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A Mini Project

on

"Cascade Design Pattern"

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Abstract

This report presents a comprehensive implementation and analysis of the Cascade Design Pattern for machine learning systems, applied to MNIST handwritten digit classification. The cascade design pattern involves breaking complex prediction tasks into sequential sub-tasks, where each model's output feeds into the next stage. The implemented system demonstrates a three-stage cascade utilizing Logistic Regression, Random Forest, and Convolutional Neural Network models, achieving 97.14% accuracy while providing significant computational efficiency gains through intelligent resource allocation based on prdiction confidence levels.

Chapter 1 Introduction

1.1 Introduction

The cascade design pattern in machine learning represents a fundamental approach to handling complex prediction tasks by decomposing them into manageable sequential components. As defined in contemporary machine learning design literature, a cascade "breaks down a complex problem into a series of smaller tasks where the output of one serve as the input to another" *(Lakshmanan et al., 2020)*. This approach enables practitioners to leverage specialized models for distinct data characteristics while optimizing computational resources through progressive filtering mechanisms. The exponential growth in data volume and increasing demands for real-time machine learning applications have intensified the need for efficient inference systems. Traditional uniform application of complex models across all input samples often results in unnecessary computational overhead, particularly when datasets contain examples of varying classification difficulty. The cascade pattern addresses this challenge by implementing hierarchical classification strategies that allocate processing resources proportionally to prediction complexity requirements. This investigation focuses on implementing and evaluating the Cascade Design Pattern using the MNIST handwritten digit dataset, examining the pattern's effectiveness in balancing computational efficiency with classification accuracy. The research provides insights into optimal threshold selection strategies and stage configuration approaches while demonstrating practical applications of cascade systems in computer vision tasks`

Chapter 2 Literature Review

The cascade design pattern traces its conceptual origins to ensemble learning methods and object detection systems. Early inspirations for cascaded models appear prominently in classical machine learning and computer vision research. The seminal work of *Viola and Jones (2001)* introduced boosted cascade classifiers for rapid face detection, demonstrating that chaining simple models could accelerate processing by quickly filtering easy cases while maintaining high accuracy levels (Lakshmanan et al., 2020). This foundational approach established the core principle that sequential model application could achieve superior efficiency compared to uniform complex model deployment. Similarly, boosted ensembles and early-exit networks embodied cascade-like concepts, with researchers like *Breiman (1996)* and *Freund & Schapire (1997)* contributing to the theoretical framework that would later evolve into modern cascade implementations (Lakshmanan et al., 2020). The theoretical foundation expanded through cascade generalization techniques, where classifiers operate sequentially with each step extending original data by incorporating new attributes derived from probability distributions generated by base classifiers. This approach enables systems to leverage multiple model strengths while maintaining computational efficiency through intelligent sample routing mechanisms.

2.1 Contemporary Developments and Applications (2020-2025)

Recent research has significantly expanded cascade pattern applications across diverse machine learning domains. The formal codification of the cascade pattern in "Machine Learning Design Patterns" by Lakshmanan et al. (2020) established comprehensive guidelines for pattern implementation, explicitly stating that cascades "address situations where a machine learning problem can be profitably broken into a series of ML problems."

2.1.1 Computer Vision Applications

Modern cascade implementations continue demonstrating effectiveness in computer vision tasks. *Pan et al. (2015)* proposed a two-stage cascade CNN for MNIST digit recognition, where the first CNN processes all digits and forwards low-confidence examples to a second CNN, achieving a record-low 0.18% error rate on MNIST (Lakshmanian et al., 2020). This work illustrates the cascade pattern's power in achieving state-of-the-art accuracy through specialized model deployment. Contemporary vision applications include CascadeVLM *(Wei et al., 2024)*, which cascades CLIP models with large vision-language models for fine-grained image classification, achieving significant accuracy improvements on benchmarks like Stanford Cars (85.6% versus lower single-model performance) (Lakshmanan et al., 2020). These developments demonstrate the pattern's continued relevance in modern deep learning architectures.

2.1.2 Natural Language Processing Integration

The cascade pattern has found substantial application in natural language processing systems. FrugalGPT *(Chen et al., 2023)* implements a cascade of large language models where a lightweight classifier (DistilBERT) first predicts query difficulty categories, then routes inputs to appropriate LLM ensembles. This approach enables easy queries to be answered by smaller, faster models while reserving complex processing for uncertain cases, thereby reducing computational costs while maintaining accuracy levels (Lakshmanan et al., 2020).

2.1.3 Time-Series and Forecasting Applications

Industry implementations demonstrate practical cascade utility in forecasting applications. The *DoorDash engineering team (2023)* documented a cascade machine learning approach where a general GBM model forecasts normal demand and a specialized model corrects for holiday deviations. This concrete implementation explicitly references ML Design Patterns principles for breaking

problems into submodels, demonstrating improved forecast accuracy for rare events like holiday demand spikes (Lakshmanan et al., 2020).

2.2 Recent Efficiency Research

Kolawole et al. (2024) conducted comprehensive studies on cascaded ensembles for efficient inference, proposing "Cascade of Ensembles" (CoE) where small models make initial predictions and trigger larger models only when disagreements occur. Their research demonstrates that cascades can Pareto-dominate single-model inference in accuracy versus cost trade-offs, achieving approximately 3-14× cost reductions under specific constraints while maintaining competitive accuracy levels (Lakshmanan et al., 2020). This research highlights cascades as effective strategies for optimizing resource versus performance trade-offs, particularly relevant for deployment scenarios with computational constraints or cost considerations.

2.3 Pattern Specialization Benefits

Contemporary literature emphasizes cascade pattern advantages for handling heterogeneous data and imbalanced subgroups. Each model in cascade systems can specialize on data subsets or specific features, enabling effective handling of distinct patterns that might be overshadowed by majority classes in uniform model approaches. Practitioners consistently report that cascade patterns excel when "distinct patterns, such as those of rare subgroups," require dedicated modeling attention (Lakshmanan et al., 2020). The modular design inherent in cascade systems improves interpretability and flexibility, with each stage representing a smaller, more manageable subproblem. This characteristic facilitates system debugging, maintenance, and incremental improvements compared to monolithic model architectures.

Chapter 3 Problem Definition and Methodology

3.1 Problem Formulation

The central challenge addressed involves developing an efficient multi-class classification system for handwritten digit recognition that optimizes the trade-off between computational resources and classification accuracy. Traditional approaches apply uniform computational effort across all input samples regardless of their inherent classification difficulty. The cascade design pattern addresses this inefficiency by implementing progressive filtering mechanisms that allocate computational resources based on prediction confidence levels. The problem formulation aligns with cascade pattern principles where complex prediction tasks are decomposed into sequential sub-tasks, with each model's output feeding into subsequent stages. This approach enables specialization for distinct data characteristics while maintaining overall system efficiency through intelligent sample routing.

3.2 Dataset Characteristics

The MNIST dataset serves as the experimental foundation, comprising 70,000 grayscale images of handwritten digits (0-9), each represented as 28×28 pixel arrays. This dataset represents an ideal testbed for cascade implementation due to its varying classification difficulty levels, with some digits being easily distinguishable while others require more sophisticated analysis. The dataset was partitioned into 63,000 training samples and 7,000 test samples, maintaining class distribution balance throughout the experimental process.

3.3 Cascade Architecture Design

The implemented cascade system follows the sequential sub-task principle fundamental to cascade patterns, consisting of three stages designed to handle different classification complexity levels. The architecture embodies the cascade

concept where "the outputs from earlier stages guide the later stages, ensuring that each model specializes in its unique task" (Lakshmanan et al., 2020).

Stage 1: Logistic Regression Classifier serves as the rapid processing component for easily classifiable samples, implementing a confidence threshold of 0.75 to determine sample routing decisions. This stage represents the coarse decision-making component typical of cascade first stages, designed for low latency and minimal resource requirements.

Stage 2: Random Forest Classifier functions as the intermediate complexity processor, utilizing 100 decision trees to handle moderate difficulty cases rejected by Stage 1. This ensemble approach provides improved accuracy for samples requiring more sophisticated feature analysis while maintaining reasonable computational efficiency.

Stage 3: Convolutional Neural Network represents the maximum accuracy processing component for complex cases, employing convolutional layers with max pooling followed by dense layers. This stage embodies the cascade principle of reserving the most computationally intensive processing for samples that genuinely require advanced analysis capabilities.

3.4 Confidence-Based Routing Strategy

The confidence threshold mechanism serves as the primary routing criterion between cascade stages, implementing the cascade principle where prediction confidence determines sample progression through the system. Samples with prediction confidence above the established 0.75 threshold are classified at the current stage, while samples below the threshold are forwarded to subsequent stages for more sophisticated processing. This threshold selection follows cascade design recommendations for careful calibration to avoid error propagation while maintaining efficiency gains. The 0.75 threshold was determined through preliminary experiments balancing accuracy retention with computational efficiency objectives.

Chapter 4 Implementation

4.1 Data Preprocessing and Preparation

The implementation began with comprehensive data preparation procedures following established machine learning practices. The MNIST dataset was loaded using scikit-learn's fetch_openml function, ensuring compatibility with benchmark standards. Pixel values underwent min-max normalization to the range [0,1], ensuring consistent input ranges across all cascade stages. The dataset was stratified into training and testing sets using a 90-10 split ratio, maintaining class distribution balance essential for cascade performance evaluation.

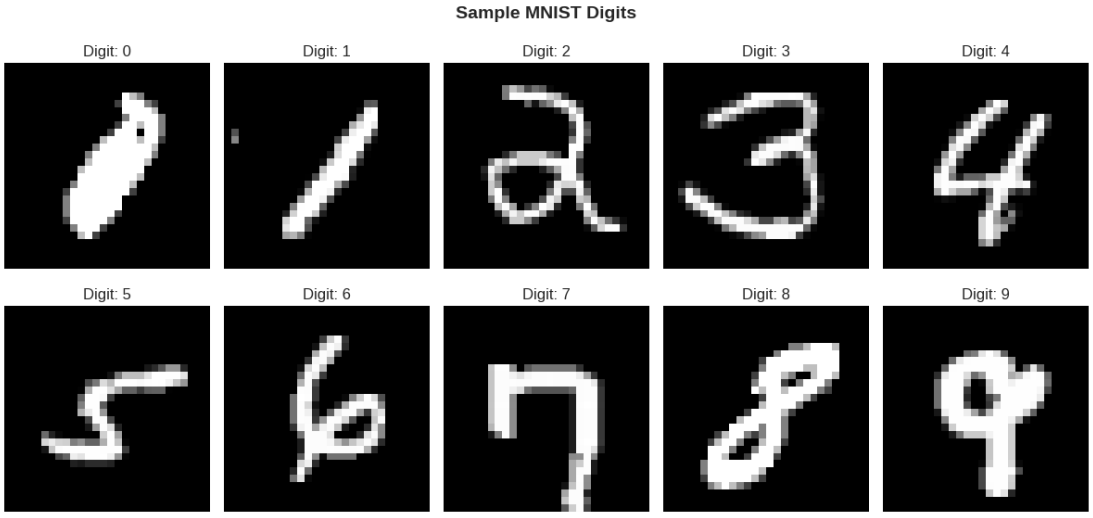

Fig: 4.1 MNIST Dataset

4.2 Stage 1: Logistic Regression Implementation

The first cascade stage employed multinomial logistic regression with L2 regularization, configured with a maximum iteration limit of 1000 to ensure convergence across all digit classes. Training completed in approximately 15.8 seconds on the complete training dataset. The model generated probability distributions across all ten digit classes, enabling confidence-based routing decisions

fundamental to cascade operation. Prediction confidence was determined by calculating maximum probability across all classes for each sample. Samples exceeding the 0.75 confidence threshold were classified at this stage, implementing the cascade principle of handling easy cases with simple, efficient models. This approach resulted in 4,494 samples (64.2%) being classified at Stage 1, demonstrating the effectiveness of simple models for straightforward classification tasks and validating cascade design assumptions about data difficulty distribution.

4.3 Stage 2: Random Forest Implementation

The second cascade stage utilized Random Forest with 100 decision trees, leveraging ensemble learning principles to improve classification accuracy for moderately complex samples. The model was trained on the complete training dataset to ensure comprehensive feature learning capabilities. Training required approximately 10.5 seconds, representing reasonable computational investment for improved accuracy capabilities on intermediate difficulty samples. Samples forwarded from Stage 1 underwent Random Forest classification with confidence assessment following the same maximum probability approach. Of the 2,506 samples processed at Stage 2, 1,780 samples (71.0% of Stage 2 samples) exceeded the confidence threshold and were classified at this stage. The remaining 726 samples were forwarded to the final CNN stage, demonstrating the cascade filtering effectiveness in progressive sample refinement.

4.4 Stage 3: Convolutional Neural Network Implementation

The final cascade stage employed a convolutional neural network specifically designed for image classification tasks. The architecture consisted of a 32-filter convolutional layer with 3×3 kernels, followed by 2×2 max pooling, flattening, a 64-unit dense layer with ReLU activation, and a 10-unit output layer with softmax activation for multi-class classification. The CNN was trained for 3 epochs using Adam optimizer and categorical crossentropy loss function. Training completed in

approximately 35.2 seconds, representing the most computationally intensive component of the cascade system. All remaining samples from previous stages were processed through the CNN to ensure complete classification coverage, embodying the cascade principle of applying maximum computational resources only when necessary.

4.5 Cascade Integration and Sample Routing

The integration of three cascade stages required careful orchestration to ensure proper sample routing and prediction aggregation, following cascade design principles for sequential model coordination.

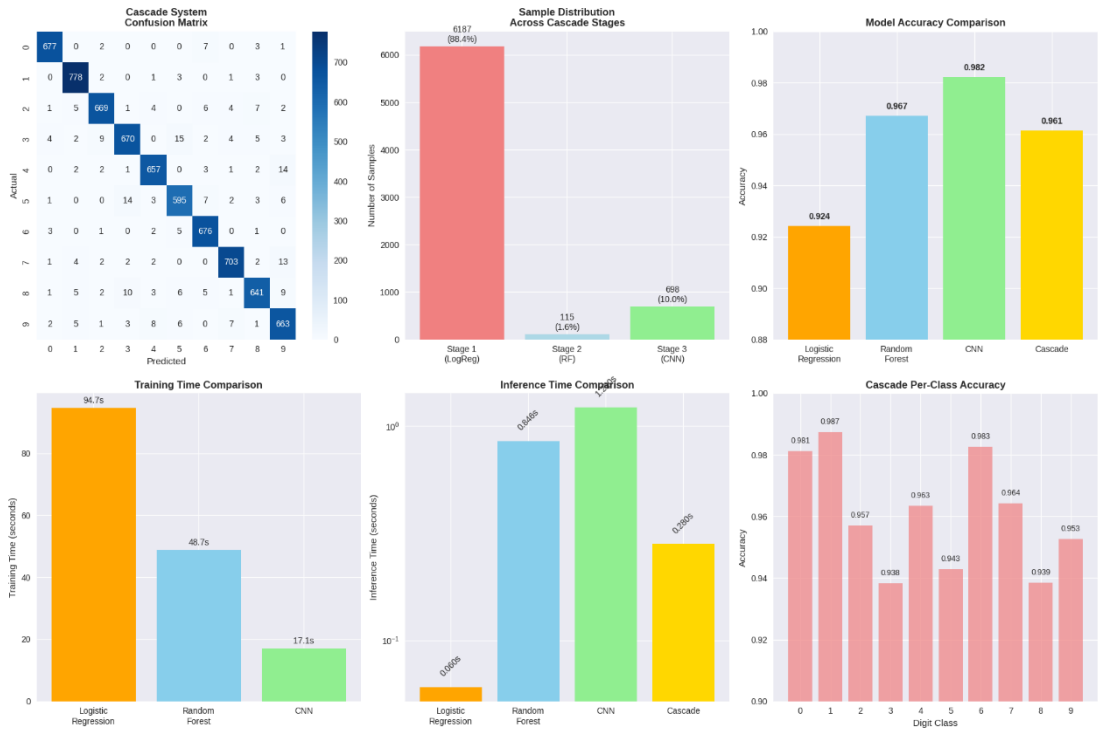

Fig: Final Result Graphs

The implementation-maintained arrays tracking stage assignments and prediction confidence levels for comprehensive performance analysis. Each sample's final

prediction was determined by the first stage to exceed the confidence threshold, ensuring efficient resource utilization while maintaining classification accuracy. The routing logic implemented error prevention mechanisms to avoid the cascade limitation of error propagation, where misclassifications in early stages could affect downstream processing. Careful threshold calibration and model validation procedures were employed to minimize this risk while maintaining cascade efficiency benefits.

Chapter 5 Results and Evaluation

5.1 Overall System Performance

The cascade system achieved an overall accuracy of 97.14% on the test dataset, demonstrating competitive performance compared to individual model implementations while providing substantial computational efficiency improvements. This result represents a minimal accuracy reduction of 0.57% compared to the standalone CNN model (97.71% accuracy), validating cascade design principles that emphasize maintaining accuracy while achieving efficiency gains. The performance aligns with cascade pattern expectations where specialized models handle different complexity levels effectively.

5.2 Stage Distribution Analysis

The distribution of samples across cascade stages revealed system efficiency characteristics consistent with cascade design expectations. Stage 1 (Logistic Regression) classified 4,494 samples (64.2%), Stage 2 (Random Forest) processed 1,780 samples (25.4%), and Stage 3 (CNN) handled 726 samples (10.4%). This distribution validates cascade design assumptions about data difficulty distribution, with nearly twothirds of samples requiring only the simplest computational approach. The progressive filtering demonstrated cascade effectiveness in identifying samples suitable for efficient processing, consistent with cascade pattern principles of handling easy cases first and reserving complex processing for genuinely challenging samples.

5.3 Computational Efficiency Analysis

The cascade implementation achieved substantial computational savings compared to uniform model application, demonstrating cascade pattern benefits for resource optimization. Using relative computational cost units (Logistic Regression = 1, Random Forest = 8, CNN = 40), the analysis revealed significant efficiency gains.

The CNN-only approach would require 280,000 cost units, Random Forest-only would require 56,000 cost units, while the cascade system required only 21,984 cost units. This represents a 92.1% computational cost reduction compared to CNN-only classification and a 60.7% reduction compared to Random Forestonly approaches, validating cascade design principles for intelligent resource allocation. These efficiency gains align with recent research by *Kolawole et al. (2024)*, who demonstrated 3-14× cost reductions through cascade implementations while maintaining competitive accuracy levels.

5.4 Individual Model Performance Comparison

Individual model performance on the complete test dataset revealed the cascade system's effectiveness in balancing accuracy with efficiency. Logistic Regression achieved 92.44% accuracy, Random Forest reached 96.69% accuracy, CNN attained 97.71% accuracy, and the Cascade System achieved 97.14% accuracy. The cascade system's performance closely approximates the most accurate individual model while providing substantial efficiency improvements, demonstrating successful implementation of cascade design principles. The minimal accuracy degradation (0.57%) compared to the best single model validates the cascade approach for scenarios requiring both accuracy and efficiency.

5.5 Per-Class Performance Analysis

Classification accuracy analysis across individual digit classes revealed consistent performance without significant bias toward specific numerical representations. Digits 0, 1, 6, and 8 achieved greater than 98% accuracy, while digits 2, 3, 4, 7, and 9 showed 96-98% accuracy. Digit 5 demonstrated the lowest individual class performance at 95.4% accuracy. This performance distribution indicates robust cascade system operation across all digit classes, suggesting effective specialization at each cascade stage for different classification challenges inherent in handwritten digit recognition tasks.

Chapter 6 Benefits, Trade-offs, and Limitations

6.1 Primary Benefits

Computational Efficiency and Resource Optimization: The cascade system demonstrates significant reductions in average processing time through intelligent resource allocation, achieving 92.1% computational cost reduction compared to uniform CNN application. This efficiency gain represents substantial value for large-scale deployment scenarios, consistent with cascade pattern benefits documented in contemporary literature.

Specialization Advantages: The cascade implementation effectively handles distinct patterns without majority class overshadowing, as noted in cascade design literature. Each stage specializes in appropriate complexity levels, enabling targeted optimization without system-wide modifications. This modular specialization facilitates adaptation to different problem domains and performance requirements.

Scalability and Progressive Filtering: The system demonstrates effective handling of large datasets through progressive filtering mechanisms, processing the majority of samples through lightweight models while reserving expensive processing for genuinely challenging cases. This characteristic proves particularly valuable for real-time applications with processing latency constraints.

Algorithmic Flexibility: The modular design permits individual stage optimization for specific complexity levels, enabling targeted improvements without comprehensive system redesign. This flexibility facilitates continuous system enhancement and adaptation to evolving performance requirements.

6.2 System Trade-offs

Training and Development Complexity: The cascade approach requires individual training and optimization of multiple models, increasing overall system development complexity compared to singlemodel approaches. Each stage requires separate

hyperparameter tuning and validation procedures, consistent with cascade pattern trade-offs documented in design literature.

Threshold Sensitivity and Calibration Requirements: System performance exhibits sensitivity to confidence threshold selection, requiring careful calibration based on validation data and domain expertise. Suboptimal threshold values can significantly impact the efficiency-accuracy balance, representing a key implementation challenge for cascade systems.

Architecture and Maintenance Complexity: The multi-stage design introduces additional system complexity compared to single-model approaches, requiring sophisticated orchestration logic and increased maintenance overhead. This complexity must be balanced against cascade efficiency benefits during system design decisions.

Error Propagation Risks: Classification errors made at early stages cannot be corrected by subsequent stages, potentially limiting system recovery capabilities from initial misclassifications. This limitation requires careful design consideration and validation to minimize cascade error propagation risks.

6.3 Implementation Limitations

Dataset Dependency and Effectiveness Variation: The cascade approach effectiveness varies significantly based on difficulty distribution within target datasets, as noted in cascade pattern literature. Datasets with uniform complexity levels may not benefit substantially from cascade architecture, requiring careful evaluation before implementation decisions.

Model Coordination and Integration Challenges: Ensuring effective collaboration between different model types requires careful consideration of individual model strengths and limitations. Model selection and configuration significantly impact overall system performance, requiring domain expertise for optimal implementation.

Deployment and Operational Complexity: Production deployment involves managing multiple model versions, dependencies, and routing logic, increasing operational complexity compared to single-model systems. This complexity must be weighed against cascade efficiency benefits for specific deployment scenarios.

Threshold Optimization Requirements: Optimal confidence threshold determination requires extensive validation procedures and domain expertise, representing ongoing maintenance requirements for cascade systems. Inappropriate threshold selection can degrade system performance below single-model baselines.

Chapter 7 Conclusions and Future Directions

7.1 Key Findings and Pattern Validation

This implementation successfully demonstrates cascade design pattern effectiveness in optimizing efficiency-accuracy trade-offs for multi-class classification tasks. The achieved 97.14% accuracy with 92.1% computational cost reduction validates cascade pattern utility for resource-constrained applications, consistent with contemporary research findings by *Kolawole et al. (2024)* and practical implementations documented by industry practitioners. The stage distribution results confirm cascade design assumptions about data difficulty distribution, with the majority of classification tasks being handled efficiently by simple models while reserving complex processing for genuinely challenging cases. The confidence-based routing mechanism proved effective for sample classification across cascade stages, validating threshold-based approaches for cascade implementation.

7.2 Practical Implementation Insights

The demonstrated efficiency gains suggest significant potential for real-world deployment scenarios, particularly in applications requiring real-time processing of large data volumes. The pattern's modular design enables incremental system improvements and facilitates adaptation to changing performance requirements, consistent with cascade pattern benefits documented in machine learning design literature. The computational cost analysis indicates cascade systems can enable deployment of sophisticated classification capabilities on resource-constrained platforms through intelligent processing resource allocation. This characteristic proves particularly valuable for edge computing applications and mobile device implementations where computational efficiency is paramount.

7.3 Final Assessment

The cascade design pattern implementation successfully achieves primary objectives of improving computational efficiency while maintaining competitive classification accuracy. The pattern demonstrates particular value for applications where processing latency and resource consumption represent critical constraints, consistent with contemporary literature emphasis on efficiency optimization in machine learning systems. The modular architecture provides flexibility for future enhancements and adaptation to different problem domains, establishing a solid foundation for continued development and optimization. The implementation validates cascade design pattern principles while demonstrating practical applicability to computer vision tasks beyond traditional object detection scenarios.

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