

ABSTRAK

Acute Lymphoblastic Leukemia merupakan salah satu jenis penyakit kanker darah yang umum terjadi pada anak-anak dengan rentang usia 3 hingga 5 tahun. Diagnosis ALL dilakukan dengan analisis morfologis sel oleh seorang ahli patologi. Akan tetapi proses identifikasi yang dilakukan masih tergolong tradisional. Dalam penelitian ini dilakukan proses klasifikasi dengan tujuan untuk mendiagnosis penyakit ALL berdasarkan citra mikroskopis pada dataset ALL-IDB2 menggunakan metode *deep learning*. Namun, dalam mengimplementasikan metode *deep learning* membutuhkan pemakaian *memory* yang cukup besar untuk menyimpan *trainable* parameter dan dibutuhkan penyesuaian nilai *learning rate* untuk mendapatkan nilai *accuracy* yang optimal. Untuk mengatasi permasalahan tersebut metode yang digunakan menerapkan kombinasi aljabar *hypercomplex-valued* pada *Convolutional Neural Network* (CNN) atau *Hypercomplex-valued CNN*, serta untuk mengetahui pengaruh nilai *learning rate* yang digunakan terhadap tingkat *accuracy* yang dihasilkan dilakukan uji coba menggunakan *learning rate* 0.1, 0.01, dan 0.001. Skenario uji coba dilakukan dengan menggunakan model CNN asli atau *real-CNN* dan empat jenis model *Hypercomplex-valued CNN* dengan *learning rate* 0.1, 0.01, dan 0.001. Pembagian data *training* dan *testing* sebesar 80:20. Dari tiga uji coba nilai *learning rate* 0.1, 0.01, dan 0.001 didapatkan bahwa nilai *learning rate* berpengaruh terhadap tingkat akurasi yang dihasilkan baik pada *real-CNN* maupun *hypercomplex-valued CNN*. Nilai *learning rate* yang semakin kecil dapat meningkatkan nilai *accuracy* yang dihasilkan. Pada *real-CNN* nilai *accuracy* tertinggi didapatkan dengan *learning rate* 0.001 yaitu sebesar 96.15%, sedangkan pada *hypercomplex-valued CNN* nilai *accuracy* tertinggi didapatkan dengan *learning rate* 0.001 sebesar 98.08%. Penerapan aljabar *hypercomplex-valued* dapat meningkatkan presentase nilai *accuracy* sebesar 2% pada *real-CNN* dan mengurangi presentase total *trainable* parameter sebesar 62% dari *real-CNN*.

Kata Kunci : *Acute Lymphoblastic Leukemia*, *Klasifikasi*, *Deep Learning*, *Convolution Neural Network* (CNN), *Hypercomplex-valued*, *Learning rate*.

ABSTRACT

Acute Lymphoblastic Leukemia is a type of blood cancer that is common in children with an age range of 3 to 5 years. Diagnosis of ALL is carried out by morphological analysis of cells by a pathologist. However, the identification process carried out is still relatively traditional. In this study, a classification process was carried out with the aim of diagnosing ALL disease based on microscopic images on the ALL-IDB2 dataset using the deep learning method. However, implementing the deep learning method requires a large enough memory usage to store trainable parameters and it takes adjusting the learning rate value to get the optimal accuracy value. To solve this problem, the method used applies a combination of hypercomplex-valued algebras to the Convolutional Neural Network (CNN) or Hypercomplex-valued CNN, , as well as to determine the effect of the learning rate value used on the resulting accuracy level, a trial was carried out using the learning rate rate of 0.1, 0.01, and 0.001. The trial scenario was performed using the original CNN or real-CNN model and four types of CNN Hypercomplex-valued models with learning rates of 0.1, 0.01, and 0.001. The division of training and testing data is 80:20. From three trials, learning rate values of 0.1, 0.01, and 0.001 found that the learning rate value affects the level of accuracy produced on both real-CNN and hypercomplex-valued CNN. The smaller learning rate can increase the accuracy value produced. In real-CNN, the highest accuracy value was obtained with a learning rate of 0.001, which was 96.15%, while in hypercomplex-valued CNN the highest accuracy value was obtained with a learning rate of 0.001 of 98.08%. The application of hypercomplex-valued algebra can increase the percentage of accuracy values by 2% on real-CNN and reduce the percentage of total trainable parameters by 62% of real-CNN.

Keywords : Acute Lymphoblastic Leukemia, Classification, Deep Learning, Convolution Neural Network (CNN), Hypercomplex-valued, Learning rate.

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