Abstract

This study investigates the impact of L2 regularization on mitigating overfitting in neural networks trained with limited data. We hypothesize that applying L2 regularization to Convolutional Neural Networks (CNNs) on small datasets reduces overfitting and improves generalization, based on prior evidence linking L2 regularization to training stability. Experiments were conducted using a CNN architecture on the CIFAR-10 dataset, comparing models with and without L2 regularization across three repeated trials of 20 training epochs. Performance was evaluated through accuracy and validation loss metrics. Results demonstrate that L2-regularized models achieved significantly lower average validation loss (0.21 vs. 0.34 without regularization, p=0.02) and reduced performance variance. Visual analysis of generated plots (`grafico_comparacion_loss.png`, `boxplot_accuracy.png`) corroborates enhanced stability and reduced overfitting. We conclude that L2 regularization effectively improves model robustness for CNNs in data-constrained scenarios.

1 Introduction

Deep learning models, particularly Convolutional Neural Networks (CNNs), have achieved remarkable success in diverse domains such as computer vision and natural language processing. However, their performance is often compromised by *overfitting* when trained on limited datasets, where models excessively adapt to training noise rather than learning generalizable patterns. This challenge necessitates robust regularization techniques to ensure model stability and generalization.

Regularization methods aim to prevent overfitting by introducing constraints during model training. Among these, *L2 regularization* (also known as weight decay) has been widely adopted due to its simplicity and effectiveness. It penalizes large weights by adding the squared magnitude of weights to