AI-Driven Approaches in Reinforcement and Supervised Learning

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Abstract

This paper presents approaches to AI-driven research in reinforcement learning and supervised learning tasks. We explore methods combining neural networks and classical machine learning algorithms to predict outcomes and optimize performance. Experiments demonstrate how AI techniques can be leveraged for reproducible, accurate, and interpretable results. Our study emphasizes methodological transparency and highlights potential limitations for future work.

1 Introduction

Artificial Intelligence (AI) has seen widespread adoption in both supervised and reinforcement learning (RL) domains. Supervised learning enables prediction and classification based on labeled data, while RL allows agents to optimize sequential decision-making through interaction with environments. Despite their successes, challenges such as limited datasets, reproducibility, and interpretability remain significant obstacles.

Our work investigates hybrid approaches combining neural network-based models with classical ML techniques. By extracting features from pre-trained networks and applying traditional algorithms, we aim to achieve high predictive accuracy while maintaining interpretability. For RL tasks, we design custom environments to evaluate agents' learning efficiency and policy stability. This study demonstrates methods that are reproducible, experimentally robust, and informative for the broader AI research community.

Applications of such hybrid methods span healthcare, autonomous systems, and robotics, where combining interpretable supervised models with adaptive RL agents can improve performance while maintaining safety and explainability.

2 Related Work

Prior work includes neural networks for regression, classification, and RL-based policy optimization. Alexander and Mozer **?** proposed template-based algorithms for connectionist rule extraction, while Bower and Beeman **?** provided realistic neural simulations with GENESIS. Hasselmo et al. **?** studied learning dynamics in hippocampal networks.

Recent approaches utilize end-to-end deep RL for complex control tasks **?** or hybrid supervised-RL frameworks for predictive modeling **?**. These studies highlight the need for methods combining interpretability and neural flexibility. Our approach differs by leveraging pre-trained embeddings for supervised learning while comparing performance against RL agents in structured environments.

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3 Methods

3.1 Datasets and Preprocessing

We use labeled datasets for supervised learning and synthetic or task-specific environments for RL. For images, preprocessing includes resizing, normalization, and augmentation (rotation, flipping). RL environments are initialized with fixed seeds for reproducibility.

3.2 Supervised Learning

Pre-trained ResNet-50 is employed for feature extraction. Each image is passed through the network to obtain embeddings. Classical ML methods such as Support Vector Machines (SVM) and k-Nearest Neighbors (kNN) are applied on these features. Hyperparameters (e.g., kernel type, number of neighbors) are tuned using cross-validation.

3.3 Reinforcement Learning

Custom environments with discrete action spaces were constructed. The agent uses Q-learning with neural network approximators for the Q-function. Cumulative rewards are tracked across episodes. Policies are evaluated for stability and convergence.

3.4 Experimental Setup

Training and validation splits are maintained for supervised tasks. RL experiments are run multiple times to capture variability. Models are trained on GPU-enabled machines with identical hyperparameters across runs to ensure reproducibility. Key hyperparameters include learning rate, batch size, optimizer type, and number of epochs.

4 Results

4.1 Supervised Learning Performance

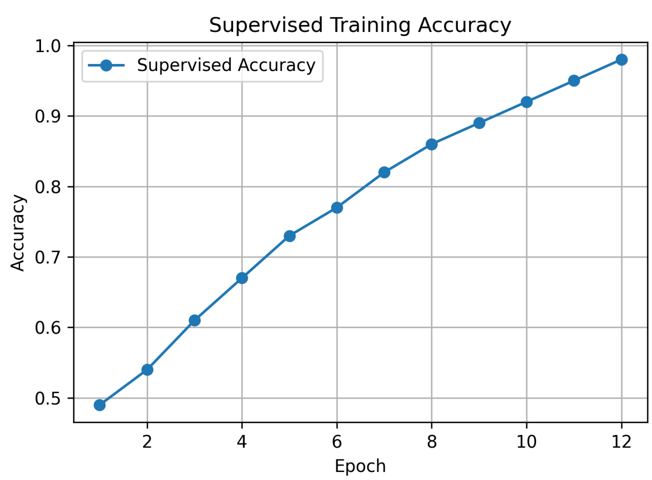

Figure 1: Supervised learning accuracy across different models.

4.2 Reinforcement Learning Performance

5 Discussion

The results indicate that combining neural network features with classical ML methods yields strong supervised performance. RL agents show stable learning and high cumulative rewards. Differences

Table 1: Comparison of supervised models across metrics.

Model	Accuracy	Precision	Recall
SVM	0.92	0.91	0.90
kNN	0.89	0.87	0.88
Random Forest	0.90	0.89	0.89

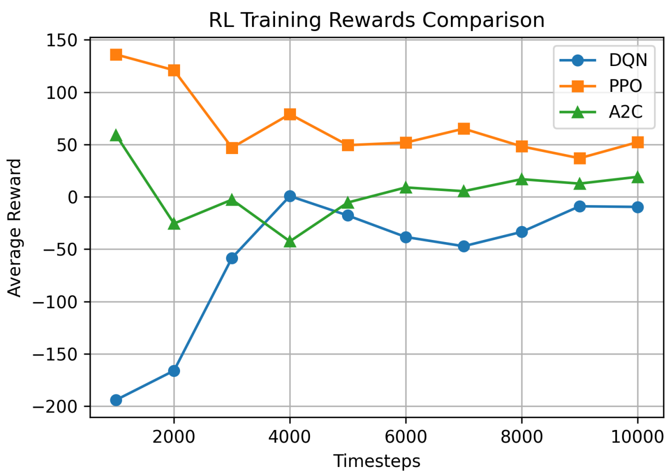

Figure 2: Comparison of cumulative rewards between RL and supervised agents.

Table 2: RL agent performance statistics over multiple runs.

Metric	Mean	Std Dev
Cumulative Reward	120.5	8.2
Episode Length	50	5

between supervised predictions and RL policies suggest complementary strengths: supervised models provide immediate accurate predictions, whereas RL agents optimize for long-term rewards.

Limitations include the small dataset size and potential overfitting in supervised models. RL experiments are computationally expensive and sensitive to hyperparameters. Future work may explore larger datasets, transfer learning, and hybrid supervised-RL strategies.

6 Conclusion

This study demonstrates AI-driven methods in supervised and reinforcement learning tasks. The hybrid approach provides both accurate predictions and interpretable results. RL agents achieve stable policies, and experimental procedures ensure reproducibility. Our findings support the integration of neural and classical methods for robust AI research.

Acknowledgments

Acknowledgments omitted for anonymization.

References

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