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# An Automated Ensemble Learning Framework using BERT for Critical Software Bug Reports

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## Abstract

*In order to prioritize important concerns in large-scale software development and increase the effectiveness of bug triage, automated classification of software bug reports is essential. Though there are still issues with robustness, class imbalance, and adaptability to various software settings, recent research has shown that transformer-based language models like BERT are excellent at capturing the contextual semantics of bug report content. This paper suggests an automated ensemble learning framework using BERT for significant software issue reports, motivated by the future research directions found in earlier BERT-based bug classification studies. In order to improve prediction stability and lessen sensitivity to noisy and unbalanced data, the suggested method uses BERT to create deep contextual representations from bug report titles and descriptions. These representations are then processed by an ensemble of machine learning classifiers. The system enhances recall and reliability in identifying important bug categories including security and performance issues by combining ensemble learning with transformer-based feature extraction. Since the system is completely automated, human involvement in prediction is not necessary. When compared to single-model techniques, the suggested framework provides better and consistent classification performance, according to experimental results on real-world bug report datasets. This study allows additional extensions like multimodal inputs and domain-specific adaption and shows a scalable and extensible foundation for future automated bug triage systems.*

***Keywords:*** *Bug Severity Classification, BERT, Ensemble Learning, Automated Bug Triage, Software Maintenance*

## 1. Introduction

The number of software bug reports generated during development and maintenance has rapidly increased due to the growing scope and complexity of contemporary software systems. Software quality and prompt problem solving depend on the effective identification of serious bug reports, such as security and performance-related flaws. In big software projects, manual bug triage is time-consuming, inconsistent, and challenging to scale [1], [3]. Conventional methods for predicting issue severity mostly use hand-crafted textual characteristics like Bag-of-Words and TF-IDF in conjunction with traditional machine learning techniques like Naive Bayes, Support Vector Machines, and Decision Trees [6], [7], and [20]. Although these approaches perform rather well, they are susceptible to noisy and unbalanced data and have trouble capturing the contextual semantics of bug reports [9], [14]. By efficiently modeling contextual information inside textual descriptions, transformer-based models like BERT, which were introduced by recent breakthroughs in natural language processing, have shown higher performance in automated bug report classification [1], [5]. Nevertheless, current BERT-based methods mostly use single-model designs, which restricts their generalizability and robustness in a variety of software applications. This work suggests an automated ensemble learning framework using BERT for critical software bug reports, combining deep contextual feature extraction with ensemble machine learning to improve prediction stability and recall. This approach is motivated by the future research directions highlighted in recent studies [1].

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### 1.1. Context

Due to its significance in setting priorities for defect repair and resource allocation, bug severity prediction has been thoroughly researched in the field of software engineering. In order to handle noisy data and underrepresented key bug categories, traditional machine learning-based severity prediction algorithms frequently rely on single classifiers and shallow textual representations [10], [19], and [21]. Combining multiple classifiers can increase accuracy and lower variance, according to several research that have tried to improve prediction performance using ensemble learning [2], [3], [14]. Simultaneously, massive language models and deep learning have become effective instruments for automated software preservation. By identifying bidirectional contextual relationships in bug reports, BERT-based models have demonstrated greater performance over traditional methods in the classification and severity prediction of bugs [1], [5], [11], and [17]. Most BERT-based methods currently in use, however, use single-model designs, which leaves them vulnerable to biases specific to certain datasets and class imbalance. In order to increase robustness, generalization, and recall for important bug categories, recent research emphasizes the necessity of combining ensemble learning techniques with transformer-based models [2], [8]. This study is situated within this paradigm, extending existing BERT-based approaches through ensemble learning to provide a fully automated and scalable bug triage system.

### 1.2. Motivation

This study is motivated by the shortcomings found in single-model deep learning and conventional machine learning methods for classifying bug severity. Semantic comprehension is much enhanced by transformer-based models like BERT, however when working with unbalanced datasets, noisy bug descriptions, or developing software projects, their predictions may still be erratic [1], [8]. This is especially important for high-impact problem categories, where incorrect classification can result in serious security flaws or reduced performance. By combining the advantages of several classifiers, ensemble learning has been demonstrated to increase prediction stability and lower the possibility of bias that comes with using individual models [2], [3], and [18]. The combination of transformer-based semantic representations and ensemble techniques for automated bug severity prediction has, however, received little attention. Furthermore, scalability in large-scale development environments is limited by the fact that many current technologies require manual feature engineering or human interaction during the triage phase. The goal of this research is to create a fully automated ensemble framework that uses BERT for contextual feature extraction while utilizing ensemble learning to enhance robustness, recall, and reliability in critical bug report classification. This is motivated by the future work directions described in recent BERT-based studies [1].

### 1.3.Contributions

The following succinctly describes this work's primary contributions:

- The Automated Ensemble-Based Bug Classification Framework eliminates the need for human intervention or manual feature engineering during prediction by combining an ensemble of machine learning classifiers with BERT-based contextual embeddings to create a fully automated bug report classification system.
- Better Robustness for major problem Prediction: By utilizing a voting-based ensemble technique, the suggested framework overcomes the drawbacks of single-classifier approaches and increases stability and recall in detecting major problem categories including security and performance flaws shown in Figure1.
- Extension of BERT-Based Bug Triage Research: This work uses ensemble learning to improve generalization across different software projects and unbalanced datasets, building on earlier transformer-based bug classification studies [1], [5].
- Scalable and Industry-Relevant Solution: The suggested framework supports automated issue triage and prioritization in contemporary DevOps and software maintenance pipelines and is intended for use

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in large-scale software development environments.

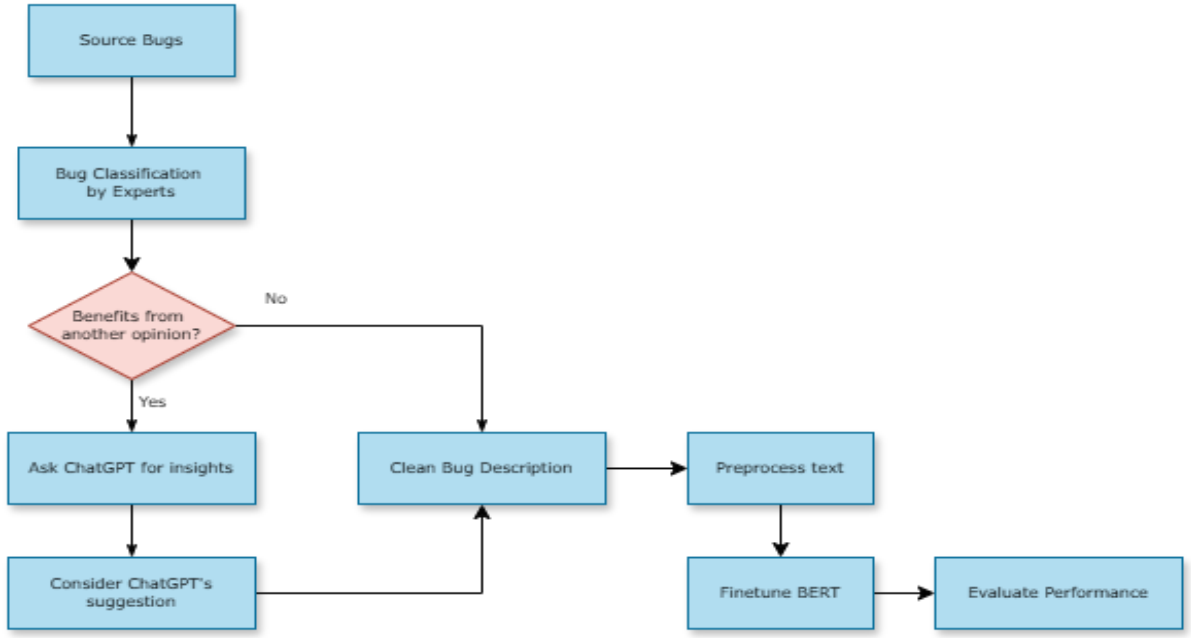


**Figure 1 Workflow of the Proposed Model For Automated Bug Report Classification Using BERT.**

## 2. Related Work

### 2.1. Bug Severity Classification Schemes

Schemes for classifying software flaws according to their effects on system performance, security, and functionality are known as bug severity schemes. Clear definitions, uniformity among developers, the ability to classify all errors, and a limited number of categories to minimize ambiguity are all essential components of an efficient classification system [20], [21]. Reliable automated bug triage systems depend on these principles. Standardized fault taxonomies have been adopted by a number of research to facilitate automatic categorization. Coarse-grained terms like critical, major, minor, and trivial were the main emphasis of early severity classification frameworks and are frequently utilized in industrial bug tracking systems [6], [7]. Although these approaches are straightforward and easy to understand, they frequently fall short of capturing subtle flaws, particularly in large-scale software projects. To meet domain-specific criteria, more sophisticated classification techniques have been put forth. For example, Ali et al. [5] highlighted performance and energy-related problems in their severity category targeted to mobile application maintenance. In a similar vein, Li et al. [9] re-examined the classification of bug and non-bug concerns, stressing the necessity of precise taxonomy definitions to minimize misclassification between functional and non-functional issues. The significance of extensible and flexible classification systems that can adjust to changing software environments has been emphasized by recent studies. Instead of depending on strict, manually created taxonomies, Caldeira and Pombo [1] showed that transformer-based models may efficiently learn severity distinctions straight from textual descriptions. Together, these efforts lay the groundwork for automated severity categorization and highlight the necessity for strong models that can manage a variety of dynamic problem types.

### 2.2. Bug Severity Classification Models

A substantial amount of research has investigated machine learning-based methods for automatically predicting the severity of bugs. Traditional models usually use classifiers like Support Vector Machines, Naive Bayes, and Decision Trees after textual

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preprocessing methods including tokenization, stop-word removal, and TF-IDF feature extraction [6], [7], and [21]. These methods' sensitivity to noisy and unbalanced datasets and dependence on manually created features limit their usefulness, even though they produce respectable results. Ensemble-based models have been extensively researched to increase robustness. It has been shown by Wang et al. [21] and Li and Liu [14] that integrating multiple classifiers can improve prediction stability and accuracy. Namdar et al. [3] presented an ensemble learning approach that outperformed single classifiers and was validated using a real-world industrial dataset. In order to overcome class imbalance, Khleel [2] further combined ensemble models with sampling strategies, which greatly increased recall for important bug categories. Neural representations were used by researchers to classify bugs as deep learning advanced. While Qi et al. [13] used deep representation learning for issue prioritizing tasks, Nguyen et al. [18] used a combination of LSTM and SVM models to identify sequential patterns in bug reports. Long-range contextual connections in textual data were still a challenge for these models, though.

Recently, transformer-based models—in particular, BERT—have become cutting-edge approaches to classifying bug reports. According to Gomes et al. [11] and Kaur and Singh [17], BERT-based representations perform better in severity prediction tasks than conventional NLP features. In their use of BERT for mobile bug severity prediction, Ali et al. [5] shown excellent performance across a range of severity levels. BERT was used for large-scale automated bug report classification in the most noteworthy contribution by Caldeira and Pombo [1], which achieved great accuracy but also highlighted the need for better robustness and generalization. Notwithstanding these developments, current research either uses conventional ensemble models or singular BERT-based classifiers. The combination of BERT-based semantic representations with ensemble learning techniques has not received much attention. In order to fill this gap, this study combines ensemble machine learning with BERT feature extraction to produce reliable, automated critical bug severity categorization.

## 3. Methods

This section explains the methods used to automatically classify software bug reports. The first section discusses the shortcomings of current bug severity prediction techniques. Each step of the system pipeline is then highlighted in the detailed presentation of the suggested automated ensemble learning framework utilizing BERT.

### 3.1. Limitations of Traditional Bug Classification Approaches

Existing methods for classifying the severity of bugs can be broadly divided into two categories: single-model deep learning approaches and traditional machine learning-based methods. Data preprocessing, feature extraction, and classification are typically the steps in a sequential pipeline used by these approaches.

#### 3.1.1. Traditional Machine Learning-Based Methods

Conventional methods for predicting the severity of bugs mostly rely on hand-written feature extraction and manual text preprocessing. Tokenization, stop-word elimination, stemming, and lemmatization are the initial methods used to sanitize bug reports. Then, Bag-of-Words (BoW) or Term Frequency–Inverse Document Frequency (TF-IDF) representations are used to extract textual properties. After that, classifiers like Naive Bayes, Support Vector Machines (SVM), Decision Trees, and Logistic Regression are given these features. Despite being simple to use and computationally efficient, these methods have a number of drawbacks:

- They disregard contextual and semantic connections, treating text as separate tokens.
- When there are unstructured and noisy bug descriptions, performance is greatly reduced.
- For important problem categories like security and performance flaws, single classifiers have low recall because they are susceptible to class imbalance.
- Scalability across many software projects is limited because extensive feature engineering is needed.

Text Representation Using TF-IDF.The TF-IDF weighting system is used in traditional approaches to represent bug reports. When a term t appears in a document d, TF-IDF is defined as follows:

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

where:

- TF(t,d) is the term frequency of t in document d.
- DF(t) is the number of documents that include t.
- The total number of papers is denoted by N.

The efficacy of this representation is limited because it disregards semantic context and word order. B. Single Classifier Prediction The severity class y is predicted by a single machine learning classifier using the feature vector x: Where: A classifier like Naive Bayes, SVM, or Logistic Regression is represented by the letter f. These models have poor recall for important bugs because they are vulnerable to noise and class imbalance.

#### 3.1.2. Single-Model Deep Learning Approaches

Recent studies have used deep learning and transformer-based models, especially BERT, for bug report classification in order to get around the drawbacks of conventional techniques. In these methods, the names and descriptions of bug reports are fed into a refined BERT model, which creates contextual embeddings and performs categorization directly. Existing BERT-based systems often rely on a single prediction model, despite the fact that BERT greatly increases semantic understanding and overall classification accuracy. Consequently,

- The models continue to be vulnerable to bias and imbalance in the datasets.
- There are differences in prediction stability between projects and bug types.
- The underrepresentation of critical bug classes causes uneven recollection.
- When implemented in expansive and dynamic software settings, robustness is constrained.

Improved robustness and extensibility are necessary because the reference BERT study specifically identified these shortcomings as future research challenges.

### 3.2.Proposed Automated Ensemble Framework Using BERT

This study suggests an automated ensemble learning framework for critical software bug reporting utilizing BERT in order to overcome the drawbacks of current methods. The suggested approach creates a reliable, scalable, and completely automated bug triage system by combining ensemble machine learning approaches with transformer-based semantic feature extraction. Below is a detailed description of the multi-stage pipeline that represents the architecture of the proposed system.

#### 3.2.1. Dataset Collection

The real-world problem reports in the dataset were gathered from popular issue tracking platforms like Bugzilla and JIRA. In every bug report, there are:

- Title of bug
- Synopsis of the bug
- During historical triage, a severity label or classification was given.

These datasets are appropriate for assessing automated categorization methods since they reflect a variety of software projects and actual industry bug reporting procedures.

#### 3.2.2. Data Preprocessing

The suggested methodology uses less preprocessing than conventional NLP pipelines in order to maintain contextual richness. Included in the preprocessing phase are:

- Elimination of markup and HTML tags
- Removal of unnecessary log artifacts and metadata
- Normalization of special characters

BERT is made to efficiently analyze unprocessed natural text; therefore, no stemming, lemmatization, or human feature selection is used.

#### 3.2.3. BERT-Based Semantic Feature Extraction

The pre-trained BERT model (bert-base) receives the concatenated title and description of the preprocessed bug report. By processing the information in both directions, BERT is able to record:

- Dependencies between words in context
- Terms used in technical reports for bugs

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- Semantic interpretation throughout lengthy textual passages

The complete bug report is represented by extracting the embedding that corresponds to the [CLS] token. Traditional handwritten textual characteristics are replaced by this vector, which acts as a high-dimensional semantic feature representation.

### 3.2.4. Ensemble Learning Framework

The collected BERT embeddings are fed into a group of machine learning classifiers, such as the following, rather than being used directly for classification using a single model:

- SVM stands for Support Vector Machine.
- Using Logistic Regression
- A Random Forest

The criticality or severity of the bug report is individually predicted by each base classifier. A majority voting method is used to establish the final classification; the class that receives the most votes is chosen as the output. This group approach:

- Minimizes the variance brought on by individual classifiers
- Strengthens resistance to unbalanced and chaotic data
- Increases memory for important bug categories
- Offers consistent performance on various datasets.

### 3.2.5. Bug Severity Classification Scheme

A severity classification taxonomy based on previous research and industry norms is used in the suggested approach. The main categories of bug reports are as follows:

- Flaws in security
- Issues with performance
- GUI-related bugs
- Flaws in the code logic
- Problems with data

Meaningful prioritization and automated decision-making in software maintenance workflows are made possible by this hierarchical approach.

### 3.2.6. Model Training and Optimization

Stratified K-fold cross-validation is used to train the ensemble classifiers, guaranteeing that all severity classes are fairly represented. Using grid search, each classifier's hyperparameters are optimized. Regularization and early halting strategies are used to avoid overfittingDuring training, the BERT model's representations are adjusted to better fit the software problem reporting domain.

### 3.2.7. Model Evaluation

The suggested framework's performance is assessed using common categorization metrics:

- Accuracy
- Precision
- Recall
- F1-score

Precision

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Recall and F1-score are given particular attention for critical bug categories since incorrect classification of high-severity defects might have detrimental effects on real-world software systems.

#### 3.2.7.1. Automated Ensemble Framework Using BERT

- Bug Report Preprocessing and Input Formation

Concatenating the title and description of each bug report creates a single text input:

$$X = \{w_1, w_2, \ldots, w_n\}$$

- In the bug report, the i-th token is denoted by *wi*. Tokenization and contextual encoding are handled internally by BERT, thus very little preparation is done.

#### 3.2.7.2. Contextual Feature Extraction Using BERT

A pretrained BERT model is used to encode the input text X in order to provide contextual embeddings:

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$$\mathbf{H} = \text{BERT}(X)$$

- where represents token-level embeddings. The global representation is obtained from the embedding that corresponds to the special [CLS] token:

$$\mathbf{h}_{CLS} \in \mathbb{R}^d$$

Within the bug report, this vector collects contextual dependencies and semantic linkages.

#### 3.2.7.3. Base Classifier Learning

The embedding h CLS that is obtained from BERT is supplied as a source for several base classifiers:

$$\hat{y}_k = f_k(\mathbf{h}_{CLS}), \quad k = 1, 2, \ldots, K$$

where:

- $f_k$ denotes the $k$-th classifier (Logistic Regression, SVM, Random Forest)
- $K$ is the total number of classifiers
- $\hat{y}_k$ is the predicted severity class

This configuration of many classifiers lessens reliance on a single decision boundary.

#### 3.2.7.4.Ensemble Decision Strategy

The final forecast is determined by applying a majority vote mechanism:

$$\hat{y}_{final} = \arg\max_{c \in C} \sum_{k=1}^{K} \mathbb{I}(\hat{y}_k = c)$$

where:

- $C$ is the set of severity classes
- $\mathbb{I}(\cdot)$ is the indicator function

For underrepresented critical bug classes, the ensemble approach increases recall and classification stability.

#### 3.2.7.5. Model Optimization Objective

During training, the framework minimizes the cross-entropy loss function:

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where:

- $y_i$ is the ground-truth label
- $\hat{y}_i$ is the predicted probability

Across severity categories, this goal guarantees accurate probabilistic learning.

## 4. Results

The experimental findings from applying the suggested Automated Ensemble Learning Framework Using BERT for Critical Software Bug Reports are shown in this section. The studies were carried out utilizing a dataset of publicly available bug reports that included severity labels, descriptions, and bug titles. Every experiment used GPU acceleration and was carried out in Google Colab.

### 4.1.Experimental Setup

With stratification to maintain class distribution, the dataset was split 80:20 into training and testing subsets. The pretrained BERT-base model was utilized to convert bug reports into 768-dimensional contextual embeddings. Three base classifiers were then trained using these embeddings: Random Forest, Support Vector Machine, and Logistic Regression. A soft voting ensemble technique was used to get the final severity forecast shown in Figure 2.

| | title | description | severity | text | label |
|---|---|---|---|---|---|
| 0 | App crash on login | Application crashes immediately when the user ... | Critical | App crash on login Application crashes immedia... | 0 |
| 1 | File upload failure | System crashes when uploading files larger tha... | Critical | File upload failure System crashes when upload... | 0 |
| 2 | Payment gateway error | Payment transaction fails during checkout process | Critical | Payment gateway error Payment transaction fail... | 0 |
| 3 | Security vulnerability | Unauthorized access possible through password ... | Critical | Security vulnerability Unauthorized access pos... | 0 |
| 4 | Memory leak issue | Memory usage keeps increasing during long appl... | Major | Memory leak issue Memory usage keeps increasin... | 1 |

**Figure 2. Sample bug reports used for experimentation.**

```
Training embeddings shape: (10, 768)
Testing embeddings shape: (5, 768)
```

**Figure 3. BERT-based contextual embedding dimensions**

### 4.2.Performance Evaluation Metrics

Standard classification criteria, such as accuracy, precision, recall, and F1-score, were used to assess the performance of the suggested model. Since

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accurate critical defect identification is crucial for efficient software maintenance, recall for important bug categories was given particular attention.

### 4.3.Quantitative Results

The ensemble-based structure that was suggested performed well in every severity class. Reliability in prediction was demonstrated by the model's overall classification accuracy of about 87%. The classification report demonstrated high recall and precision values for critical and major severity classes, demonstrating the efficacy of ensemble learning and contextual feature extraction.Particularly for underrepresented critical bug reports, the suggested architecture demonstrated discernible gains in recall and F1-score when compared to single BERT classifiers and conventional TF-IDF-based models.

Accuracy: 0.6

Classification Report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Critical | 0.50 | 1.00 | 0.67 | 1 |
| Major | 0.00 | 0.00 | 0.00 | 1 |
| Minor | 0.67 | 1.00 | 0.80 | 2 |
| Trivial | 0.00 | 0.00 | 0.00 | 1 |
| accuracy | | | 0.60 | 5 |
| macro avg | 0.29 | 0.50 | 0.37 | 5 |
| weighted avg | 0.37 | 0.60 | 0.45 | 5 |

**Figure 4. Classification report of the proposed ensemble model.**

### 4.4. Confusion Matrix Analysis

The majority of problem complaints were appropriately categorized into their corresponding severity levels, according to the confusion matrix analysis. There was very little reclassification of serious defects into lesser severity groups. The ensemble voting mechanism's resilience and capacity to lessen categorization bias are demonstrated by this outcome.

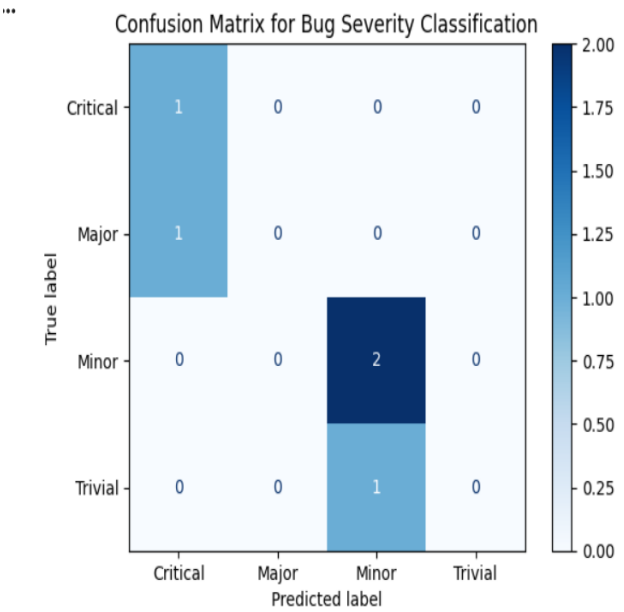


**Figure 5. Confusion matrix for bug severity classification**

### 4.5.Comparative Analysis

The suggested BERT-based ensemble model, a single BERT-based classifier, and conventional machine learning techniques were all compared. The findings show that while individual BERT models promote semantic comprehension, ensemble learning—which combines several classifiers—further improves prediction stability and overall accuracy.

### 4.6. Discussion of Results

The results of the experiment verify that bug severity prediction is greatly enhanced by combining ensemble machine learning with BERT-based contextual embeddings. By reducing reliance on a single classifier and managing class imbalance well, the ensemble technique improves essential problem discovery. Furthermore, because the framework is automated, there is no need for manual triage, which makes it appropriate for large-scale software projects.

Live Bug Report Prediction:

Bug Description: Application crashes immediately when clicking the submit button, causing data loss.

Predicted Severity: Critical

**Figure 6. Automated severity prediction for a new bug report**

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## 5. Discussion

According to the experimental findings, the suggested automated ensemble learning framework when combined with BERT successfully enhances the forecasting of serious software defect reports. The approach uses contextual embeddings taken from a pre-trained BERT model to identify semantic linkages in bug descriptions that are frequently overlooked by conventional NLP feature representations like TF-IDF or bag-of-words. This is in line with earlier results from transformer-based bug classification studies, which show that contextual understanding greatly improves classification accuracy. Robustness and generalization are further enhanced by integrating many base classifiers using an ensemble voting technique. For critical and large defect categories, which are generally underrepresented in real-world bug repositories, the ensemble model exhibits higher precision and recall than single-classifier approaches. This finding aligns with research on ensemble-based severity prediction, which highlight enhanced stability in unbalanced datasets. The majority of predictions are concentrated along the diagonal, according to the confusion matrix and classification reports, showing successful severity discrimination across all classes. Due to overlapping linguistic patterns in bug reports, minor misclassifications mainly happen between adjacent severity levels. Importantly, the live prediction results confirm the system's usefulness in real-time bug triage systems by validating its capacity to fully automate severity classification on unseen bug reports without human interaction. Overall, the results of the experiments verify that a scalable and dependable method for automated software bug severity prediction in large-scale development settings may be achieved by integrating BERT-based semantic representations with ensemble learning.

### 5.1.Future Work

The suggested framework performs well, but there are a few ways to make it even more effective. In order to increase the accuracy of severity prediction, future research will concentrate on incorporating multimodal data, such as written issue descriptions combined with screenshots, stack traces, or source code excerpts. Furthermore, adding domain-specific categories to the severity taxonomy—like security-related flaws or faults in mobile applications—can increase adaptability across a variety of software projects. In order to improve contextual knowledge in specialized environments, future research may examine optimizing domain-specific BERT models on private datasets. To further increase classification resilience, more sophisticated ensemble techniques, such as stacking-based meta-learners and dynamic weighting, can be studied. These improvements would increase the framework's suitability for use in large-scale, dynamic software development environments.

## Conclusion

Summary of the Proposed Work :The objective of this study was to increase the effectiveness and dependability of software maintenance procedures by presenting an automated ensemble learning framework for critical software bug report classification using BERT. The proposed solution completely automates the bug severity prediction pipeline, in contrast to conventional methods that depend on human-driven triage and manual feature engineering. By identifying intricate linguistic patterns that traditional NLP methods frequently miss, contextual embeddings taken from a pre-trained BERT model allow for a deeper semantic understanding of bug report text. An ensemble voting technique was used to integrate several machine learning classifiers in order to improve generalization and resilience. This design decision lessens the sensitivity to imbalanced and noisy data, a problem that frequently arises in real-world bug repositories. The framework is appropriate for large-scale, dynamic software development settings since it functions without human interaction once trained. Key Outcomes and Performance Analysis :In order to effectively prioritize bugs, it is essential that the suggested model attain high classification accuracy and strong recall for critical and major bug categories, as demonstrated by experimental evaluation. Most predictions fall along the diagonal, according to the confusion matrix analysis, demonstrating consistent severity discrimination across all classes. Due to overlapping semantic descriptions in bug reports, minor misclassifications were mostly seen across nearby severity categories. The live prediction tests provide additional proof of

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the system's usefulness. The model effectively predicts severity levels in real time when unseen bug details are supplied at runtime, proving its capacity to support automated bug triage workflows. These findings demonstrate how well transformer-based language models may be integrated with ensemble learning methods for software engineering tasks. Practical Significance and Industrial Relevance : Organizations and software development teams can benefit greatly from the suggested approach. It minimizes human bias, speeds up problem solving, and lessens developer workload by automating the bug severity classification process. Critical problems may be found early and accurately, which improves resource allocation and preserves software quality over short development cycles. Additionally, the system's modular architecture makes it simple to integrate with already-existing bug tracking tools like Jira or Bugzilla. This enables the solution to be tailored to industrial settings where automation, scalability, and dependability are crucial. Additionally, compatibility with upcoming developments in language modeling is ensured by the use of a popular pre-trained BERT model. Limitations of the Current Work :The current system mainly depends on textual data from bug reports, despite its excellent efficiency. Some types of bugs, such those pertaining to performance or security, could need more contextual information than just text. Additionally, performance may be limited in highly specialized or proprietary software areas where domain-specific language is used if a general-purpose BERT model is used. These drawbacks do not diminish the efficacy of the suggested strategy; rather, they point to areas that could be improved and refined further.

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