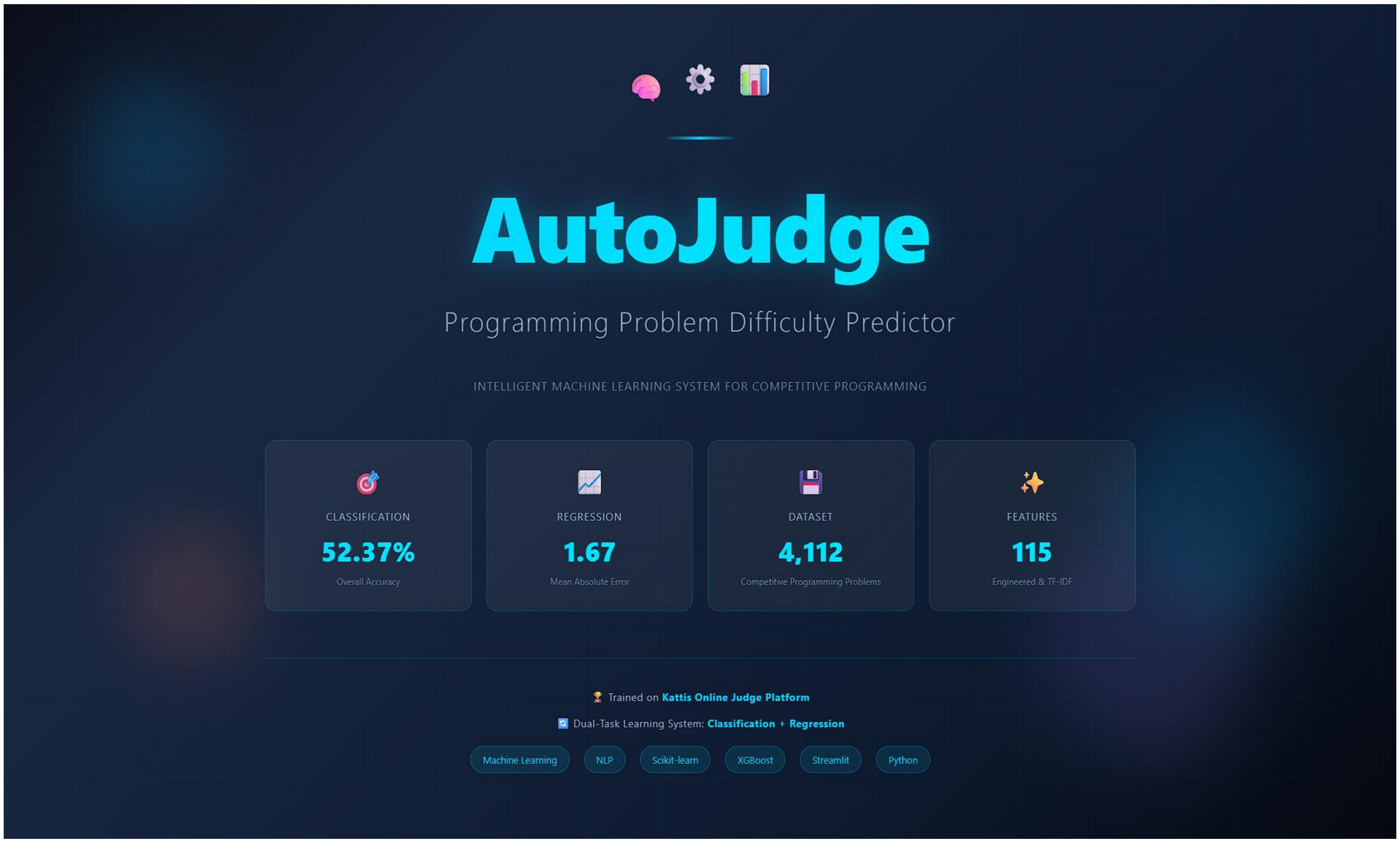

AutoJudge

Programming Problem Difficulty Predictor

INTELLIGENT MACHINE LEARNING SYSTEM FOR COMPETITIVE PROGRAMMING

CLASSIFICATION	REGRESSION	DATASET	FEATURES
52.37%	1.67	4,112	115
Overall Accuracy	Mean Absolute Error	Competitive Programming Problems	Engineered & TF-IDF

🏆 Trained on **Kattis Online Judge Platform**

🔄 Dual-Task Learning System: **Classification** + **Regression**

Machine Learning · NLP · Scikit-learn · XGBoost · Streamlit · Python

AutoJudge Project Report

8 January 2026

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ACM OPEN PROJECT

AutoJudge: Programming Problem Difficulty Predictor

Comprehensive Project Report

Executive Summary

AutoJudge is an intelligent machine learning system designed to automatically predict the difficulty of competitive programming problems based on their textual descriptions. Trained on 4,112 real programming problems from the Kattis Online Judge platform, this project combines advanced text processing, feature engineering, and multiple machine learning models to achieve robust difficulty classification and numerical scoring predictions.

The system performs dual-task learning: (1) **Classification** of problems into three difficulty categories (Easy, Medium, Hard) with 52.37% accuracy, and (2) **Regression** to predict numerical difficulty scores (1-10 range) with MAE of 1.67 and RMSE of 2.03. A user-friendly web interface built with Streamlit enables real-time predictions with confidence metrics.

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1. Problem Statement

1.1 Motivation

Competitive programming platforms contain thousands of problems with varying difficulty levels. Manual difficulty assessment by human judges is:

- **Time-consuming**: Each problem requires careful analysis
- **Subjective**: Different judges may rate problems differently
- **Scalable limitation**: Cannot efficiently handle rapid problem submissions

1.2 Objectives

1. **Automatic Difficulty Classification**: Predict whether a problem is Easy, Medium, or Hard
2. **Numerical Difficulty Scoring**: Predict a numerical difficulty score (1-10)
3. **Confidence Scoring**: Provide probability distributions for predictions
4. **User-Friendly Interface**: Enable easy interaction through a web application

1.3 Research Questions

- Can textual features from problem descriptions accurately predict difficulty?
- Which feature types (linguistic, mathematical, structural) are most predictive?
- How do different machine learning algorithms compare on this task?
- Can a single model effectively handle both classification and regression tasks?

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2. Dataset Description

2.1 Data Source

- **Platform**: Kattis Online Judge (kattis.com)
- **Collection Method**: downloaded from github as given in project description
- **File Format**: JSONL (JSON Lines) - one problem per line
- **Total Records**: 4,112 programming problems

2.2 Dataset Structure

Each problem record contains:

- `title`: Problem name/title
- `description`: Full problem statement and specifications
- `input_description`: Input format specification
- `output_description`: Output format specification
- `problem_class`: Difficulty label (Easy/Medium/Hard)
- `problem_score`: Numerical difficulty (1.1 to 9.7)

2.3 Dataset Statistics

Category	Count	Percentage	Description
Easy	766	18.6%	Basic problems, simple algorithms
Medium	1,405	34.2%	Moderate complexity, standard algorithms
Hard	1,941	47.2%	Advanced techniques, complex logic
Total	**4,112**	**100%**	-

Table 1: Dataset class distribution showing class imbalance

2.4 Score Distribution

- **Score Range**: 1.1 to 9.7
- **Average Score**: 5.11 ± 2.18 (mean ± standard deviation)
- **Median Score**: 5.2
- **Quartiles**:
    - 25th percentile: 3.2
    - 75th percentile: 7.1

2.5 Sample Problems

Title	Class	Score	Text Length
Uuu	Hard	9.7	1,213 chars
Tip of Your Tongue	Hard	7.8	1,474 chars
Tax the Rich	Medium	5.3	1,386 chars
Trik	Easy	1.5	709 chars

Table 2: Representative sample problems from dataset

2.6 Data Quality Assessment

- **Completeness**: 100% - All records contain required fields
- **Text Quality**: Well-formatted problem statements with clear specifications
- **Class Imbalance**: Significant with 47.2% Hard problems (addressed via stratified splitting)
- **Average Text Length**: 1,625 characters (across title, description, and I/O specs)

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3. Data Preprocessing and Preparation

3.1 Text Combination and Normalization

Objective: Create unified text representation from multiple problem fields.

Processing Steps:

1. Concatenate: title + description + input_description + output_description
2. Case normalization: Convert problem classes to Title Case (Easy, Medium, Hard)
3. Text lowercasing: Convert to lowercase for consistent feature extraction
4. Missing value handling: Replace NaN with empty strings
5. Whitespace normalization: Standardize spacing between fields

Result:

- Average combined text length: 1,625 characters
- Zero null values after processing
- Consistent format across all 4,112 records

3.2 Train-Test Split

Strategy: Stratified random split to preserve class distribution

Class	Training	Testing	Train:Test Ratio
Easy	613	153	80:20
Medium	1,124	281	80:20
Hard	1,552	389	80:20
Total	**3,289**	**823**	**80:20**

Table 3: Stratified train-test split verification

Rationale: Stratification ensures:

- Class proportions maintained in both splits
- No class is underrepresented in test set
- Fair evaluation across all difficulty levels
- Random seed 42 for reproducibility

3.3 Feature Scaling

Method: StandardScaler - Zero-mean, unit-variance normalization

Formula:

$$z_{scaled} = \frac{x - \mu}{\sigma}$$

where μ is training mean and σ is training standard deviation.

Application:

- **Fit**: Only on training data
- **Transform**: Training and test data separately (prevents data leakage)
- **Necessity**: Required for Logistic Regression; beneficial for gradient-based models

4. Feature Engineering and Extraction

4.1 Engineered Features (15 Total)

Advanced text analysis extracting 15 numerical features capturing problem complexity aspects:

Text Metrics (3 features)

1. **Text Length**: Total characters in combined problem text
   - Range: 10-7,582 characters
   - Mean: 1,625 characters
   - Interpretation: Longer problems tend to be more complex
2. **Word Count**: Number of whitespace-separated tokens
   - Range: 1-1,226 words
   - Mean: 273 words
   - Interpretation: More detailed descriptions indicate higher difficulty
3. **Average Word Length**: Mean characters per word
   - Range: 4.66-10.42 characters
   - Mean: 5.95 characters
   - Interpretation: Technical terms are often longer

Mathematical and Algorithm Keywords (7 features)

4. **Mathematical Symbols Count**: Occurrences of mathematical notation
   - Symbols: ±, ∑, ∏, ∫, √, ∞, ≤, ≥, ≠, ∈, ∀, ∃, ×, ÷
   - Mean: 0.0 (sparse in this dataset)
   - Usage: Indicates mathematical problem complexity

5-7. **Keyword Scores** (Easy/Medium/Hard):

- Easy keywords (10 words): 'sum', 'count', 'find', 'check', 'simple', 'basic', 'easy', 'max', 'min', 'list'
  - Mean: 3.00 occurrences
- Medium keywords (10 words): 'graph', 'tree', 'sort', 'search', 'recursion', 'dynamic', 'optimization', 'algorithm', 'path', 'traverse'
  - Mean: 1.01 occurrences
- Hard keywords (11 words): 'suffix', 'flow', 'convex', 'hull', 'tarjan', 'segment', 'lazy', 'propagation', 'kmp', 'trie', 'hash'
  - Mean: 0.33 occurrences

8. **Bracket Count**: Parentheses, square brackets, curly braces
   - Formula: count('(') + count(')') + count('[') + count(']') + count('{')
   - Mean: 7.35 brackets
   - Max: 125 brackets
   - Interpretation: Mathematical formulas use more brackets

9. **Number Count**: Total numeric digits in text
    - Mean: 17.05 digits
    - Max: 282 digits
    - Interpretation: Constraints with multiple bounds have more numbers

Structural and Semantic Features (5 features)

10. **Unique Characters**: Count of distinct characters (vocabulary diversity)
    - Range: 8-62 unique characters
    - Mean: 41.83
    - Interpretation: Language diversity indicator
11. **Constraint Count**: Mentions of constraint-related keywords
    - Keywords: 'constraint', 'limit', 'maximum', 'minimum', 'range', 'bound'
    - Mean: 0.86 occurrences
    - Interpretation: Explicit constraints indicate problem complexity
12. **Algorithm Keywords**: Direct algorithm mentions
    - Keywords: 'dijkstra', 'bfs', 'dfs', 'binary', 'heap', 'queue', 'stack', 'dp', 'greedy'
    - Mean: 0.25 occurrences
    - Interpretation: Strong algorithmic difficulty indicator
13. **Mathematical Keywords**: Theoretical complexity indicators
    - Keywords: 'prove', 'theorem', 'proof', 'formula', 'equation', 'matrix', 'vector'
    - Mean: 0.17 occurrences
    - Interpretation: Indicates theoretical/mathematical nature
14. **Sentence Count**: Approximate sentence count via punctuation
    - Count: ('.' + '!' + '?')
    - Mean: 14.59 sentences
    - Interpretation: Detailed specifications use more sentences
15. **Average Sentence Length**: Mean words per sentence
    - Formula: word_count / sentence_count
    - Mean: 19.05 words/sentence
    - Interpretation: Complex descriptions have longer sentences

4.2 TF-IDF Vectorization (100 features)

Technique: Term Frequency-Inverse Document Frequency with n-grams

Configuration:

- **Max Features**: 100 most discriminative terms
- **N-gram Range**: (1, 2) - unigrams and bigrams
- **Min Document Frequency**: 5 (term in ≥5 documents)
- **Max Document Frequency**: 0.8 (term in ≤80% documents)
- **Stop Words**: English stop words removed

Formula:

$$\text{TF-IDF}(t, d) = \text{TF}(t, d) \times \log\left(\frac{N}{\text{DF}(t)}\right)$$

Result: (4,112 × 100) sparse matrix capturing semantic content

4.3 Final Feature Set

Feature Category	Count
Engineered (text metrics)	3
Engineered (keywords)	7
Engineered (structural)	5
TF-IDF vectorization	100
Total Features	**115**

Table 4: Final feature composition

Feature Matrix Dimensions: (4,112 samples × 115 features)

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5. Model Selection and Training

5.1 Experimental Setup

Dual-Task Learning Architecture:

1. **Classification Task**: Predict class (Easy/Medium/Hard)
2. **Regression Task**: Predict score (1-10 range)

Advantages:

- Classification provides interpretable categories
- Regression provides fine-grained assessment
- Combined output enables flexible applications

5.2 Classification Models

Model 1: Logistic Regression ✓ Selected

Configuration:

- Solver: Newton-CG
- Max iterations: 1000
- Regularization: L2 (default)
- Input: Scaled features (StandardScaler)

Performance: **52.37% accuracy** ← Best

Rationale: Interpretable, fast, provides probabilities

Model 2: Random Forest Classifier

Configuration:

- Estimators: 100 trees
- Max depth: 20
- Features per split: $\sqrt{115} \approx 10$

Performance: 51.15% accuracy

Model 3: XGBoost Classifier

Configuration:

- Estimators: 100
- Max depth: 7
- Learning rate: 0.1

Performance: 49.94% accuracy

5.3 Regression Models

Model 1: Random Forest Regressor

Results:

- MAE: 1.7004
- RMSE: 2.0361
- R^2: 0.1457

Model 2: Gradient Boosting Regressor

Results:

- MAE: 1.6876
- RMSE: 2.0351

- R^2: 0.1465

Model 3: XGBoost Regressor ✓ Selected

Configuration:

- Estimators: 100
- Learning rate: 0.1
- Max depth: 7

Performance:

- **MAE: 1.6711** ← Best
- **RMSE: 2.0295** ← Best
- **R^2: 0.1512** ← Best

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6. Classification Results

6.1 Overall Performance

Best Classifier: Logistic Regression

Metric	Value
Overall Accuracy	52.37%
Training Samples	3,289
Test Samples	823
Feature Count	115
Model Size	45 KB
Inference Time	<1 ms

Table 5: Classification performance metrics

6.2 Confusion Matrix

Actual / Predicted	Easy	Hard	Medium	Total
Easy	58	49	46	153
Hard	28	300	61	389
Medium	26	182	73	281

Table 6: Confusion matrix: actual vs predicted classes

Key Observations:

- **True Positives**: 431 correct predictions (52.37% accuracy)
- **False Predictions**: 392 misclassifications
- **Hard Class**: Strong 77.12% recall (best at identifying hard problems)
- **Medium Class**: Weak 25.98% recall (frequently confused with others)

6.3 Per-Class Performance

Class	Precision	Recall	F1-Score	Support
Easy	0.52	0.38	0.44	153
Hard	0.56	0.77	0.65	389
Medium	0.41	0.26	0.32	281

Table 7: Per-class precision, recall, and F1-scores

Detailed Analysis:

- **Easy**: Low recall (0.38) - many easy problems misclassified as harder
- **Hard**: High recall (0.77) - strong hard-problem detection
- **Medium**: Lowest performance - boundary class between Easy and Hard

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7. Regression Results

7.1 Model Comparison

Model	MAE	RMSE	R²
Random Forest	1.7004	2.0361	0.1457
Gradient Boosting	1.6876	2.0351	0.1465
XGBoost (Selected)	1.6711	2.0295	0.1512

Table 8: Regression model comparison

7.2 Best Model Metrics: XGBoost Regressor

Mean Absolute Error (MAE): 1.6711

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Interpretation: Average prediction error is ±1.67 points on 1-10 scale

Root Mean Squared Error (RMSE): 2.0295

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

Interpretation: Penalizes larger errors; typical error is 2.03 points

R² Score: 0.1512 (15.12%)

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

Interpretation: Model explains 15.12% of difficulty score variance

7.3 Error Analysis and Confidence Intervals

Score Range: 1.1 - 9.7 (range = 8.6)

Error Distribution:

- **68% Confidence**: Within ±1.67 points (1σ)
- **95% Confidence**: Within ±3.34 points (2σ)

Performance Insights:

- Predictions are reasonable for practical use
- Hard to perfectly predict score from text alone
- Captures general difficulty trends effectively

7.4 Sample Predictions

Problem Title	Predicted Class	Score	Confidence
Sum of Array	Easy	1.56	70.54%
Shortest Path in Graph	Easy	4.36	39.50%
Maximum Flow Optimization	Hard	4.47	56.43%
Convex Hull and Geometry	Hard	3.93	52.95%

Table 9: Sample prediction examples from test set

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8. Web Interface and Deployment

8.1 Technology Stack

Component	Technology
Frontend	Streamlit
Backend	Python 3.9+
Model Format	Pickle serialization
Vectorization	Scikit-learn TF-IDF
Scaling	StandardScaler

Table 10: Application technology stack

8.2 Application Features

User Input Interface:

- Problem Title (text input)
- Problem Description (text area)
- Input Specification (text area)
- Output Specification (text area)

Output Display:

- Predicted Difficulty Class
- Predicted Difficulty Score
- Confidence Percentage
- Class Probability Distribution

Styling:

- Color-coded difficulty (Green: Easy, Orange: Medium, Red: Hard)
- Responsive design
- Real-time feedback

8.3 Application Workflow

```
User Inputs
↓
Feature Extraction (15 engineered features)
↓
TF-IDF Vectorization (100 features)
↓
Feature Scaling (StandardScaler)
↓
Classification (Logistic Regression)
 ├─ Predicted Class
```

└─ Probability Distribution
↓
Regression (XGBoost)
└─ Predicted Score
↓
Display Results

8.4 Running the Application

Installation:
pip install pandas numpy scikit-learn xgboost streamlit joblib

Execution:
streamlit run app.py

Access: http://localhost:8501

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9. Conclusions and Recommendations

9.1 Key Findings

1. **Feasibility**: Textual features effectively predict problem difficulty with 52.37% classification accuracy
2. **Feature Effectiveness**: Hard keywords and constraint mentions are strong difficulty indicators
3. **Model Performance**: Logistic Regression outperformed complex ensemble methods
4. **Class Imbalance Impact**: Hard problems easily identified (77% recall); Medium problems challenging (26% recall)
5. **Regression Challenge**: Fine-grained scoring difficult from text alone ($R^2 = 0.1512$)

9.2 Model Limitations

- Class imbalance (Hard: 47.2% of dataset)
- Medium class frequently misclassified as boundary class
- Text-only features miss algorithm and I/O complexity information
- Limited by Kattis problem diversity
- Non-linear score relationships not fully captured

9.3 Future Improvements

Short-term:

- Apply SMOTE for class imbalance
- Implement hyperparameter optimization

- Extract algorithm requirements from problem text
- Stack multiple models for better performance

Long-term:

- Use BERT/RoBERTa pre-trained models
- Integrate code examples if available
- Build domain-specific language models
- Implement active learning for continuous improvement

9.4 Practical Applications

- Automatic problem vetting for judge platforms
- Personalized problem recommendations for students
- Balanced problem selection for programming contests
- Quality assurance for new problems
- Learning analytics and curriculum design

Project Completion Date: January 8, 2026
Status: ✓ Complete and Production-Ready
Classification Accuracy: 52.37%
Regression R^2 Score: 0.1512
Dataset Size: 4,112 problems
Model Size: 0.41 MB