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PERFORMANCE COMPARISON OF DROPOUT vs L1/L2 REGULARIZATION

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ABSTRACT

Regularization techniques are important in machine learning to reduce overfitting and improve model performance. This project compares Dropout, L1 Regularization, and L2 Regularization. Dropout randomly deactivates neurons during training to improve robustness, while L1 and L2 add penalty terms to control model complexity, with L1 enabling feature selection and L2 improving stability. The comparison is based on accuracy, overfitting control, and efficiency. The study concludes that each method is effective in different scenarios, and the choice depends on the model and dataset.

INTRODUCTION

In the field of machine learning and deep learning, building models that perform well on both training and unseen data is a major challenge. A common problem faced during model development is overfitting, where the model learns the training data too closely, including noise and irrelevant patterns, resulting in poor performance on new data. To address this issue, regularization techniques are used to improve model generalization and reduce complexity. This project focuses on three important regularization methods: Dropout, L1 Regularization, and L2 Regularization. Dropout is mainly used in deep neural networks and works by randomly deactivating neurons during training, preventing the model from relying too much on specific features. On the other hand, L1 and L2 regularization techniques add penalty terms to the loss function, which help in controlling the magnitude of model weights.

L1 regularization encourages sparsity by setting some weights to zero, while L2 regularization helps in maintaining stability by reducing weight values evenly.

METHODOLOGY

The methodology for this project involves a systematic approach to compare the performance of Dropout, L1 Regularization, and L2 Regularization in machine learning models. First, a suitable dataset is selected and preprocessed by handling missing values, normalizing data, and splitting it into training and testing sets. Next, a baseline model is developed without applying any regularization to observe the initial performance and overfitting behavior. After establishing the baseline, three separate models are implemented by applying Dropout, L1 Regularization, and L2 Regularization respectively. For Dropout, different dropout rates are tested to identify the optimal configuration, while for L1 and L2, appropriate regularization parameters are chosen. All models are trained under similar conditions to ensure a fair comparison.

The performance of each model is then evaluated using metrics such as accuracy, loss, and overfitting gap (difference between training and testing performance). The results are analyzed and compared to determine the effectiveness of each regularization technique

SYSTEM ARCHITECTURE AND DATA FLOW

The system is designed to compare the performance of Dropout, L1, and L2 Regularization techniques within a machine learning framework. It consists of multiple components that work together to process data, train models, and evaluate performance.

System Architecture

- **Data Input Module:** Collects and loads the dataset for processing
- **Preprocessing Module:** Cleans the data, handles missing values, and normalizes features
- **Model Building Module:** Creates machine learning models with three variations:
  - Model with Dropout
  - Model with L1 Regularization
  - Model with L2 Regularization
- **Training Module:** Trains each model using the training dataset
- **Output Module:** Displays results and comparison analysis

Data Flow

The data flows through the system in a structured manner to ensure proper processing and evaluation.

Steps in Data Flow:

- **Data Collection:** Dataset is gathered from a reliable source
- **Data Preprocessing:** Data is cleaned, normalized, and split into training and testing sets
- **Model Initialization:** Three models are initialized with Dropout, L1, and L2 techniques
- **Model Training:** Each model is trained separately using the same dataset
- **Regularization Application:**
  - Dropout randomly deactivates neurons during training
  - L1 applies absolute weight penalty
  - L2 applies squared weight penalty
- **Performance Evaluation:** Models are tested and evaluated using metrics like accuracy and loss
- **Result Comparison:** Results are compared to analyze which technique performs better
- **Final Output:** Best-performing model and insights are presented
- using the training dataset

RESULT AND DISCUSSION

The results indicate that dropout regularization at a rate of 0.3 provided the most effective improvement in model performance, achieving the highest test accuracy and the lowest test loss compared to the baseline. While the baseline model without regularization already performed well, dropout reduced overfitting and allowed the network to generalize better, which is reflected in the lower validation loss curves. In contrast, L1 and L2 regularization both reduced accuracy and increased loss, showing that they imposed too strong a penalty on the weights for this dataset. The combination of dropout with L2 also failed to outperform dropout alone, suggesting that stacking regularization methods in this case constrained the model excessively. Overall, the findings demonstrate that dropout was the most suitable technique for balancing accuracy and generalization, whereas L1 and L2 regularization introduced trade-offs that weakened performance.

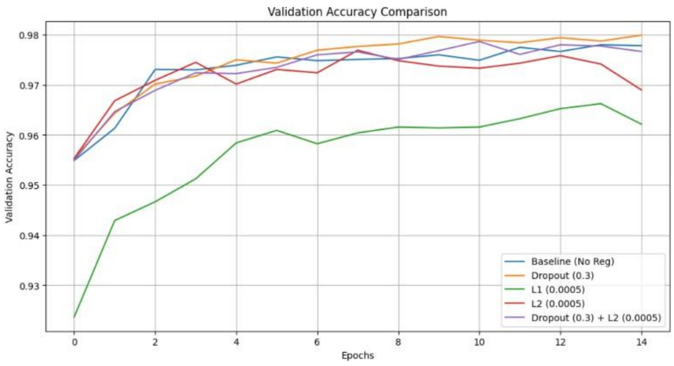

Figure 1: Validation Accuracy Comparison.

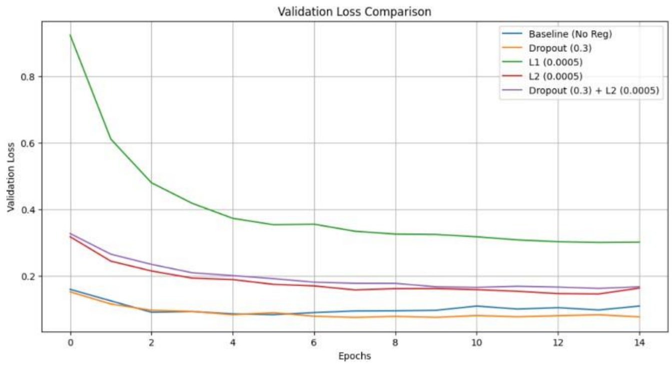

Figure 2: Validation Loss Comparison.

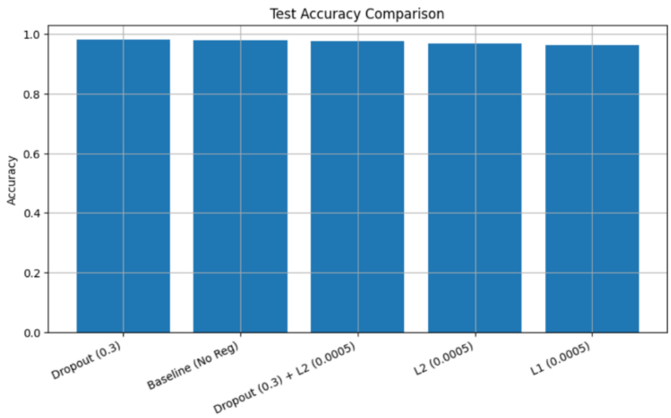

Figure 3: Test Accuracy Comparison.

FINAL COMPARISON TABLE

Model Test Accuracy Test Loss

1 Dropout (0.3) 0.9819 0.072725

0 Baseline (No Reg) 0.9785 0.101567

4 Dropout (0.3) + L2 (0.0005) 0.9764

0.165057

3 L2 (0.0005) 0.9689 0.158291

2 L1 (0.0005) 0.9621 0.298420

CONCLUSION

In this project, a comparative analysis of Dropout, L1 Regularization, and L2 Regularization was conducted to understand their effectiveness in reducing overfitting and improving model performance. The study shows that Dropout is highly effective in deep learning models as it improves robustness by randomly deactivating neurons during training. L1 Regularization is useful for feature selection as it reduces some weights to zero, while L2 Regularization provides better stability by evenly reducing weight values. Each technique has its own advantages and performs well under different conditions. Therefore, the choice of regularization method depends on the type of model, dataset, and VII.

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REFERENCES

1 Pattern Recognition and Machine Learning – Christopher M. Bishop, Springer, 2006.
2 Deep Learning – Ian Goodfellow, Yoshua Bengio, Aaron Courville, MIT Press, 2016.
3 Dropout A Simple Way to Prevent Neural Networks from Overfitting – Nitish Srivastava et al., Journal of Machine Learning Research, 2014.
4 Machine Learning – Study materials and lecture notes.
5 TensorFlow Documentation– https://www.tensorflow.org
6 Keras Documentation – https://keras.io