KLASIFIKASI PENYAKIT MATA DENGAN KUSTOMISASI ARSITEKTUR *CONVOLUTION NEURAL NETWORK*

SKRIPSI

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ABSTRAK

KLASIFIKASI PENYAKIT MATA DENGAN KUSTOMISASI ARSITEKTUR CONVOLUTION NEURAL NETWORK

Oleh :

Moh. Faqih Bahreisy

Penyakit mata dapat mempengaruhi dampak signifikan terhadap kualitas hidup masyarakat karena mata adalah indera penting untuk melihat, jika dibiarkan kondisi ini dapat menyebabkan kebutaan, sehingga perlu campur tangan dari tim medis untuk menanganinya. Saat ini penyakit mata beragam jenisnya, dalam rangka mengurangi gejala dan mencegah berkembangnya penyakit mata yang semakin beragam jenisnya ini, perlu adanya terobosan yang dapat membantu tim medis dalam melakukan diagnosa penyakit pada mata. *Convolutional Neural Network* (CNN), sebagai salah satu metode *deep learning* yang dapat menawarkan peluang besar dalam deteksi dan diagnosa penyakit mata melalui analisis citra digital. arsitektur ini terbukti efektif dalam klasifikasi dan deteksi penyakit mata. Penelitian ini dilakukan untuk mencari arsitektur CNN yang memiliki hasil keakuratan dan estimasi waktu yang lebih cepat. Perancangan arsitektur menjadi riset untuk menghasilkan arsitektur tersebut seperti melakukan kustomisasi dengan mengkombinasikan penerapan lapisan *convolution* dengan *separable convolution*. Kustomisasi arsitektur CNN yang dirancang menunjukkan akurasi yang cukup baik untuk klasifikasi penyakit mata, terutama setelah diterapkan teknik augmentasi data. Arsitektur 5 blok *convolution* dan *separable convolution layer* dengan fungsi aktivasi *Leaky ReLU*, menghasilkan performa terbaik dengan akurasi 84,4% pada skenario normal dan pada skenario augmentasi dengan fugnsi aktivasi *ReLU* mencapai 97,6%. Performa dalam klasifikasi penyakit mata juga terbilang sangat cepat dan akurat, hal tersebut terjadi karena penggunaan *separable convolution layer* yang dapat mengurangi jumlah parameter dan kompleksitas komputasi tanpa mengorbankan akurasi.

Kata Kunci : Klasifikasi Gambar, Penyakit Mata, Kustomisasi Arsitektur, Convolution Neural Network, Separable Convolution

ABSTRACT

EYE DISEASE CLASSIFICATION USING CONVOLUTION NEURAL NETWORK ARCHITECTURE CUSTOMIZATION

By :

Moh. Faqih Bahreisy

Eye diseases can significantly affect people's quality of life because the eye is an important sense to see, if this condition is left unchecked it can cause blindness, so it needs intervention from the medical team to handle it. Currently, there are various types of eye diseases, in order to reduce symptoms and prevent the growth of eye diseases that are increasingly diverse, there is a need for a breakthrough that can help the medical team in diagnosing eye diseases. Convolutional Neural Network (CNN), as one of the deep learning methods that can provide great opportunities in the detection and diagnosis of eye diseases through digital image analysis. This architecture has proven to be effective in the classification and detection of eye diseases. This research was conducted to find a CNN architecture that has accuracy results and faster estimation time. Architectural design becomes research to produce such architectures such as customization by combining the application of convolution layers with separable convolution. The customization of the designed CNN architecture shows good accuracy for eye disease classification, especially after applying data augmentation techniques. The architecture of 5 block convolution and separable convolution layers using *Leaky ReLU* activation function, produced the best performance with 84,4% accuracy in the normal scenario and in the augmentation scenario using *ReLU* activation function reached 97.6%. The performance in eye disease classification is also very fast and very accurate, due to the use of separable convolution layers that can reduce the number of parameters and computational complexity without losing accuracy.

Keywords : Image Classification, Eye Disease, Architecture Customization, Convolution Neural Network, Separable Convolution

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