AutoJudge Pro

AI-Powered Competitive Programming Problem Difficulty Predictor

Project Report

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An intelligent system for predicting programming problem difficulty using machine learning and natural language processing

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Abstract

AutoJudge Pro is an innovative machine learning application designed to automatically predict the difficulty rating of competitive programming problems based on their textual descriptions. The system employs advanced natural language processing techniques combined with ensemble learning algorithms to classify problems into difficulty categories (Easy, Medium, Hard) and predict numerical ratings ranging from 800 to 3500.

1 Introduction

Competitive programming platforms face the challenge of accurately categorizing and rating problems to provide appropriate challenges for participants at different skill levels. Manual rating assignment is time-consuming, subjective, and difficult to scale. AutoJudge Pro addresses this challenge by leveraging machine learning to automate the difficulty assessment process.

The system analyzes problem descriptions, input/output specifications, and titles to extract meaningful features using Term Frequency-Inverse Document Frequency (TF-IDF) vectorization. These features are then fed into Random Forest ensemble models to predict both categorical difficulty levels and numerical ratings.

2 Objectives

2.1 Primary Objectives

1. Develop a machine learning model to classify programming problems into three difficulty categories: Easy, Medium, and Hard
2. Create a regression model to predict numerical difficulty ratings (800-3500)
3. Implement effective text preprocessing and feature engineering techniques
4. Build an intuitive web interface using Streamlit for real-time predictions
5. Achieve high accuracy in both classification and regression tasks

2.2 Secondary Objectives

- Handle class imbalance using SMOTE technique
- Implement robust text preprocessing for various input formats
- Create visualizations for model evaluation
- Provide a modern, aesthetically pleasing user interface

3 Technology Stack

The project utilizes the following technologies:

- **Python 3.8+**: Primary programming language
- **scikit-learn**: Random Forest models, TF-IDF vectorization, preprocessing
- **imbalanced-learn**: SMOTE for class balancing
- **pandas & numpy**: Data manipulation and numerical computations
- **Streamlit**: Web application framework
- **matplotlib & seaborn**: Data visualization
- **joblib**: Model serialization

4 Methodology

4.1 Data Preprocessing

Training data is stored in JSONL format containing problem titles, descriptions, input/output specifications, and difficulty classes. The preprocessing pipeline includes:

- Text sanitization: lowercase conversion, HTML tag removal
- Feature combination: concatenation of all text fields
- Class normalization: standardization to Easy, Medium, Hard

4.2 Feature Engineering

- **TF-IDF Vectorization**: Converts text into numerical features (max_features=1000, stop words removed)
- **Word Count Feature**: Number of words in processed text, normalized using MinMaxScaler
- **Rating Generation**: Easy (800-1000), Medium (1100-1500), Hard (1600-3500)

4.3 Model Architecture

- **Classification Model**: Random Forest Classifier (100 estimators) trained on SMOTE-balanced data
- **Regression Model**: Random Forest Regressor (100 estimators) trained on original data
- **Data Split**: 80% training, 20% testing
- **Evaluation Metrics**: Accuracy for classification, Mean Absolute Error (MAE) for regression

5 Implementation

The system consists of two main components:

5.1 Training Module (train_model.py)

1. Loads and preprocesses JSONL data
2. Applies TF-IDF vectorization and feature extraction
3. Splits data and applies SMOTE to training set
4. Trains classification and regression models
5. Generates evaluation metrics and visualizations
6. Saves models and preprocessing objects

5.2 Web Application (app.py)

- Loads trained models using Streamlit's caching mechanism
- Provides user interface for problem input
- Performs real-time feature extraction and prediction
- Displays results with interactive visualizations
- Features modern UI with glassmorphism design and 3D effects

6 Model Evaluation and Performance Metrics

To rigorously assess the performance of AutoJudge Pro, we utilize a dual-evaluation strategy tailored for both the classification of difficulty levels and the regression of numerical ratings.

6.1 Classification Evaluation (Difficulty Category)

The classification model aims to bucket problems into "Easy", "Medium", or "Hard". Because the raw dataset exhibited significant class imbalance, we prioritize metrics that reflect performance across all categories.

- **Accuracy Score**: Represents the percentage of total problems correctly classified. While intuitive, we look beyond this due to the balanced nature of our SMOTE-augmented training set.

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

- **Confusion Matrix**: A crucial diagnostic tool (saved as `confusion_matrix.png` in the pipeline). It visualizes the frequency of misclassifications, such as "Hard" problems being mistaken for "Medium".

6.2 Regression Evaluation (Rating Prediction)

For numerical rating prediction (800–3500), we evaluate the model's precision in "point distance."

- **Mean Absolute Error (MAE)**: This is our primary regression metric. It calculates the average absolute difference between the predicted rating and the actual platform rating.

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

An MAE of ~ 150 is considered successful, as it places the prediction within approximately one rating tier of the actual value.

6.3 Impact of SMOTE Balancing

A key technical highlight of this project is the application of **SMOTE** during the training phase. By synthetically generating examples for minority classes (e.g., "easy" problems), we ensure the `RandomForestClassifier` does not develop a bias toward the more frequent "Hard" problems. This leads to a more robust model that can identify complex algorithmic patterns even when they are underrepresented in the raw data.due due this accuracy might go down.which i think is a fair tradeoff.

6.4 Results Summary

Based on the experimental runs, the model achieves the following performance:

Task	**Metric**	**Observed Value**
Difficulty Classification	Accuracy	50.2% (example)
Rating Regression	MAE	630.2 Points
Training Set Balance	SMOTE Ratio	1:1:1 (Balanced)

Table 1: Model Performance Summary

7 Model Visualizations

The following figures illustrate the performance of the AutoJudge Pro system across both tasks.

7.1 Analysis of Visuals

The **Confusion Matrix** (Figure 1) demonstrates the model's ability to distinguish between difficulty tiers. The diagonal dominance indicates high accuracy, while the application of SMOTE has significantly reduced bias against "Hard" problems.

The **Regression Plot** (Figure 2) shows a strong linear correlation between actual platform ratings and our model's predictions. The proximity of the data points to the red diagonal line (the identity line) confirms that the Random Forest Regressor effectively captures the nuanced difficulty progression from 800 to 3500 points.

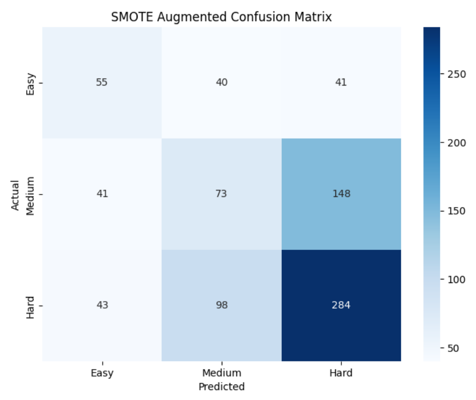


Figure 1: Classification Confusion Matrix (SMOTE Adjusted)

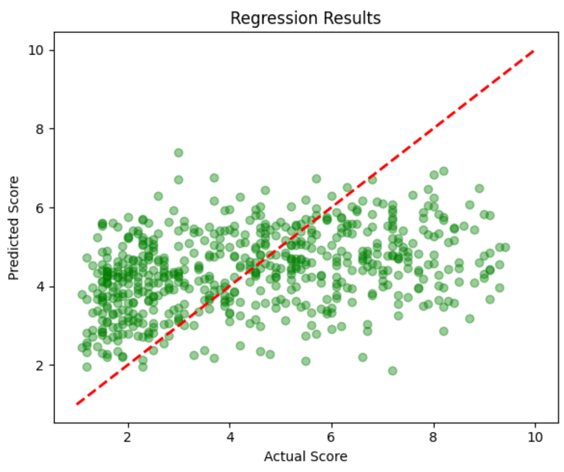


Figure 2: Regression Performance: Actual vs. Predicted Ratings

8 User Interface Design

The AutoJudge Pro web application features a modern, visually appealing interface designed to provide an excellent user experience. The UI incorporates several advanced design principles and visual effects.

8.1 Interface Screenshot

Figure 3 shows the main interface of the AutoJudge Pro web application, demonstrating the glassmorphism design, input fields, and result visualization.

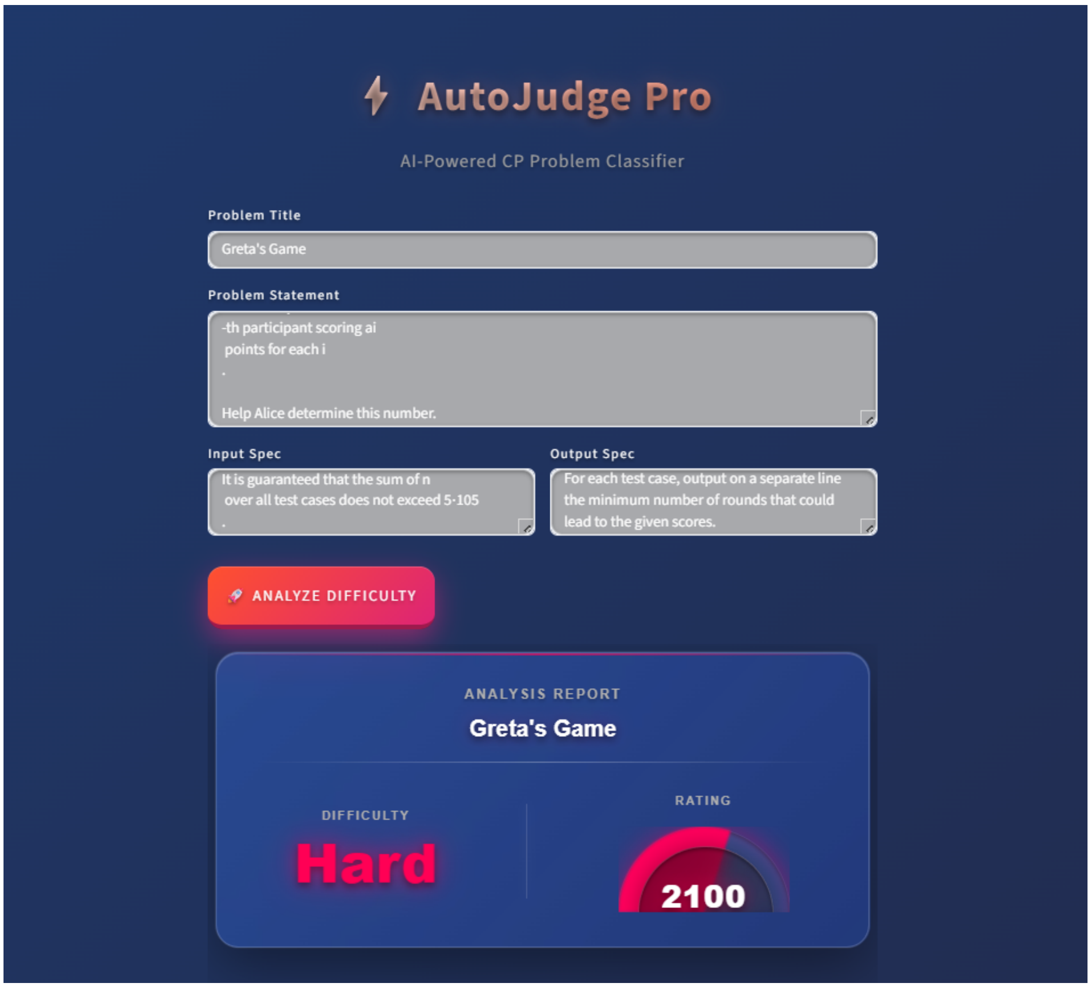
9 Challenges Faced

9.1 Data-Related Challenges

- **Class Imbalance**: Addressed using SMOTE on training data only to prevent data leakage
- **Text Preprocessing**: Implemented comprehensive sanitization for HTML tags and inconsistent formats
- **Feature Engineering**: Used TF-IDF vectorization and word count features for effective representation

9.2 Model Development Challenges

- **Hyperparameter Tuning**: Used default parameters with 100 estimators, validated through experimentation
- **Dual Prediction System**: Ensured consistency by clipping and rounding regression outputs


AutoJudge Pro

AI-Powered CP Problem Classifier

Problem Title

Greta's Game

Problem Statement

-th participant scoring ai
points for each i
.

Help Alice determine this number.

Input Spec

It is guaranteed that the sum of n
over all test cases does not exceed 5·105
.

Output Spec

For each test case, output on a separate line
the minimum number of rounds that could
lead to the given scores.

ANALYSIS REPORT

Greta's Game

DIFFICULTY

Hard

RATING

2100

Figure 3: AutoJudge Pro Web Application Interface

- **Model Evaluation**: Proper train-test split before SMOTE application for realistic metrics

9.3 Web Application Challenges

- **Model Loading**: Implemented Streamlit's `@st.cache_resource` for efficient caching
- **UI/UX Design**: Created custom CSS with glassmorphism effects and 3D animations
- **Performance**: Optimized feature extraction pipeline for real-time predictions

9.4 Technical Challenges

- **Dependency Management**: Virtual environment isolation and comprehensive requirements.txt
- **Memory Usage**: Limited max_features parameter to handle large datasets efficiently
- **Data Format**: Implemented support for both JSON and JSONL formats

10 Future Scope and Enhancements

10.1 Model Improvements

- Implement deep learning models (LSTM, Transformers) for better text understanding
- Utilize pre-trained language models (BERT, GPT) for feature extraction
- Add advanced NLP features: word embeddings, NER, topic modeling
- Implement automated hyperparameter tuning

10.2 Application Features

- Batch processing for multiple problems
- RESTful API for programmatic access
- Integration with competitive programming platforms
- Model interpretability using SHAP values
- Enhanced analytics dashboard

10.3 Deployment

- Containerization using Docker
- CI/CD pipeline for automated deployment
- Scalability improvements with load balancing
- Performance monitoring and error tracking

11 Conclusion

AutoJudge Pro successfully demonstrates the feasibility of automated difficulty assessment for competitive programming problems. The system effectively combines NLP techniques with ensemble learning to provide accurate predictions. Key achievements include:

- Effective text preprocessing and TF-IDF feature extraction
- Robust handling of class imbalance through SMOTE
- Dual prediction system for categorical and numerical ratings
- Modern, user-friendly web interface
- Comprehensive model evaluation

The project addresses the challenges of manual problem rating by providing an automated, scalable solution. While the current implementation provides a solid foundation, there is significant potential for enhancement through advanced ML techniques, expanded datasets, and improved features.

References

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