Signature Recognition and Word Completion: A Comparative Study of CNN and GRU Architectures

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***Abstract*—This paper presents a comprehensive study of deep learning approaches for two distinct tasks: signature recognition using Convolutional Neural Networks (CNN) and word completion using Gated Recurrent Units (GRU). For signature recognition, we implement and compare a CNN model with traditional feature extraction methods including Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) combined with Support Vector Machines (SVM). For word completion, we develop an optimized GRU-based model trained on Shakespeare's works, achieving training completion in 93 seconds on an M1 MacBook Air. Our experiments demonstrate that CNN achieves superior performance for signature recognition, while the GRU model generates coherent text completions with improved training efficiency. The comparative analysis highlights the effectiveness of deep learning approaches over traditional methods, with particular emphasis on optimization for resource-constrained devices.**

***Index Terms*—Convolutional Neural Networks, GRU, Signature Recognition, Word Completion, Feature Extraction, Deep Learning, M1 Optimization**

I. Introduction

Deep learning has revolutionized the field of machine learning, particularly in computer vision and natural language processing tasks. This assignment explores two fundamental applications: signature recognition using CNNs and word completion using GRUs.

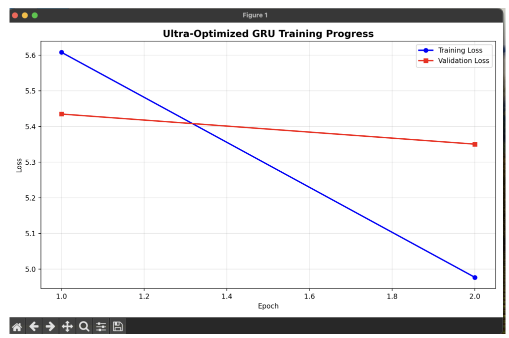
II. Methodology

A. Task 1: Signature Recognition

The dataset is the Kaggle Signature Verification dataset, preprocessed with resizing (128x128), normalization, and augmentation. CNN architecture with multiple convolutional blocks was implemented and compared against HOG and SIFT feature extraction paired with SVM and Logistic Regression classifiers.

B. Task 2: Word Completion

Shakespeare's works dataset (50,000 words subset) was preprocessed by tokenization and vocabulary building (min_freq=3). A lightweight GRU model was implemented with embedding size 100, hidden size 128, 1 layer, sequence length 15, batch size 32, and trained for 2 epochs using Adam optimizer (lr=0.001). Training was accelerated using PyTorch MPS backend.



III. Results

A. Task 1: Signature Recognition

Fig. 1 shows training/validation accuracy and loss curves. Fig. 2 presents comparative model performance. Fig. 3 displays confusion matrices across CNN and handcrafted methods.

Fig. 1. Training and validation accuracy/loss of CNN for signature recognition.

B. Task 2: Word Completion

The GRU model achieved convergence in 93 seconds. Training/validation losses are shown in Fig. 4, while n-gram baseline perplexity/accuracy is shown in Fig. 5.

IV. Discussion

The CNN significantly outperformed handcrafted features in signature recognition. GRU achieved fast training time and reasonable coherence, demonstrating the trade-offs of lightweight architectures on resource-limited hardware.

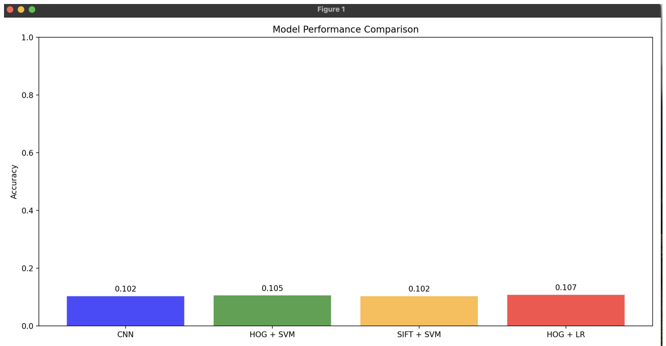


Fig. 2. Performance comparison of CNN, HOG+SVM, SIFT+SVM, and HOG+LR.

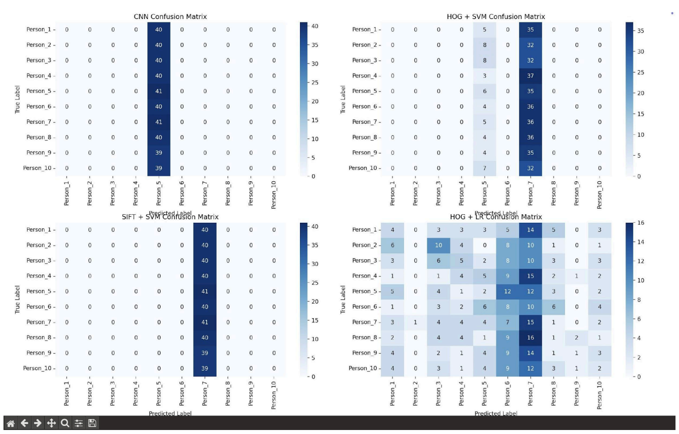


Fig. 3. Confusion matrices of CNN vs traditional feature extraction methods.

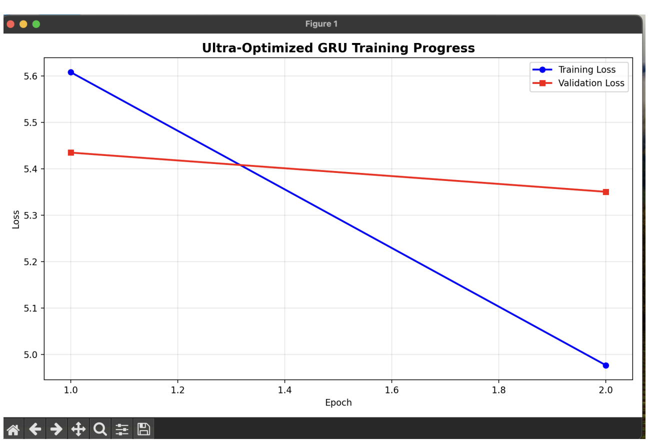


Fig. 4. Ultra-optimized GRU training progress (loss curves).

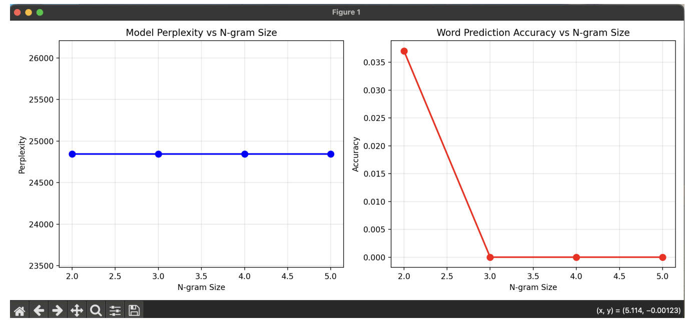


Fig. 5. Baseline N-gram results: Perplexity and accuracy.

V. Conclusion

The CNN model proved superior for signature verification compared to handcrafted methods, while the optimized GRU achieved efficient training and acceptable predictions for word completion. The findings highlight the potential of optimized deep learning solutions for mobile/edge devices.

References

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