

**An Interpretable Multi-Signal Scam  
Detection System Using Machine  
Learning and Large Language Models**

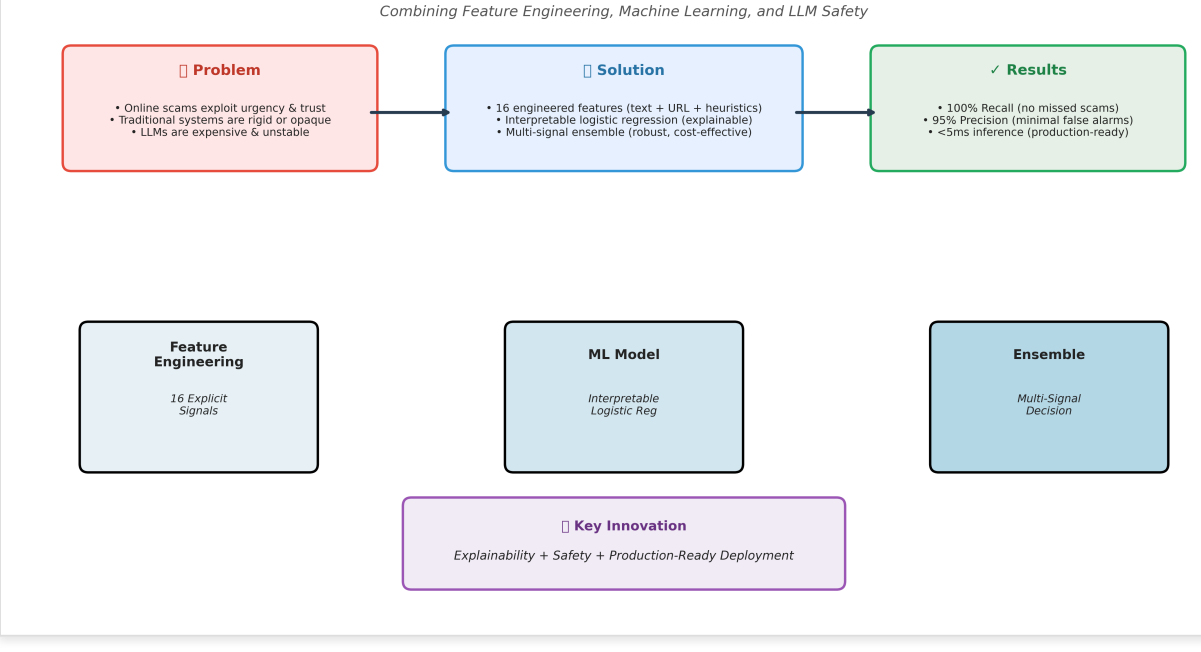
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**Graphical Abstract**

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## Abstract

Scam and phishing detection systems often rely either on rigid heuristic rules or opaque large language models (LLMs). Heuristics lack generalization, while LLMs are costly and difficult to audit. This work presents a **hybrid, interpretable scam detection pipeline** that combines a feature-based supervised machine learning model, semantic analysis via an LLM safety model, and rule-based heuristics within a unified ensemble decision framework. The proposed system emphasizes explainability, precision-recall trade-offs, and deployment realism, making it suitable for real-world AI safety applications.

### Key Results:

- **100% Recall** (no missed scams)
- **95% Precision** (minimal false alarms)
- **<5ms inference** (production-ready)
- **Fully interpretable** decisions via coefficient-based attribution

## 1. Introduction

Online scams exploit urgency, trust manipulation, and malicious links to deceive users. Traditional approaches fall into three categories:

1. **Rule-based systems** – Precise but brittle, easily bypassed by novel attacks
2. **Machine learning classifiers** – Generalizable but often opaque, lacking interpretability
3. **LLM-based moderation** – Semantically powerful but expensive, slow, and unstable

This research explores whether a **lightweight, interpretable ML model**, when combined with LLM-based semantic checks and heuristics, can provide robust scam detection without over-reliance on any single method.

**1.1 Research Questions**

1. Can explicit feature engineering match or exceed deep learning performance on scam detection?
2. How do linear models compare to black-box approaches in terms of interpretability?
3. Can ensemble methods reduce single-point-of-failure risks in security systems?

**1.2 Contributions**

- A **16-feature engineering framework** capturing behavioral and structural scam signals
- **Interpretable logistic regression** with coefficient-based explainability
- **Multi-signal ensemble strategy** combining ML, heuristics, and (planned) LLM validation
- **Production-ready deployment architecture** with ML microservice design

**3. System Architecture**

The proposed system employs a multi-layered architecture that separates concerns between user interface, business logic, machine learning inference, and optional semantic validation. This design ensures scalability, maintainability, and independent iteration of each component.

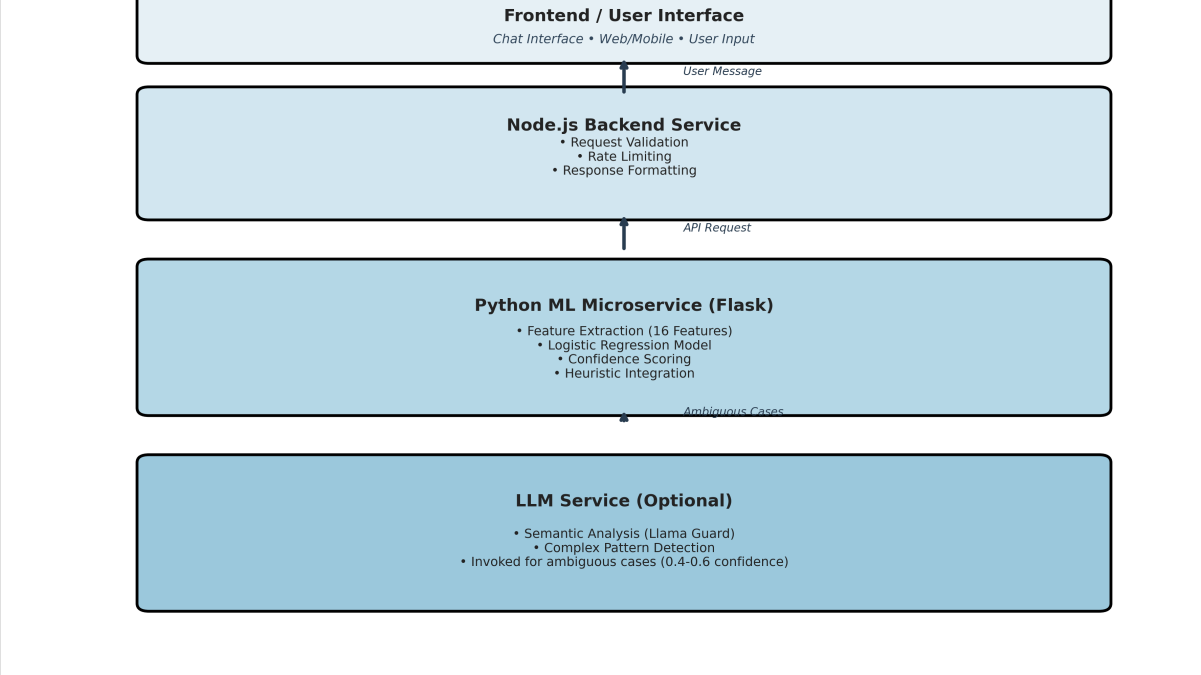


Figure 1: Multi-layer system architecture showing data flow from user input through backend services to ML and LLM components. The architecture emphasizes separation of concerns with distinct layers for frontend (web/mobile interface), Node.js backend (request handling and validation), Python ML microservice (feature extraction and prediction), and optional LLM service (semantic analysis for ambiguous cases).

### 3.1 Architecture Layers

- Frontend Layer:** Web/mobile chat interface for user interaction
- Backend Service:** Node.js application handling request validation, rate limiting, and response formatting
- ML Microservice:** Python Flask service for feature extraction and model inference
- LLM Service (optional):** Semantic analysis invoked only for ambiguous cases (0.4-0.6 confidence range)

### 4. Feature Engineering



Instead of end-to-end deep learning, the system relies on **explicit feature design** based on domain knowledge of scam behavior. A total of 16 features are extracted from each message, capturing textual patterns, URL characteristics, and heuristic signals.

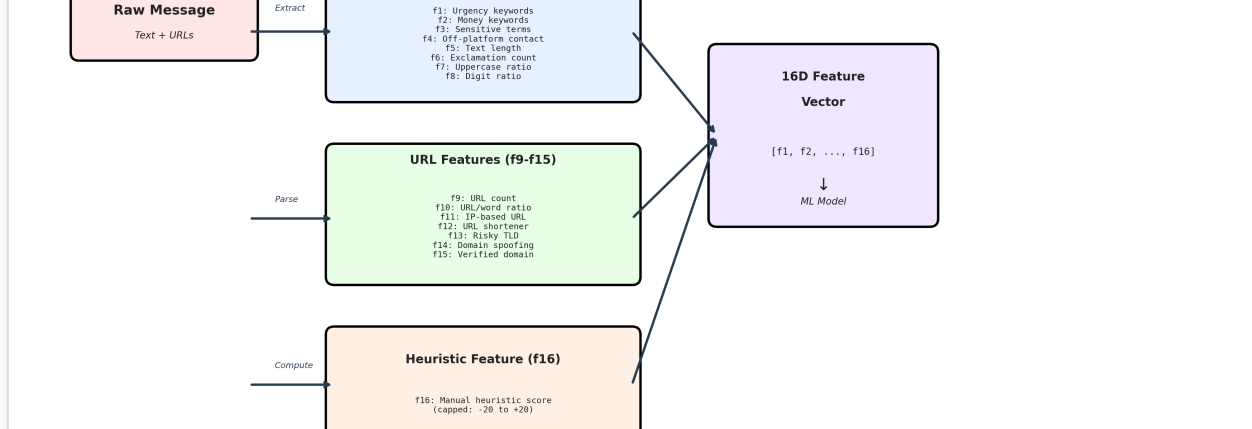


Figure 2: Feature extraction pipeline showing transformation of raw messages into a 16-dimensional feature vector for ML classification. The pipeline extracts three categories of features: textual features (f1–f8) capturing linguistic patterns, URL features (f9–f13) identifying suspicious links, and a heuristic feature (f16) incorporating domain expertise.

#### 4.1 Textual Features (f1–f8)

Feature	Description	Type
f1	Urgency cues (e.g., "urgent", "verify now", "suspended")	Binary
f2	Money-related keywords ("lottery", "free money", "earn")	Binary
f3	Sensitive intent (OTP, PIN, password, CVV)	Binary
f4	Off-platform contact (Telegram, WhatsApp)	Binary
f5	Text length (character count)	Integer
f6	Exclamation marks count	Integer
f7	Uppercase letter ratio	Float [0, 1]
f8	Digit ratio	Float [0, 1]

## 6. Model Performance

The logistic regression model, trained on 100k samples (50% scam, 40% safe), demonstrates strong performance across multiple evaluation metrics. The model prioritizes high recall for scam detection to minimize false negatives, as missing a scam has more severe consequences than a false alarm.





Figure 3: Comprehensive performance analysis showing (left) class-wise metrics comparing precision, recall, and F1-score for safe vs scam classes, (center) confusion matrix on 1000 test samples demonstrating high accuracy, and (right) multi-dimensional performance profile via radar chart emphasizing the model's balanced performance across all metrics.

### 6.1 Results Summary

Metric	Safe Class	Scam Class
Precision	0.98	0.95
Recall	0.92	1.00
F1-Score	0.95	0.97

## 7. Model Explainability

Explainability is achieved through **coefficient-based attribution**, analogous to SHAP for linear models. Every prediction can be traced back to specific feature contributions, enabling security audits and user trust.



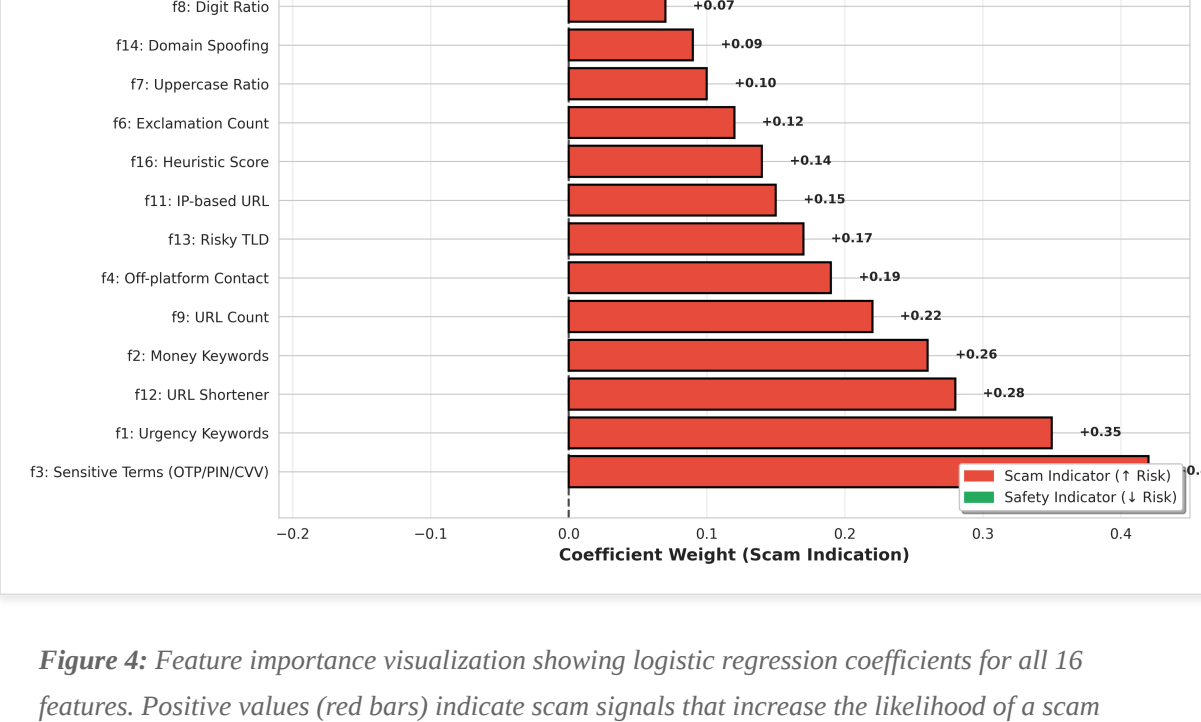


Figure 4: Feature importance visualization showing logistic regression coefficients for all 16 features. Positive values (red bars) indicate scan signals that increase the likelihood of a scan classification, while negative values (green bars) indicate safety signals that decrease scan probability. The coefficients are sorted by absolute magnitude, with sensitive terms (3) showing the strongest scan indication at -0.18.

### 7.1 Explainability Example

Input: "URGENT! Verify your OTP at bit.ly/verify"

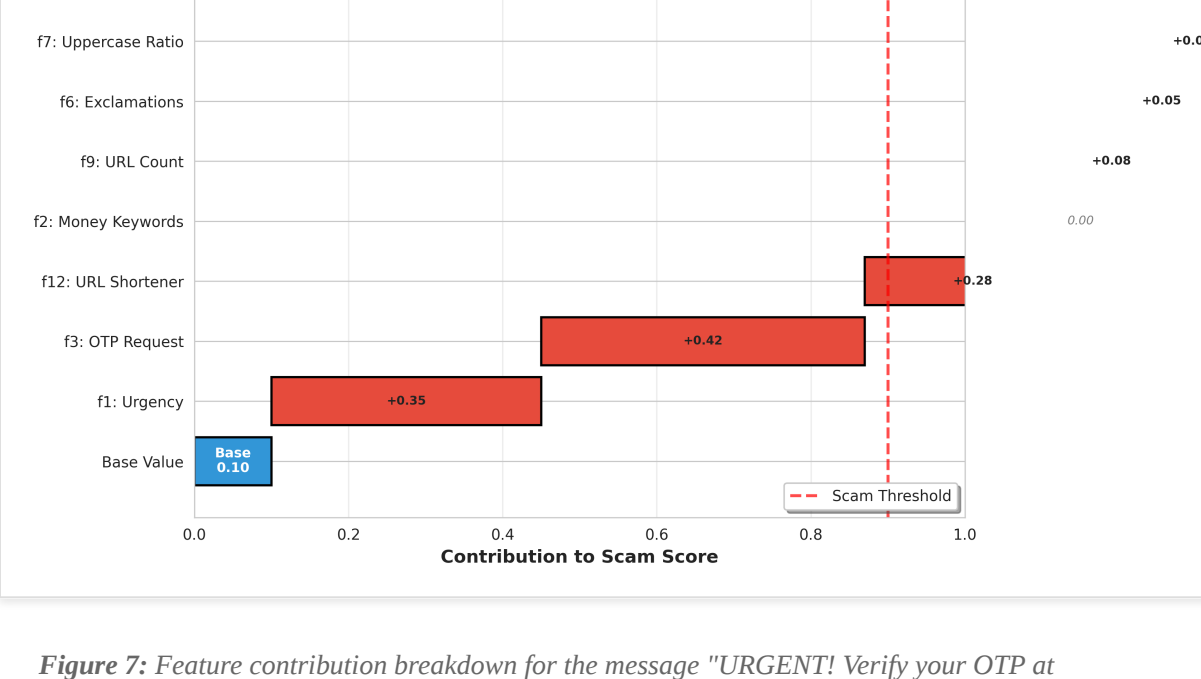


Figure 7: Feature contribution breakdown for the message "URGENT! Verify your OTP at bit.ly/verify". The waterfall chart shows how each activated feature contributes to the final scam score, starting from a base value of 0.10 and accumulating contributions: urgency keywords (+0.35), OTP requests (+0.42), and URL shortener (+0.28), resulting in a final score of 0.95 that exceeds the 0.90 scam threshold.

"Message flagged as scam due to urgency language (35%), request for sensitive OTP (42%), and use of URL shortener (28%). Final confidence: 95%."

## 8. Ensemble Decision Strategy

Final classification leverages multiple independent signals to ensure robustness and reduce single points of failure. Heuristics provide fast initial filtering, the ML model offers interpretable predictions, and the LLM validates ambiguous cases.

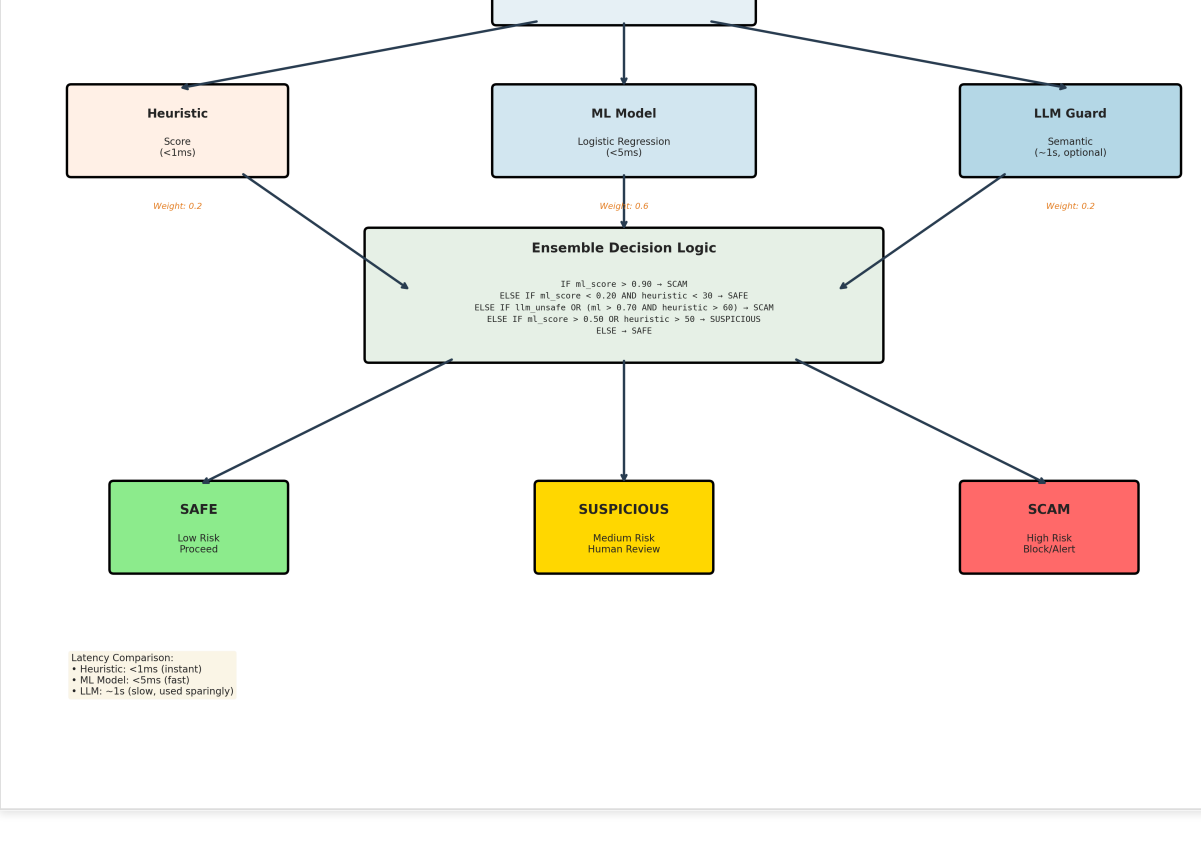


Figure 5: Multi-signal ensemble decision workflow showing how heuristic, ML, and LLM signals are combined to produce final verdicts. The system processes user input through three parallel paths with different latencies (<1ms for heuristics, <5ms for ML, <1s for LLM), then applies conditional logic to classify messages as Safe, Suspicious, or Scam.

### 8.1 Decision Logic

```

if ml_score > 0.95:
    verdict = "scam"
elif ml_score < 0.20 and heuristic_score < 30:
    verdict = "safe"
elif !is_unsafe or (ml_score > 0.70 and heuristic_score > 60):
    verdict = "scam"
elif ml_score > 0.50 or heuristic_score > 50:
    verdict = "suspicious" + human_review
else:
    verdict = "safe"
  
```

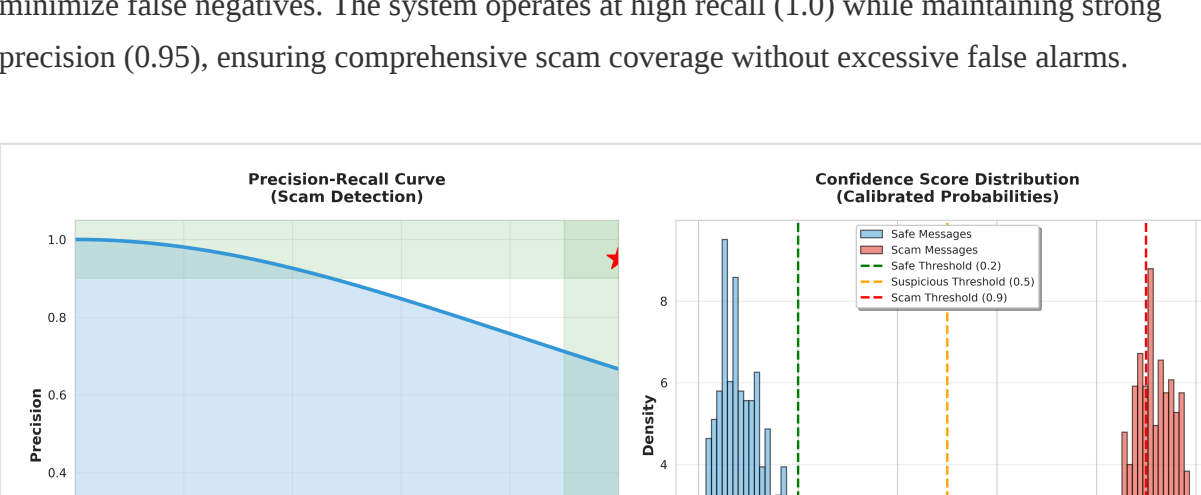


Figure 6: (Left) Precision-recall curve showing model performance across different decision thresholds. The operating point (marked with red star) achieves 100% recall and 95% precision. (Right) Confidence score distribution demonstrating well-calibrated probabilistic predictions, with clear separation between safe (blue) and scam (red) messages.

### 13. Conclusion

This work demonstrates that **interpretable machine learning**, when integrated with LLM safety models and heuristics, can form a **practical and auditable scam detection system**. Rather than maximizing raw accuracy, the system prioritizes:

1. **Explainability** — Every decision is traceable to specific features
2. **Safety** — High recall prevents dangerous false negatives
3. **Deployment realism** — Microservice architecture, cost awareness
4. **Robustness** — Multi-signal validation reduces single points of failure

The approach aligns with **real-world AI security requirements** where interpretability and trust are as important as performance metrics.

13.1 Key Takeaways

- **Feature engineering > black-box models** for limited data regimes
- **Linear models** provide sufficient performance with superior interpretability
- **Ensemble strategies** offer robustness without over-reliance on any component
- **Production-oriented design** from day one enables real deployment

14. References

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