Understanding Regularisation in Neural Networks: A Practical Comparison of L2, Dropout, and Early Stopping

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Abstract

This tutorial explores how three widely used regularisation techniques L2 regularisation, dropout, and early stopping affect the performance and generalisation of multilayer perceptrons. Using a subset of the Fashion-MNIST dataset, I compare these techniques through controlled experiments and visual analysis of training and validation behaviour. The results show that unregularised models overfit rapidly, while each regularisation method reduces overfitting in distinct ways. Dropout and L2 regularisation improve stability and validation accuracy, and early stopping provides an efficient safeguard against unnecessary training. This tutorial aims to give readers a practical understanding of how and when to apply these methods in their own work.

Introduction

Neural networks have become a central tool in modern machine learning due to their ability to approximate complex, non-linear functions. However, this expressive power also makes them susceptible to overfitting, where the model performs well on training data but generalises poorly to unseen examples. Regularisation techniques are therefore essential when training neural networks, especially on moderately sized datasets.

This tutorial focuses on three common forms of regularisation: L2 regularisation, dropout, and early stopping, and demonstrates their impact on model behaviour using a simple multilayer perceptron trained on Fashion-MNIST. The goal is to provide an accessible, experiment-driven explanation that helps readers understand when and why each method is effective.

Background Theory

1. **Overfitting in Neural Networks**

   Overfitting occurs when a model memorises the training data instead of learning general patterns. In practice, this appears as a widening gap between training and validation loss: the training loss continues decreasing, while validation loss stalls or increases. Neural networks with many parameters are especially prone to this behaviour unless regularisation techniques are applied.

2. **L2 Regularisation (Weight Decay)**

   L2 regularisation adds a penalty proportional to the squared magnitude of the model's weights. This encourages smaller, more stable weights and reduces variance. In optimisation, this is implemented as weight decay, causing the optimiser to gently pull weights toward zero. Models trained with L2 typically show smoother learning curves and improved validation performance, especially when the unregularised model overfits sharply.

3. **Dropout**

   Dropout randomly deactivates a proportion of neurons during each training iteration. This prevents hidden units from becoming overly dependent on one another and forces the network to learn more robust, distributed representations. Dropout usually increases training loss because learning is effectively noisier but often lowers validation loss by reducing co-adaptation and overfitting.

4. **Early Stopping**

   Early stopping monitors validation loss during training and halts the process once improvements stop. Even without explicit mathematical penalties, this acts as a strong form of regularisation by preventing the model from fitting noise in the final training epochs. It is computationally efficient and particularly useful when training time is limited.

Experimental Setup

1. **Dataset**

   Fashion-MNIST consists of 28×28 grayscale images across ten clothing categories. It was chosen because it is simple enough for rapid experimentation yet challenging enough to exhibit meaningful overfitting in small networks. For efficiency, a subset of 5,000 training images and 1,000 validation images was used, along with the full 10,000-image test set.

2. **Model Architecture**

   All experiments use the same multilayer perceptron with two hidden layers (256 and 128 units) and ReLU activations. Images are flattened into 784-dimensional vectors. For dropout-enabled models, a dropout layer with probability 0.5 is added after each hidden layer.

3. **Training Configuration**

   Models were trained for up to 30 epochs using the Adam optimiser with a learning rate of 0.001. Batch sizes were 128 for training and 256 for validation and testing. Early stopping, when enabled, used a patience of five epochs.

4. **Model Variants**

   The following model variants were compared:

   - Baseline model with no regularisation
   - L2 regularisation (weight decay = 1e–4)
   - Dropout (p = 0.5)
   - Early stopping (patience = 5)
   - Combined L2 + dropout model

Results and Analysis

1. Training vs Validation Loss

The baseline model exhibits a noticeable divergence between training and validation loss, indicating overfitting. L2 regularisation reduces this gap by penalising large weights. Dropout increases training loss but consistently lowers validation loss, reflecting its ability to reduce co-adaptation. Early stopping halts training before overfitting becomes severe, producing a relatively smooth validation curve.

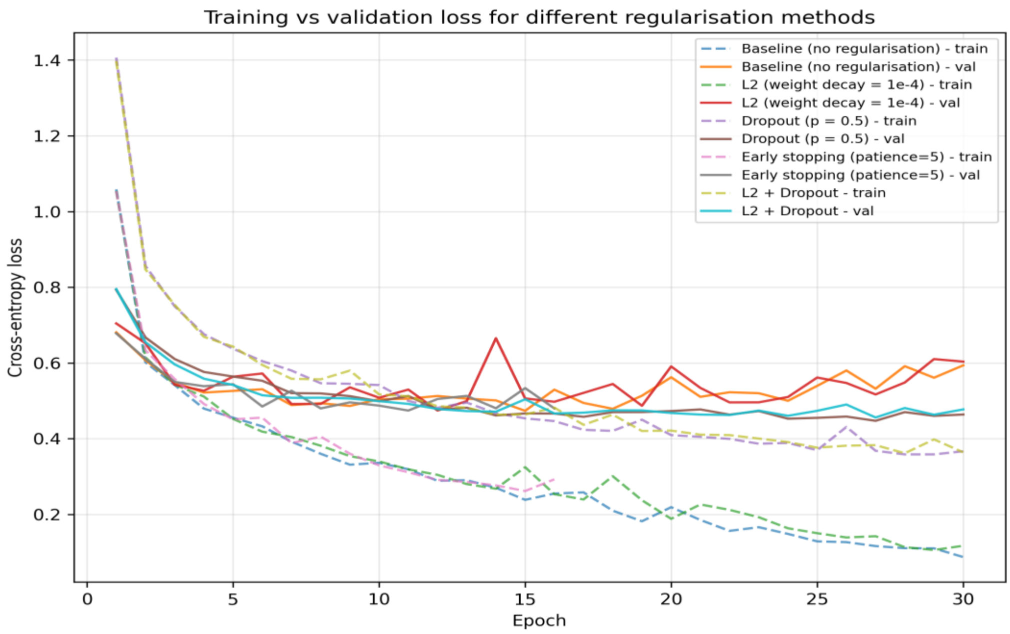

Figure 1. Training and validation loss curves for all regularisation configurations.

2. Training vs Validation Accuracy

Accuracy trends mirror the loss curves. The baseline achieves very high training accuracy but noticeably lower validation accuracy. L2 and dropout reduce the discrepancy, with dropout generally providing the most consistent validation performance. Early stopping produces balanced training and validation accuracy without requiring many epochs.

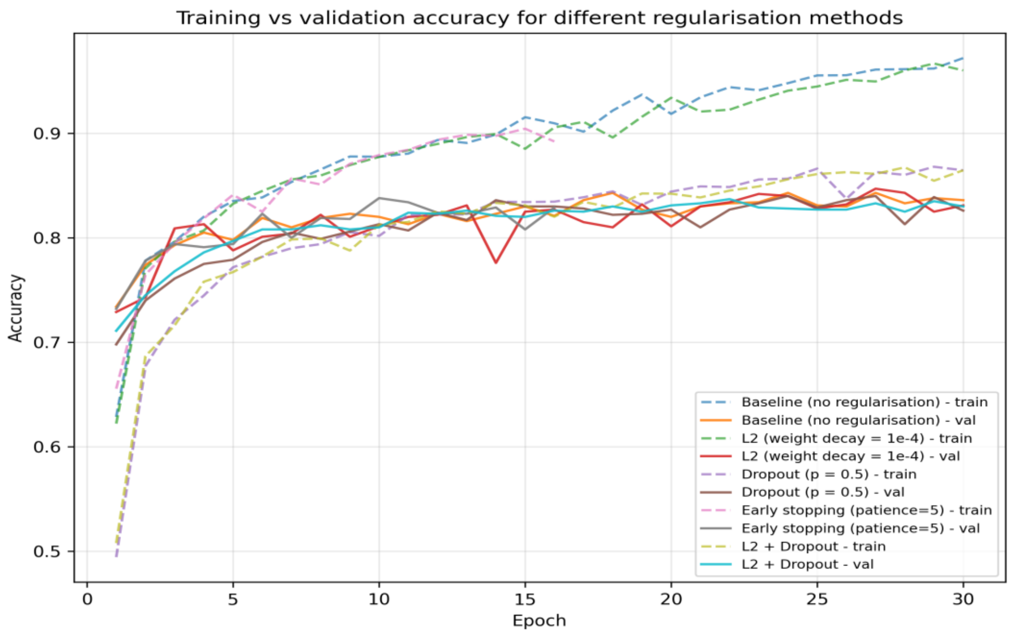

Figure 2. Training and validation accuracy for each regularisation method.

3. Test Accuracy Comparison

A comparison of final test accuracies shows that regularised models outperform the baseline. Dropout and L2 regularisation both improve generalisation, and the combined L2 + dropout model often yields the best performance. Early stopping performs well with significantly reduced training time.

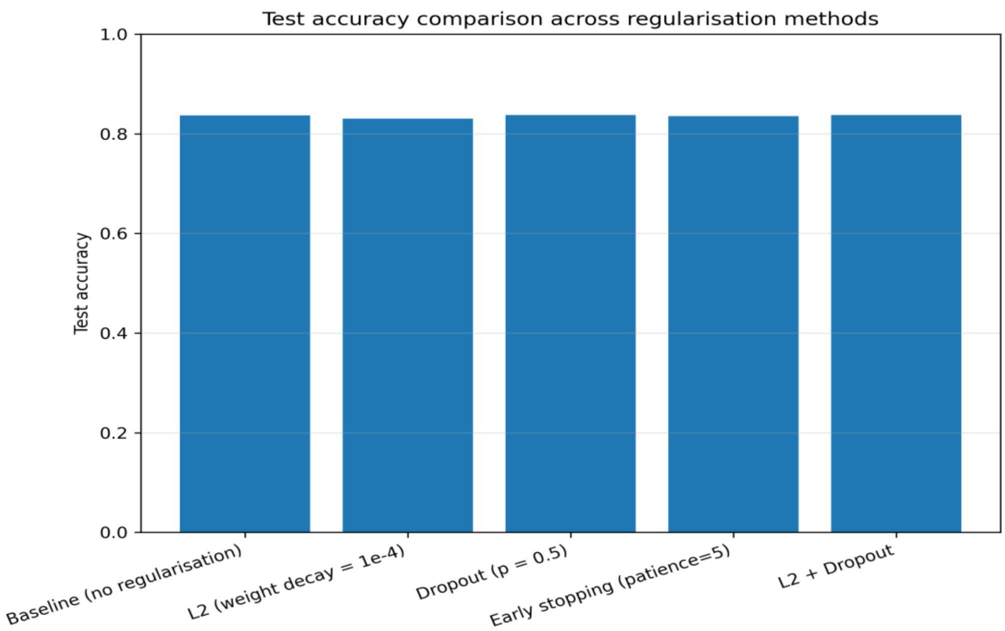

Figure 3. Final test accuracy comparison across all model variants.

4. Misclassified Examples

Misclassified images from the baseline model highlight its tendency to confuse visually similar classes, such as “shirt” and “T-shirt/top.” The dropout model still makes errors but often displays more robust decision boundaries, demonstrating the qualitative benefits of regularisation.

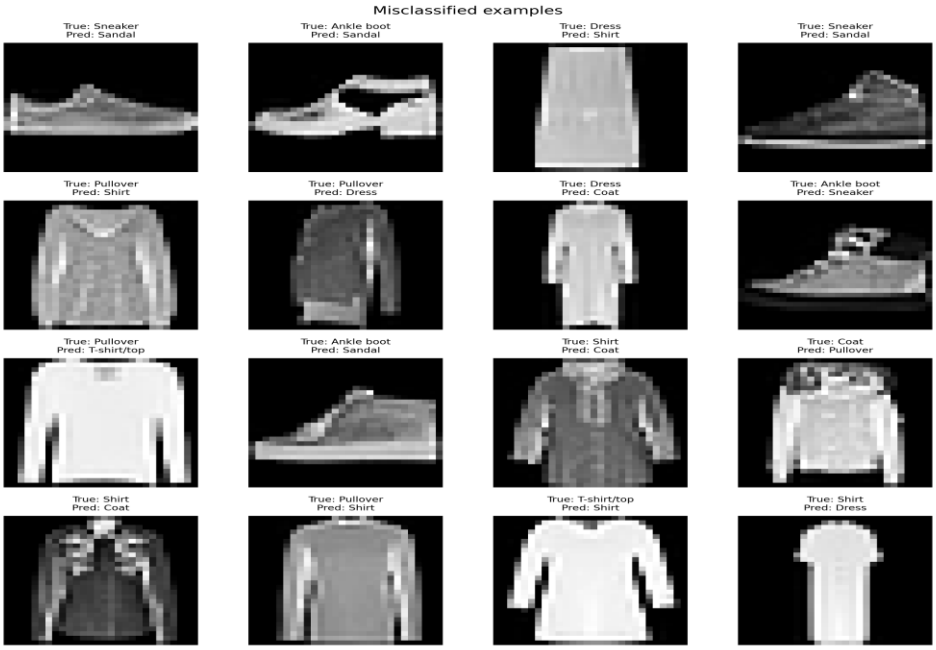

Figure 4. Example misclassified Fashion-MNIST images from the baseline model with no regularisation.

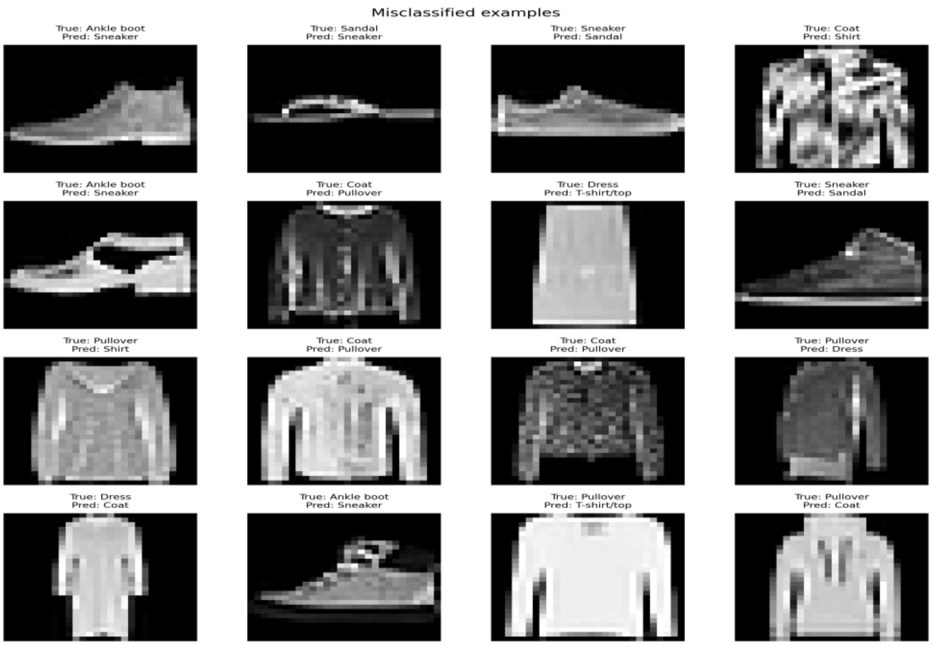

Figure 5. Example misclassified Fashion-MNIST images from the dropout-regularised model.

Discussion

Regularisation plays a central role in improving the generalisation performance of neural networks. These experiments demonstrate that unregularised models tend to overfit small datasets rapidly, while simple techniques such as L2, dropout, and early stopping substantially reduce this effect. Each method operates differently: L2 encourages small weights, dropout injects noise that reduces reliance on specific neurons, and early stopping prevents late-epoch memorisation. In practice, combining multiple regularisation methods often gives the most reliable results.

Ethical and Practical considerations

Well-regularised models are generally more reliable in deployment, reducing risks associated with unpredictable or biased predictions. However, regularisation cannot fix dataset imbalance or structural bias; these must be addressed through data collection and auditing. Early stopping contributes to energy efficiency by avoiding unnecessary computation, which is increasingly important in large-scale AI systems. Transparency and reproducibility are also key components of ethical AI practice, and the inclusion of code, figures, and configuration details in this project supports that requirement.

Conclusion

This tutorial demonstrated the impact of three common regularisation techniques on neural network training using a simple MLP and the Fashion-MNIST dataset. L2 regularisation and dropout both improved validation and test performance, while early stopping provided an efficient safeguard against overfitting. The combined regularisation strategy offered the most consistent generalisation benefits. These findings reinforce the importance of incorporating regularisation into practical neural network workflows and provide readers with actionable guidance on when to apply each method.

References

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Repository Link

This project's full code, notebook, and figures are available:

https://github.com/aniket12341/Regularisation_assignment.git