika retina neurosensori terlepas dari lapisan dasarnya, yaitu epitel pigmen retina (EPR), karena kehilangan kerekatan. RD bisa menjadi kondisi yang serius jika tidak segera ditangani, seperti gangguan penglihatan hingga kebutaan permanen. Di Indonesia, diperkirakan terdapat 17.500—25.000 kasus baru setiap tahunnya. Namun, dengan jumlah dokter yang terbatas, pendeteksian RD secara konvensional mungkin tidak dapat dilakukan dengan cepat. Dengan memanfaatkan metode machine learning, khususnya deep learning, yang kini berkembangan pesat, dapat dilakukan pendeteksian RD melalui citra fundus mata menggunakan Convolutional Neural Network (CNN) dengan arsitektur ResNeSt. Terdapat masalah keterbatasan jumlah data pada kelas RD sehubungan dengan perlindungan privasi pasien yang membatasi akses terhadap data medis. Untuk meningkatkan jumlah data, dilakukan augmentasi data dengan GAN untuk menghasilkan data baru berupa citra sintetis untuk kelas RD. Dilakukan pula percobaan dengan menerapkan Contrast Limited Adaptive Histogram Equalization (CLAHE) sebagai tahap preprocessing sebelum augmentasi dengan GAN dengan tujuan meningkatkan kualitas citra yang masuk sebagai input dari GAN. Lebih lanjut, penelitian ini menguji tiga skenario dengan dua rasio splitting data, yaitu 6:2:2 dan 6:1:3. Skenario 1 menjalankan model ResNeSt tanpa preprocessing CLAHE dan augmentasi GAN pada data input. Skenario 2 menjalankan model ResNeSt dengan augmentasi GAN pada data input. Sementara itu, skenario 3 menjalankan model ResNeSt dengan menerapkan preprocessing CLAHE dan augmentasi GAN pada data input. Untuk splitting data dengan rasio 6:2:2, skenario 1 menghasilkan nilai rata-rata accuracy 89,9%, sensitivity 76,3%, specificity 94,3%, dan loss 52,4%, skenario 2 menghasilkan nilai rata-rata accuracy 92,3%, sensitivity 88,2%, specificity 94,8%, dan loss 18,6%, sedangkan skenario 3 menghasilkan nilai rata-rata accuracy 95,9%, sensitivity 94,4%, specificity 96,8%, dan loss 9,8%. Sementara itu, untuk splitting data dengan rasio 6:1:3, skenario 1 menghasilkan nilai rata-rata accuracy 91,3%, sensitivity 78,6%, specificity 94,9%, dan loss 27,9%, skenario 2 menghasilkan nilai rata-rata accuracy 94%, sensitivity 90,2%, specificity 96,3%, dan loss 17,9%, sedangkan skenario 3 menghasilkan nilai rata-rata accuracy 97,9%, sensitivity 97%, specificity 98,4%, dan loss 5,4%. Didapatkan bahwa performa model terbaik adalah ketika menggunakan skenario 3 dengan rasio splitting data 6:1:3.

...... Retinal detachment (RD), also known as retinal ablation, is a condition where the neurosensory retina separates from its underlying layer, the retinal pigment epithelium (RPE), due to the loss of adhesion. RD can become a serious condition if not promptly treated, potentially leading to vision impairment, even permanent blindness. In Indonesia, an estimated 17,500–25,000 new cases of RD occur annually. However, with a limited number of doctors, conventional detection methods for RD may not be performed swiftly enough. Leveraging machine learning, particularly deep learning, which has rapidly advanced, RD detection can be facilitated through fundus imaging using Convolutional Neural Network (CNN) with ResNeSt architecture. A significant challenge arises due to the limited amount of data available for the RD class, as patient privacy regulations restrict access to medical data. To address this, data augmentation is applied using Generative Adversarial Networks (GAN) to generate synthetic images for the RD class. Additionally, experiments were conducted by applying Contrast Limited Adaptive Histogram Equalization (CLAHE) as a preprocessing step before GAN augmentation, aiming to enhance the quality of the images inputted into the GAN. This study further evaluates three scenarios with two data splitting ratios, 6:2:2 and 6:1:3. Scenario 1 involved training the ResNeSt model without CLAHE preprocessing or GAN augmentation. Scenario 2 involved training the ResNeSt model with GAN augmentation. Scenario 3 involved training the ResNeSt model with both CLAHE preprocessing and GAN augmentation. For the 6:2:2 data splitting ratio, Scenario 1 achieved an average accuracy of 89.9%, sensitivity of 76.3%, specificity of 94.3%, and loss of 52.4%. Scenario 2 achieved an average accuracy of 92.3%, sensitivity of 88.2%, specificity of 94.8%, and loss of 18.6%. Meanwhile, Scenario 3 achieved an average accuracy of 95.9%, sensitivity of 94.4%, specificity of 96.8%, and loss of 9.8%. For the 6:1:3 data splitting ratio, Scenario 1 achieved an average accuracy of 91.3%, sensitivity of 78.6%, specificity of 94.9%, and loss of 27.9%. Scenario 2 achieved an average accuracy of 94%, sensitivity of 90.2%, specificity of 96.3%, and loss of 17.9%. Meanwhile, Scenario 3 achieved an average accuracy of 97.9%, sensitivity of 97%, specificity of 98.4%, and loss of 5.4%. The best model performance was observed in Scenario 3 with a 6:1:3 data splitting ratio.