

AutoJudge

Problem Difficulty Prediction System

Project Report - January 8, 2026

1. Executive Summary

AutoJudge is a machine learning-based system designed to automatically predict the difficulty level of competitive programming problems. The system analyzes problem descriptions, input/output specifications, and other textual features to classify problems into difficulty categories (Easy, Medium, Hard) and predict difficulty scores.

2. Dataset Overview

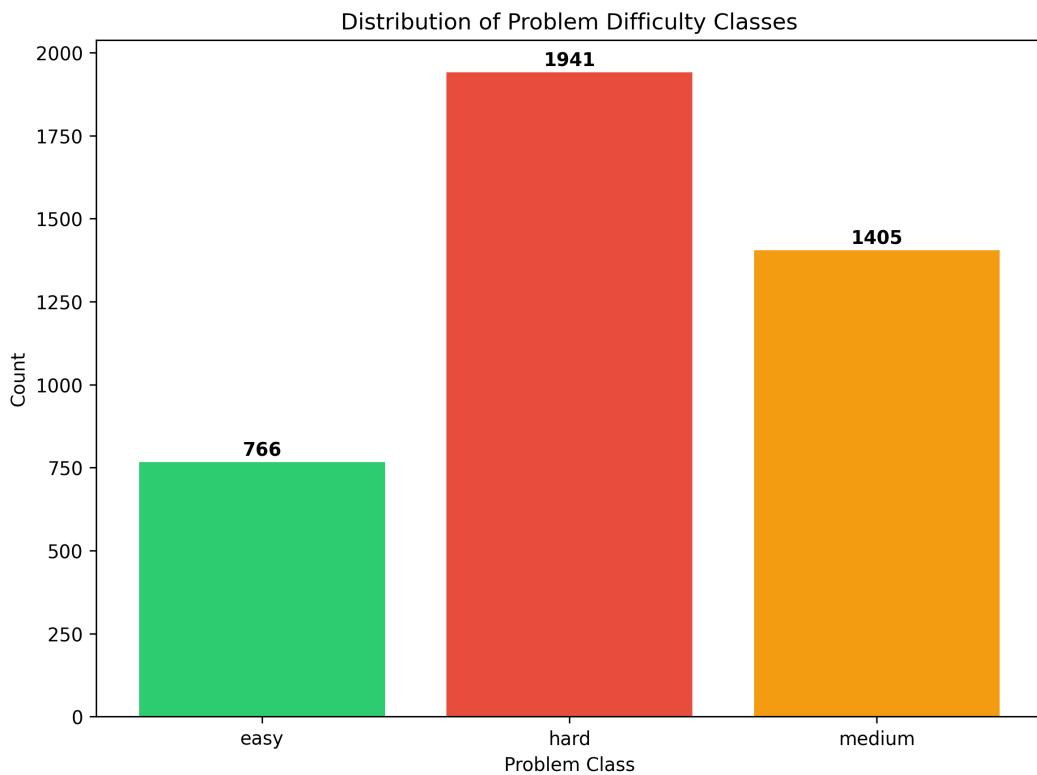
2.1 Dataset Statistics

| Metric | Value |
|----------------|-------------|
| Total Samples | 4,112 |
| Training Set | 3,289 (80%) |
| Test Set | 823 (20%) |
| Total Features | 1,094 |

2.2 Class Distribution

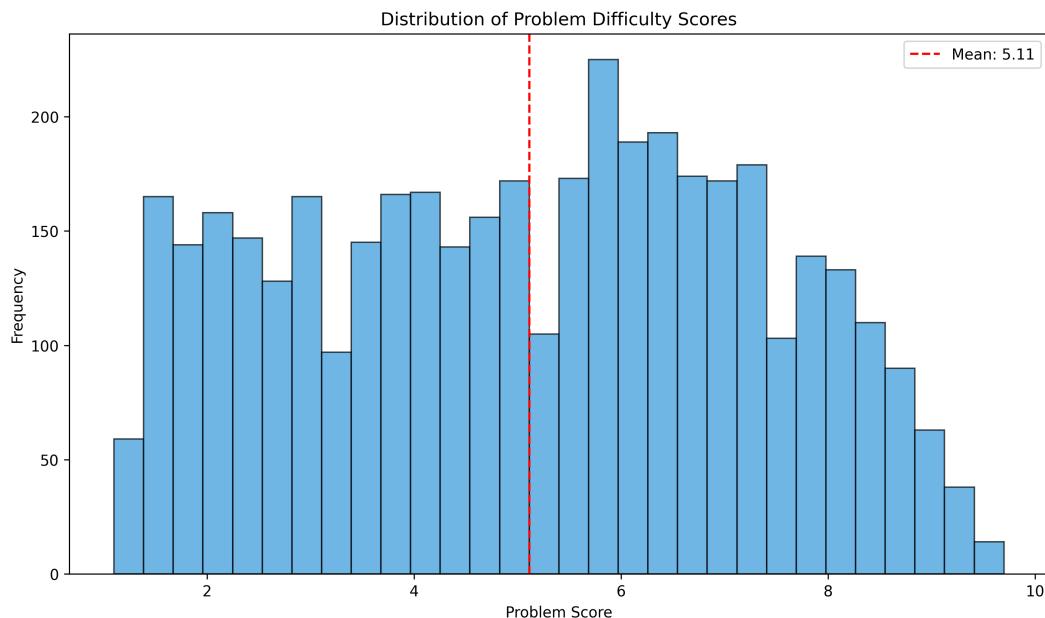
| Difficulty Class | Count | Percentage |
|------------------|-------|------------|
| Easy | 766 | 18.6% |
| Medium | 1,405 | 34.2% |
| Hard | 1,941 | 47.2% |

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2.3 Score Distribution

The problem difficulty scores range from 1.10 to 9.70 on a 10-point scale.



3. Feature Engineering

3.1 Text Preprocessing

- Combined multiple text fields: title, description, input/output specifications
- Applied text cleaning and normalization
- Removed stop words and special characters

3.2 Feature Categories

Basic Statistical Features

Text length, word count, average word length, mathematical symbol count, digit patterns, power notation detection

Algorithm Keyword Features

Detection of 50+ algorithm-related keywords including: Graph algorithms (DFS, BFS, Dijkstra), Dynamic Programming, Data structures (Tree, Heap, Stack), Advanced concepts (Segment Tree, Trie, FFT)

TF-IDF Features

N-gram range: (1, 3), Maximum features: 1,000, Sublinear TF scaling applied

4. Model Architecture

4.1 Classification Model

Model Type: Random Forest Classifier

| Parameter | Value |
|----------------------|-------|
| Number of Estimators | 200 |
| Maximum Depth | 20 |
| Min Samples Split | 5 |
| Min Samples Leaf | 2 |

4.2 Regression Model

Model Type: Gradient Boosting Regressor (Best performing)

| Parameter | Value |
|----------------------|-------|
| Number of Estimators | 300 |
| Learning Rate | 0.05 |
| Maximum Depth | 6 |
| Subsample Ratio | 0.8 |

5. Classification Results

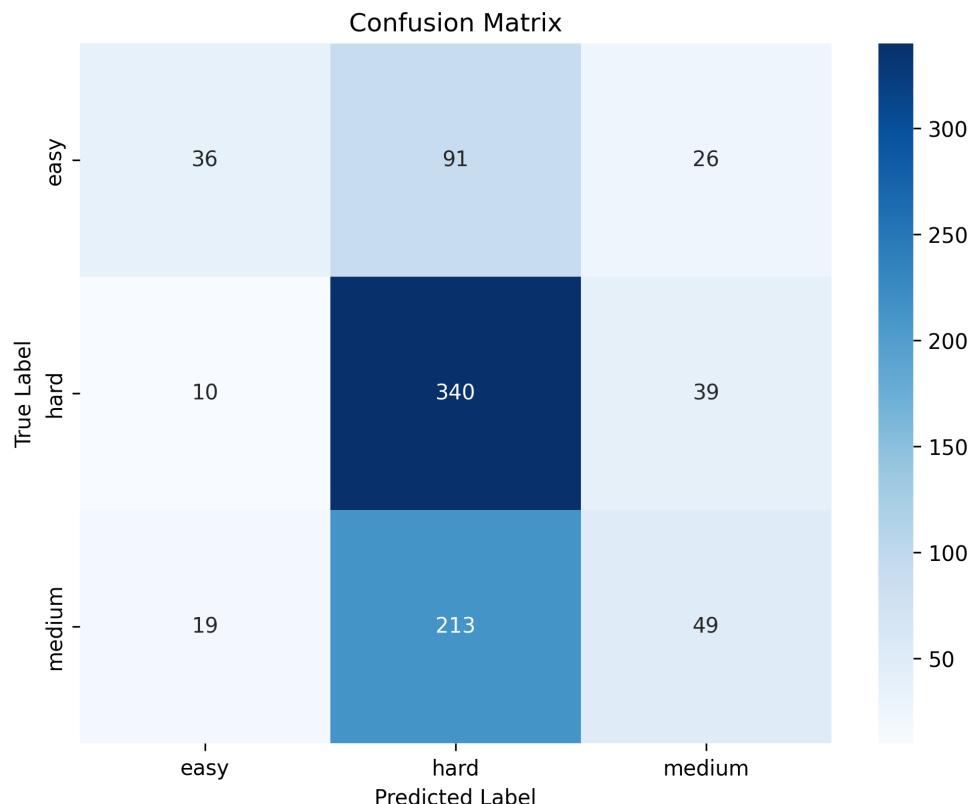
5.1 Overall Performance

| Metric | Value |
|-----------------------|--------|
| Accuracy | 51.64% |
| Macro Avg F1-Score | 0.41 |
| Weighted Avg F1-Score | 0.46 |

5.2 Per-Class Performance

| Class | Precision | Recall | F1-Score |
|--------|-----------|--------|----------|
| Easy | 0.55 | 0.24 | 0.33 |
| Medium | 0.43 | 0.17 | 0.25 |
| Hard | 0.53 | 0.87 | 0.66 |

5.3 Confusion Matrix



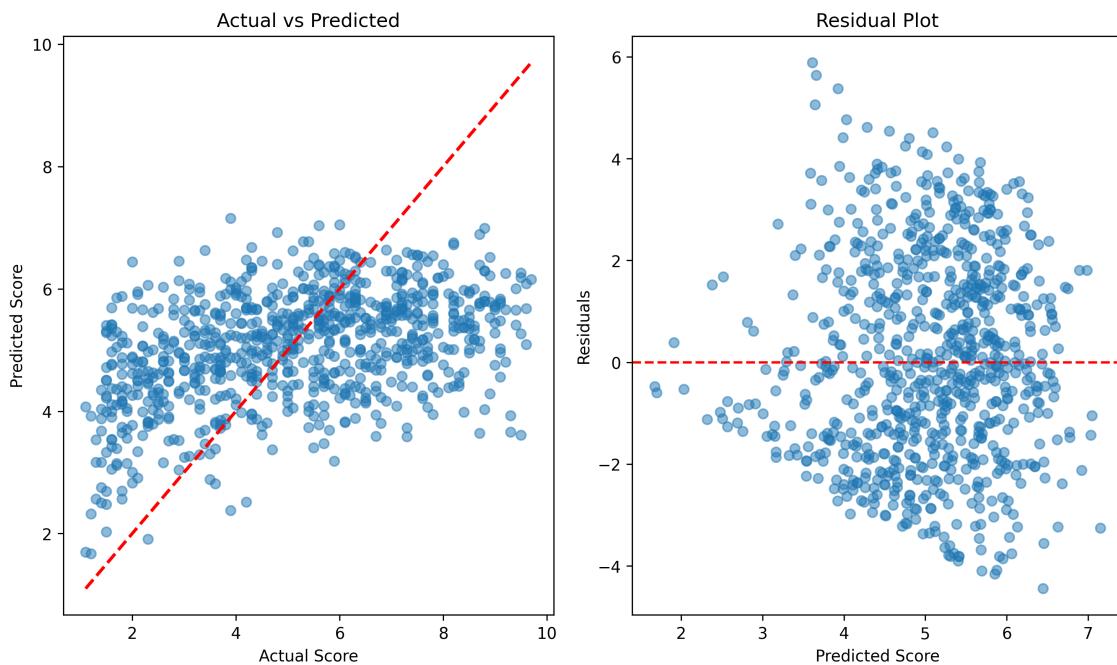
Analysis: The model shows strong performance in identifying "Hard" problems (87% recall). "Easy" and "Medium" classes show lower recall due to class imbalance.

6. Regression Results

6.1 Error Metrics

| Metric | Value |
|--------------------------------|-------|
| Mean Absolute Error (MAE) | 1.66 |
| Root Mean Squared Error (RMSE) | 2.00 |

6.2 Prediction Analysis



On average, predictions are within +/- 1.66 points of actual scores on a 10-point scale.

7. Models Compared

| Model | RMSE | Performance |
|-------------------|------|-------------|
| Gradient Boosting | 1.99 | Best |
| XGBoost | 2.01 | Good |
| Extra Trees | 2.02 | Moderate |
| Random Forest | 2.04 | Baseline |

8. Files and Artifacts

8.1 Trained Models

| File | Description |
|-----------------------|-------------------------------|
| classifier.pkl | Trained classification model |
| classifier_scaler.pkl | Feature scaler for classifier |
| regressor.pkl | Trained regression model |
| regressor_scaler.pkl | Feature scaler for regressor |
| feature_extractor.pkl | Fitted feature extractor |

9. Future Improvements

1. Data Augmentation: Collect more samples for underrepresented classes
2. Advanced NLP: Incorporate transformer-based embeddings (BERT, RoBERTa)
3. Ensemble Methods: Combine multiple models for better predictions
4. Feature Selection: Apply feature importance analysis
5. Active Learning: Continuously improve with user feedback

10. Conclusion

AutoJudge successfully demonstrates the feasibility of automated problem difficulty assessment using machine learning. The system achieves:

- **51.64% classification accuracy across three difficulty levels**
- **MAE of 1.66 for score prediction on a 10-point scale**
- **Strong identification of hard problems (87% recall)**

The model provides a solid foundation for assisting competitive programming platforms in automatically categorizing problem difficulty, with clear paths for future enhancement.

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