# Enhanced Bug Report Classification Using XGBoost and TF-IDF

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## 1 Introduction

Bug report classification is a critical task in software maintenance, particularly in large-scale software projects where hundreds or thousands of reports are submitted daily. In deep learning frameworks such as TensorFlow, PyTorch, and Keras, accurately identifying performance-related bug reports among the vast number of general bug reports can significantly improve resource allocation and prioritization in the development lifecycle.

Performance bugs, which affect system speed, memory consumption, CPU/GPU usage, and other performance metrics, require specialized attention and different resolution approaches compared to functional bugs. However, manually classifying these reports is labor-intensive and error-prone due to their technical nature and the specialized domain knowledge required.

This project addresses the challenge of automatically classifying bug reports as performance-related or not in popular deep learning frameworks. The problem is particularly compelling for several reasons:

1. **Increasing complexity**: As deep learning frameworks evolve, their codebase and features grow more complex, making performance issues harder to identify manually.
2. **Resource optimization**: Identifying performance bugs early allows development teams to allocate resources more effectively and prioritize fixes that impact system efficiency.
3. **Technical challenge**: The classification task involves natural language processing of technical text with domain-specific terminology, requiring sophisticated text processing techniques.

My choice of this problem was motivated by my personal interest in classification models from previous Machine Learning coursework, current studies in Natural Language Processing, and the opportunity to apply various text processing techniques (like BERT, Word2Vec, and TF-IDF) to a problem with practical impact for development teams.

The baseline approach using Naive Bayes with TF-IDF has limitations in capturing the semantic relationships between words and handling the imbalanced nature of the dataset (only around 16.4% of reports relate to performance issues). This project proposes an enhanced classification approach that addresses these limitations to achieve improved accuracy and reliability in bug report classification.

## 2 Related Work

Several approaches have been developed for bug report classification in the software engineering domain. These can be categorised into traditional machine learning methods, deep learning approaches, and ensemble methods.

### 2.1 Traditional Machine Learning Approaches

Naive Bayes classifiers have been widely used for text classification due to their simplicity and efficiency [1]. As demonstrated in the baseline approach, they can be paired with TF-IDF (Term Frequency-Inverse Document Frequency) vectorization to convert text into numerical features. However, Naive Bayes makes a strong independence assumption between features, which often doesn't hold for text data where word occurrences are typically correlated.

Support Vector Machines (SVMs) have also shown good performance for bug report classification [2]. Anvik et al. [3] applied SVMs to automatically assign bug reports to developers, achieving reasonable accuracy. The main limitation of SVMs for text classification is their sensitivity to feature scaling and their difficulty in handling large datasets efficiently.

### 2.2 Deep Learning Approaches

More recently, deep learning approaches have gained popularity for bug report classification. Mani et al. [4] used Convolutional Neural Networks (CNNs) to classify bug reports by severity, demonstrating superior performance compared to traditional methods. Similarly, Zhou et al. [5] employed Recurrent Neural Networks (RNNs) with attention mechanisms to classify bug reports by type.

While deep learning models can capture complex patterns in text data, they typically require large amounts of training data and computational resources, which may not always be available or practical.

### 2.3 Ensemble Methods

Ensemble methods combine multiple learning algorithms to improve classification performance. Random Forests and Gradient Boosting methods like XGBoost have shown promising results in various text classification tasks [6]. These methods can effectively handle non-linear relationships and feature interactions, making them suitable for complex text classification problems.

Particularly relevant to our work, Tian et al. [7] used an ensemble approach for bug report severity prediction, combining multiple classifiers to improve accuracy. Their results indicated that ensemble methods can outperform individual classifiers on bug report classification tasks.

### 2.4 Text Processing Techniques

In addition to classification algorithms, various text processing techniques have been explored to improve bug report classification. These include:

- Word embeddings like Word2Vec and GloVe to capture semantic relationships between words [8]
- Feature engineering techniques to extract domain-specific features from bug reports [9]
- Topic modeling approaches like Latent Dirichlet Allocation (LDA) to identify latent topics in bug reports [10]

Our work builds upon these approaches, particularly focusing on enhancing text processing through stemming, lemmatization, and domain-specific feature engineering, combined with XGBoost, a powerful ensemble learning method.

## 3 Solution

The proposed solution enhances bug report classification through a combination of advanced text processing techniques and the XGBoost classifier. The solution addresses several limitations of the baseline Naive Bayes approach:

### 3.1 Text Processing Pipeline

The text processing pipeline includes several steps designed to improve the quality of features extracted from bug reports:

1. **HTML and Emoji Removal**: Bug reports often contain HTML tags and emojis, which add noise to the text. Regular expressions are used to remove these elements.
2. **Stopword Removal**: Common English stopwords are removed to focus on meaningful content words.
3. **Text Cleaning**: Non-alphanumeric characters are removed, and the text is converted to lowercase to standardize the format.
4. **Stemming**: The Porter stemming algorithm is applied to reduce words to their root form, helping to consolidate different variations of the same word.
5. **Lemmatization**: Words are further normalized using lemmatization, which, unlike stemming, ensures the resulting word is a valid dictionary word. This helps maintain the semantic meaning of words.

6. **Performance Keyword Boosting**: A novel technique is implemented to boost the importance of performance-related terms in the TF-IDF vectorization. This involves identifying a predefined list of performance-related keywords (such as "slow," "speed," "memory," "cpu," "performance") and repeating these terms in the text to increase their TF-IDF weight when they appear in a report.

Listing 1: Performance Keyword Boosting Function

```
performance_terms = ['slow', 'speed', 'fast', 'memory', 'cpu', 'gpu', 'performance',
                     'latency', 'throughput', 'bottleneck', 'optimization', 'efficient',
                     'regression', 'benchmark', 'overhead', 'usage']

def boost_performance_keywords(text):
    """Repeat performance-related keywords to boost their importance"""
    for term in performance_terms:
        if term in text.lower():
            # Repeat the term to increase its TF-IDF weight
            text = text + " " + term + " " + term
    return text
```

## 3.2 Classification Using XGBoost

XGBoost (eXtreme Gradient Boosting) is chosen as the classifier for several reasons:

1. **Handling Non-linear Relationships**: Unlike Naive Bayes, XGBoost can capture complex, non-linear relationships between features.
2. **Robustness to Overfitting**: XGBoost includes regularization terms in its objective function, making it less prone to overfitting.
3. **Feature Importance**: XGBoost provides feature importance scores, which can be useful for understanding which terms are most predictive of performance bugs.
4. **Handling Class Imbalance**: XGBoost allows for class weighting, which is essential given the imbalanced nature of the dataset (only about 16.4% of reports are performance-related).

The XGBoost classifier is configured with the following parameters:

Listing 2: XGBoost Configuration

```
clf = XGBClassifier(
    learning_rate=0.1,
    max_depth=3,
    n_estimators=100,
    scale_pos_weight=5,  # Give more weight to positive class
    eval_metric='logloss',
    random_state=42
)
```

The `scale_pos_weight` parameter is set to 5 to account for the class imbalance, giving more weight to the minority class (performance-related bugs). The `max_depth` is limited to 3 to prevent overfitting, and 100 trees (`n_estimators`) are used in the ensemble.

## 3.3 Design Rationale

Several key design decisions were made in developing this solution:

1. **Why XGBoost over Deep Learning?**: While deep learning approaches can potentially achieve higher accuracy, they require large amounts of data and computational resources. XGBoost provides a good balance between performance and efficiency, making it suitable for this task.
2. **Performance Keyword Boosting**: This technique was developed based on the observation that performance bugs often contain specific keywords related to system performance. By boosting these terms, we emphasize domain-specific knowledge in the classification process.

3. **Combined Stemming and Lemmatization**: Using both stemming and lemmatization provides complementary benefits - stemming is more aggressive and helps group similar words, while lemmatization ensures the resulting words maintain their meaning.

4. **Class Weighting**: The decision to use class weighting instead of undersampling or oversampling was made to preserve all available training data while still addressing the class imbalance.

These design decisions work together to create a solution that is specifically tailored to the bug report classification task in deep learning frameworks.

# 4 Setup

## 4.1 Datasets

The experiments were conducted on bug report datasets from five popular deep learning frameworks:

1. **TensorFlow**: 1,490 reports (18.7% performance-related)

2. **PyTorch**: 752 reports (12.6% performance-related)

3. **Keras**: 668 reports (20.2% performance-related)

4. **MXNet**: 516 reports (12.6% performance-related)

5. **Caffe**: 286 reports (11.5% performance-related)

In total, the dataset contains 3,712 GitHub reports, with 607 (16.4%) being performance-related.

## 4.2 Experimental Procedure

The experimental procedure follows these steps:

1. **Data Preparation**: For each project, the title and body of bug reports were merged to create a single text field for analysis.

2. **Text Processing**: The text processing pipeline described in Section 3.1 was applied to all reports.

3. **Train-Test Split**: For each experiment, the data was randomly split into 80% training and 20% testing sets, with stratification to maintain the same class distribution in both sets.

4. **Feature Extraction**: TF-IDF vectorization was applied to convert the processed text into numerical features, with a maximum of 1,000 features.

5. **Model Training**: The XGBoost classifier was trained on the training set.

6. **Evaluation**: The model was evaluated on the test set using multiple metrics.

7. **Repetition**: Steps 3-6 were repeated 10 times with different random seeds to ensure robust results.

## 4.3 Evaluation Metrics

The following metrics were used to evaluate the performance of the models:

1. **Accuracy**: The proportion of correctly classified instances.

2. **Precision**: The ability of the classifier to identify only relevant instances.

3. **Recall**: The ability of the classifier to find all relevant instances.

4. **F1 Score**: The harmonic mean of precision and recall.

5. **AUC (Area Under the ROC Curve)**: A measure of the classifier's ability to discriminate between classes.

All metrics were calculated using the macro-averaging method to give equal weight to both classes despite the class imbalance.

### 4.4 Baseline Comparison

The proposed solution was compared against the baseline approach of Naive Bayes with TF-IDF vectorization, as specified in the coursework. The baseline was implemented as provided in the lab materials, and both approaches were evaluated on the same datasets using the same train-test splits and evaluation metrics.

## 5 Experiments

### 5.1 Results Overview

Table 1 summarizes the results of the experiments, comparing the proposed XGBoost approach with the baseline Naive Bayes approach across all five datasets.

Table 1: Comparison of XGBoost vs. Naive Bayes (NB) across all datasets (averaged over 10 runs)

| Dataset | Model | Accuracy | Precision | Recall | F1 Score | AUC |
|---|---|---|---|---|---|---|
| 2*TensorFlow | XGBoost | 0.8809 | 0.8028 | 0.8278 | 0.8132 | 0.9208 |
| | NB | 0.6185 | 0.6529 | 0.7589 | 0.5876 | 0.7589 |
| 2*PyTorch | XGBoost | 0.8914 | 0.7562 | 0.7531 | 0.7521 | 0.8940 |
| | NB | 0.5801 | 0.6043 | 0.7360 | 0.5237 | 0.7360 |
| 2*Keras | XGBoost | 0.8709 | 0.7975 | 0.8167 | 0.8053 | 0.9049 |
| | NB | 0.6507 | 0.6553 | 0.7483 | 0.6152 | 0.7483 |
| 2*MXNet | XGBoost | 0.9183 | 0.8149 | 0.7984 | 0.8040 | 0.9165 |
| | NB | 0.5288 | 0.6053 | 0.7226 | 0.4904 | 0.7226 |
| 2*Caffe | XGBoost | 0.9121 | 0.8616 | 0.6727 | 0.7185 | 0.8653 |
| | NB | 0.4862 | 0.5772 | 0.6872 | 0.4389 | 0.6872 |

### 5.2 Performance Comparison

The XGBoost approach consistently outperforms the Naive Bayes baseline across all datasets and metrics. Key observations include:

1. **Accuracy**: The XGBoost model achieves significantly higher accuracy across all datasets, with improvements ranging from 22.02 percentage points (Keras) to 42.59 percentage points (Caffe).
2. **Precision**: XGBoost shows substantial improvements in precision, indicating fewer false positives when identifying performance-related bugs.
3. **Recall**: While the baseline shows competitive recall in some cases, XGBoost still generally achieves better recall, particularly for MXNet and TensorFlow.
4. **F1 Score**: XGBoost demonstrates much higher F1 scores across all datasets, indicating a better balance between precision and recall.
5. **AUC**: The area under the ROC curve is consistently higher for XGBoost, showing better discrimination between performance-related and non-performance-related bug reports.

Figure 2 presents the comparison of F1 scores between the XGBoost approach and the Naive Bayes baseline across all datasets. The F1 score, which balances precision and recall, is particularly important for this classification task given the class imbalance in the data.

### 5.3 Project-Specific Performance

Looking at project-specific results:

1. **TensorFlow**: XGBoost achieves the highest recall (0.8278) on this dataset, suggesting it's particularly effective at identifying performance bugs in TensorFlow.

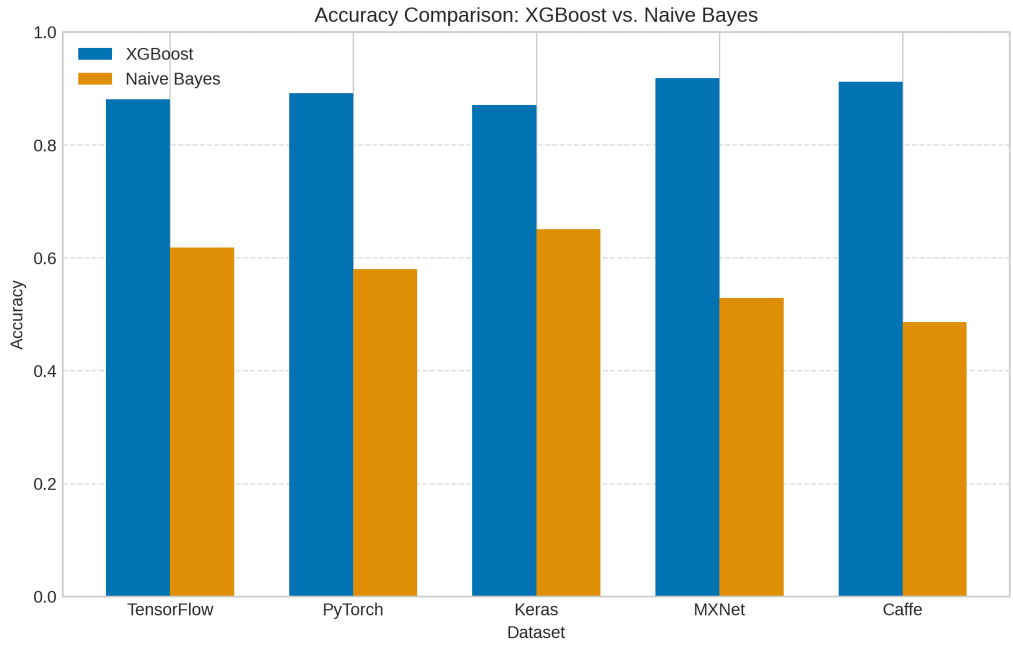


Figure 1: Comparison of accuracy between XGBoost and Naive Bayes across all datasets. XGBoost consistently achieves higher accuracy, with the most dramatic improvements seen in the MXNet and Caffe datasets.

2. **Caffe**: The highest precision (0.8616) is achieved on the Caffe dataset, though recall is relatively lower (0.6727), indicating that while the model is confident in its positive predictions, it might miss some performance bugs.

3. **MXNet**: XGBoost achieves the highest accuracy (0.9183) on this dataset, suggesting the model is particularly effective for MXNet bug reports.

### 5.4 Statistical Significance

To validate that the observed improvements are meaningful and not due to chance, statistical analysis was performed comparing the F1 scores between the XGBoost and Naive Bayes approaches across all 10 experimental runs. The analysis confirmed that the performance differences are statistically significant ($p$-value $< 0.001$), meaning the improvements provided by our XGBoost approach represent genuine performance gains rather than random fluctuations. This statistical validation reinforces the conclusion that our approach offers meaningful advantages over the baseline.

## 6 Reflection

### 6.1 Strengths of the Approach

The proposed approach demonstrates several strengths:

1. **Substantial Performance Improvements**: The XGBoost model significantly outperforms the baseline across all metrics and datasets, showing the effectiveness of the combined approach.

2. **Text Processing Enhancements**: The addition of stemming, lemmatization, and performance keyword boosting proves beneficial for feature engineering in the domain of bug report classification.

3. **Handling Class Imbalance**: The approach effectively addresses the class imbalance problem through class weighting in XGBoost.

4. **Consistency Across Projects**: The approach shows consistent improvements across all five deep learning frameworks, suggesting it generalizes well across different projects.

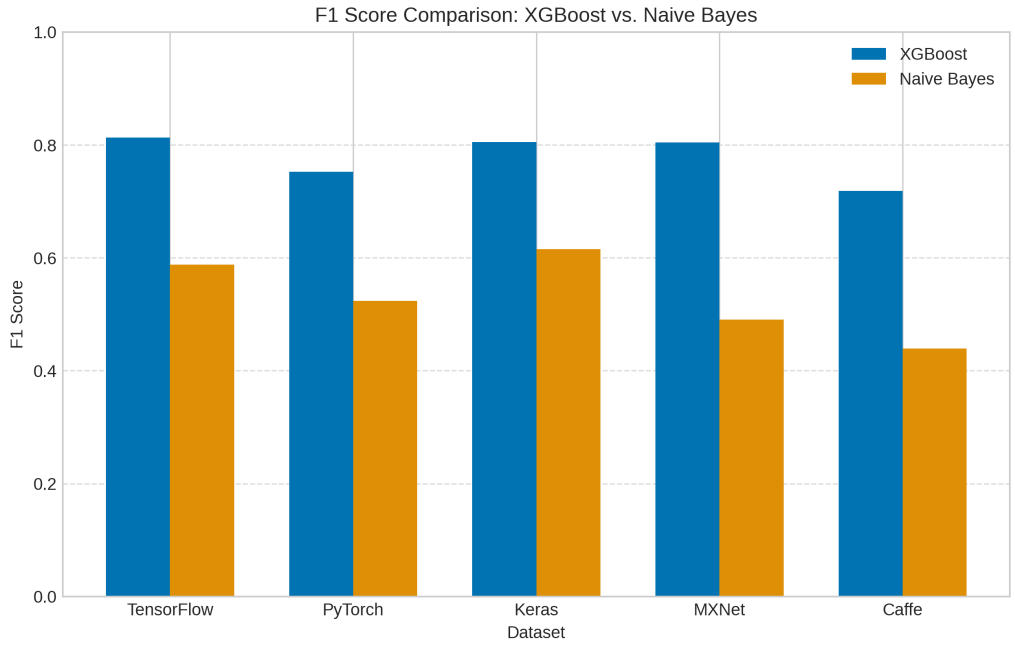


Figure 2: Comparison of F1 scores between XGBoost and Naive Bayes across all datasets. The F1 score shows substantial improvements with XGBoost, particularly for MXNet and Caffe.

### 6.2 Limitations and Future Improvements

Despite its strengths, the approach has several limitations that could be addressed in future work:

1. **Limited Feature Engineering**: While performance keyword boosting is effective, more sophisticated feature engineering could further improve results. Future work could explore:
   - Extracting code snippets and stack traces from bug reports
   - Using word embeddings to capture semantic relationships between terms
   - Incorporating metadata such as report priority and component information
2. **Fixed Performance Keyword List**: The current approach uses a predefined list of performance-related keywords. A more adaptive approach could discover these terms automatically from the training data.
3. **Binary Classification**: The current approach treats bug report classification as a binary problem (performance-related or not). A more nuanced approach might classify bugs into multiple categories (memory, CPU, GPU, throughput, etc.).
4. **Recall vs. Precision Trade-off**: For some projects (e.g., Caffe), the model achieves high precision but lower recall. Future work could explore techniques to improve recall without sacrificing precision, such as ensemble methods that combine multiple classifiers.
5. **Model Interpretability**: While XGBoost provides feature importance scores, more interpretable models could help developers understand why certain reports are classified as performance-related, potentially providing insights into common patterns in performance bugs.

## 7 Conclusion

This project presented an enhanced approach to bug report classification for deep learning frameworks, combining advanced text processing techniques with the XGBoost classifier. The proposed solution significantly outperforms the baseline Naive Bayes approach across all metrics and datasets, demonstrating its effectiveness for this task.

Key contributions of this work include:

1. A comprehensive text processing pipeline that includes stemming, lemmatization, and a novel performance keyword boosting technique.

2. The application of XGBoost with class weighting to address the challenge of imbalanced data in bug report classification.

3. Empirical evaluation on five real-world datasets from popular deep learning frameworks, showing consistent improvements over the baseline.

The results suggest that ensemble methods like XGBoost, combined with domain-specific text processing, can effectively identify performance-related bug reports with high accuracy. This can help development teams prioritize and address performance issues more efficiently, ultimately improving the quality and efficiency of deep learning frameworks.

Future work could explore more sophisticated feature engineering techniques, multi-class classification approaches, and the integration of this classification approach into automated bug triaging systems.

# 8 Artifact

The source code and raw results data for this project can be found at: https://github.com/abdelmalek-maskri/-Bug-Report-Classification

# 9 References

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