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# Predicting the objective and priority of issue reports in software repositories

Maliheh Izadi[1] · Kiana Akbari[1] · Abbas Heydarnoori[1]

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## Abstract

Software repositories such as GitHub host a large number of software entities. Developers collaboratively discuss, implement, use, and share these entities. Proper documentation plays an important role in successful software management and maintenance. Users exploit Issue Tracking Systems, a facility of software repositories, to keep track of issue reports, to manage the workload and processes, and finally, to document the highlight of their team's effort. An issue report is a rich source of collaboratively-curated software knowledge, and can contain a reported problem, a request for new features, or merely a question about the software product. As the number of these issues increases, it becomes harder to manage them manually. GitHub provides labels for tagging issues, as a means of issue management. However, about half of the issues in GitHub's top 1000 repositories do not have any labels. In this work, we aim at automating the process of managing issue reports for software teams. We propose a two-stage approach to predict both the objective behind opening an issue and its priority level using feature engineering methods and state-of-the-art text classifiers. To the best of our knowledge, we are the first to fine-tune a Transformer for issue classification. We train and evaluate our models in both project-based and cross-project settings. The latter approach provides a generic prediction model applicable for any unseen software project or projects with little historical data. Our proposed approach can successfully predict the objective and priority level of issue reports with 82% (fine-tuned RoBERTa) and 75% (Random Forest) accuracy, respectively. Moreover, we conducted human labeling and evaluation on unlabeled issues from six unseen GitHub projects to assess the performance of the cross-project model on new data. The model achieves 90% accuracy on the sample set. We measure inter-rater reliability and obtain an average Percent Agreement of 85.3% and Randolph's free-marginal Kappa of 0.71 that translate to a substantial agreement among labelers.

**Keywords** Software evolution and maintenance · Mining software repositories · Issue reports · Classification · Prioritization · Machine learning · Natural language processing

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Dr. Abbas Heydarnoori is also a corresponding author for this work.

Extended author information available on the last page of the article

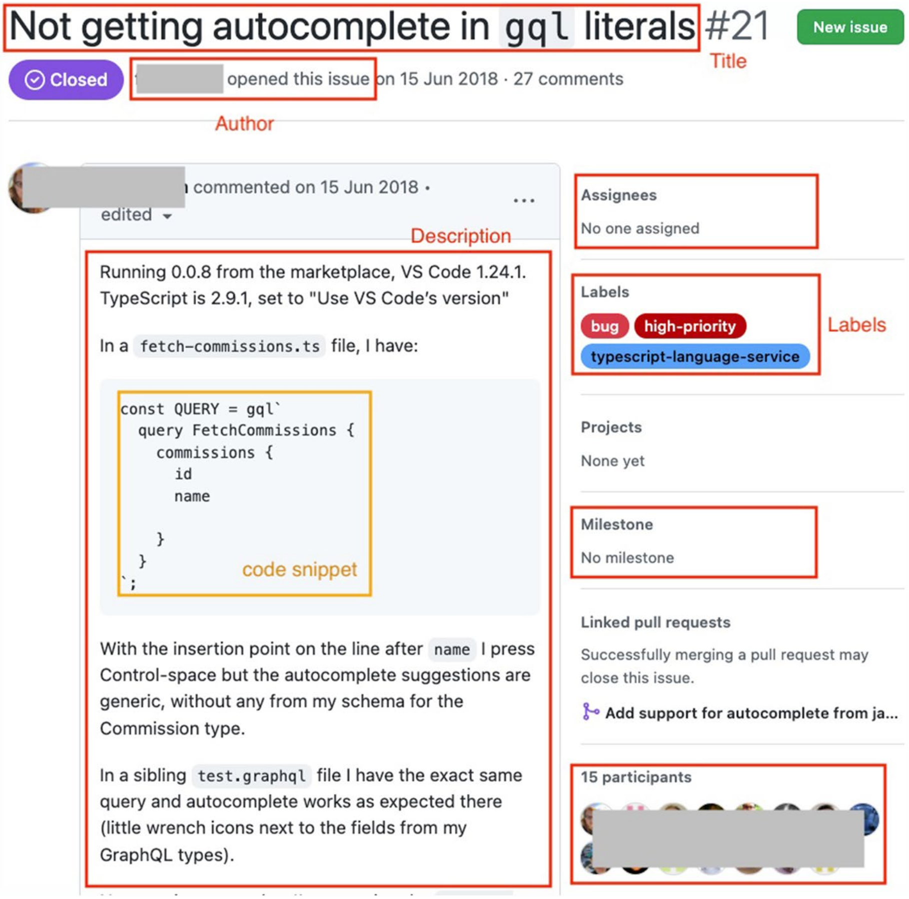
## 1 Introduction

Due to the possibility of having public discussions and contributions, software engineers and developers can collaboratively develop and maintain software projects. In doing so, a growing base of knowledge has formed on software-related platforms such as GitHub and Stack Overflow. This knowledge encapsulates various types of information such as source code, user reports, software Q&A posts, and more. This raw yet invaluable knowledge can be transformed into automatic and practical solutions using data-driven approaches to help developers achieve their tasks more efficiently.

Most software repositories have a tracker for recording and managing tasks of a project. These trackers are the primary mean for communication, discussion, getting help, sharing opinions, making decisions, and finally collecting users' feedback. GitHub's tracker is called *Issues*. Issue reports are an important source of knowledge provided with the help of the community. Any GitHub user is able to discuss, and contribute to the progress of a software project using issue reports. Users can create an issue in a repository for various reasons including reporting bugs in the system, requesting new features, or asking for support. This source of collaboratively-curated knowledge can be of great assistance in the process of software development and maintenance. Team members should address these issues as soon as possible to keep their audience engaged and improve their software product. As the project grows, the number of users and reported issues increases. For instance, *Elastic-search* project has more than 27*K* issue reports since 2017. It has on average, 25 and 760 daily and monthly new issues, respectively. Consequently, timely management of issues including determining the goal of issues (classification of issue objectives), identifying urgent issues to address (prioritizing issues), and selecting the most important changes to include in product reports such as release notes, becomes harder.

Issues in software repositories must have a title, a description, and a state (open or closed). They can also have additional data such as labels, assignees, milestone, comments, etc. Figure 1 presents an issue from GitHub which contains various types of information including title, description, author, and participants. As shown, the description of this issue contains useful information including the reported problem and code snippets to elaborate the reported problem. Moreover, it has several labels such as `bug report` to denote its objective and `high-priority` to indicate its importance. Labels, as a sort of project metadata, describe the goal and content of an issue. They are mainly used for categorizing, managing, searching, and retrieving issues. Thus, assigning labels to issues facilitates task assignment, maintenance, and management of a software project. Consequently, issue management is a vital part of the software development process.

Labels are assigned to issues to indicate their objective, status, priority level, etc. Such labels can help team members manage and track their tasks more efficiently. Cabot et al. (2015) analyzed about three million non-forked GitHub repositories to investigate the label usage and its impact on resolving issues. They showed only about 3% of these repositories had labeled issues, which indicates labeling issues is rarely done by developers. Furthermore, in the repositories which incorporated issue labeling, only about 58% of issues were labeled. In their study, each issue had 1.14 labels on average. The authors showed addressing an issue and the engagement rate both have a high correlation with the number of labeled issues in a repository (Cabot et al. 2015). This may indicate that labeling issues can benefit project management. Recently, Liao et al. (2018) investigated the effect of labeling issues on issue management. They analyzed six popular projects and found labeled



Not getting autocomplete in gql literals #21

[redacted] opened this issue on 15 Jun 2018 · 27 comments

[redacted] commented on 15 Jun 2018 · edited

Running 0.0.8 from the marketplace, VS Code 1.24.1. TypeScript is 2.9.1, set to "Use VS Code's version"

In a `fetch-commissions.ts` file, I have:

```
const QUERY = gql`
  query FetchCommissions {
    commissions {
      id
      name

    }
  }
`;
```

With the insertion point on the line after `name` I press Control-space but the autocomplete suggestions are generic, without any from my schema for the Commission type.

In a sibling `test.graphql` file I have the exact same query and autocomplete works as expected there (little wrench icons next to the fields from my GraphQL types).

Assignees
No one assigned

Labels
bug high-priority typescript-language-service

Projects
None yet

Milestone
No milestone

Linked pull requests
Successfully merging a pull request may close this issue.
Add support for autocomplete from ja...

15 participants
[redacted]

**Fig. 1** Issue sample

issues were addressed immediately, while unlabeled issues could remain open for a long time. They also emphasized the need for correct labeling. Previously, Herzig et al. (2013) also reported about 34% of bug reports submitted by various users are misclassified (has a wrong label). Misclassified reports can be misleading and result in a prolonged resolving process. They can cause failed task assignment and/or impact the performance of bug prediction models. This indicates the need for proper labeling of issue reports using an unbiased model.

In this study we consider two types of labels, namely *objective* and *priority* labels for an issue. Based on our label analysis (refer to Section 2.2), we take the three most frequent reasons for opening issues as the main objectives. These are *Bug* reports, *Enhancement* requests, and *Support/Document*. We also consider two priority levels, *High* and *Low*. The former should be addressed as soon as possible while the latter can be handled with less urgency. Detecting the priority level of issue reports has a two-fold gain; not only it helps with accurate and timely resource allocation for bug triaging, but also it results in less cost regarding maintenance and documentation purposes of the project. For instance, the high-priority addressed issues can be listed in release notes or other performance reports of a project.

Using a two-staged approach, we aim to predict both the objective and priority of an issue. We first predict an issue's objective by inspecting its textual information, namely its title and description. We fine-tune a pre-trained transformer-based model to classify issue objectives into three categories of Bug, Enhancement, or Support/Document. More specifically, we adapt the Robustly-optimized BERT approach (RoBERTa) (Liu et al. 2019) proposed by Facebook to our case. Our experiments indicate that using these types of textual information is sufficient for successfully predicting these objectives. In the second stage, to train our classifiers we define three sets of features, namely Textual Features, Label Features, and Normalized Features that can potentially help in predicting the importance of an issue. Textual Features include TF-IDF vectors of title and description of issues. Label Features are one-hot encoded vectors of available labels for an issue. For the third input vector, Normalized Features, we apply feature engineering methods and scale the numerical information from five different information resources including textual-based, developer-related, discussion-related, event-related, and sentiment of the issues. Finally, we train multiple classifiers for predicting the priority of an issue. We obtain the best result using a Random Forest (RF) classifier.

For the first task, we use about 817, 743 issues and train a single generic model applicable for all repositories. For the second task, we train our models in both project-based and cross-project settings using about 82, 719 issues. We evaluate our models in both tasks using standard metrics including precision, recall, F1-measure, and accuracy. Our fined-tuned RoBERTa-based classifier achieves 82% of accuracy, outperforming baseline models. Moreover, our priority prediction model scores 75% of accuracy. The results show that both project-based and cross-project prediction models for the second task perform comparably. Therefore, our model is expected to efficiently work for unseen repositories without the need for more training. Nonetheless, we conducted a human labeling and evaluation experiment to assess the proposed model's performance on new data, i.e., unlabeled issue reports from six unseen projects. Sixty issues were randomly selected from these projects. Thirty software engineers participated in our study, and we collected 300 votes for the sample set. The results indicate the high accuracy of the proposed model on unseen data. Moreover, we also asked the participants the factors they take into account while determining priority levels of issues and report their insights in this work. Our contributions are:

- We train a model to predict issue objectives (bug report, enhancement, and support) and obtain 82% accuracy. To the best of our knowledge, we are the first to adapt transformer-based models to predict labels for issue reports.
- We train project-based models for predicting the priority of issue reports using feature engineering methods and state-of-the-art text classifiers. We also train a generic model for priority prediction in a cross-project setting. This model performs on par with the project-based models with 74% accuracy.
- We conducted a human labeling and evaluation task to assess the performance of the proposed model on unseen data and achieved high accuracy (90%). We obtain Percent Agreement of 85.3% and Kappa of 0.71 which translate to a *substantial* agreement among our participants.
- We collected and pre-processed two sets of large-scale datasets with objective and priority labels from GitHub. We manually inspected synonym but differently-written

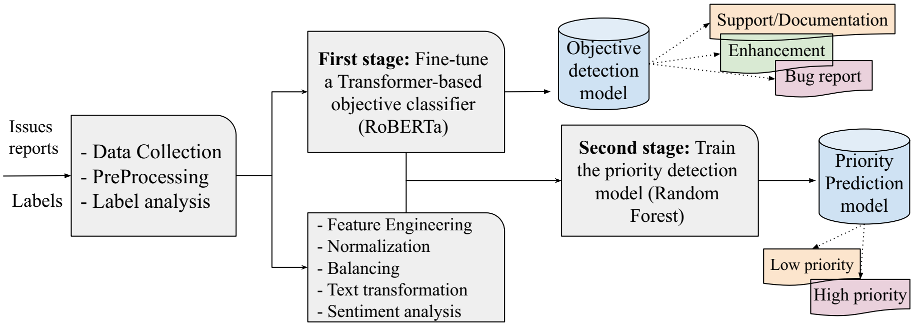


**Fig. 2** Summary of the proposed approach

labels and clustered them to mitigate the noise of user-defined tags. We release our source code and datasets for replication and use by other researchers.[1,2]

## 2 Approach

In this section, we first present an overview of our proposed approach. Then, we elaborate on each phase with more details.

### 2.1 Approach Overview

Figure 2 presents a concise summary of our proposed approach. Our two-stage approach for predicting the objective and priority of issues consists of (1) analyzing issue labels on GitHub to determine which labels to use in our training, (2) data collection and preprocessing, (3) issue-objective prediction, (4) feature engineering and model training, and finally (5) predicting priority labels.

We first collect the data of issue reports using the GitHub API.[3] Then, we extract textual information of issue reports, i.e., their title and description. We also extract all labels assigned to issues. Finally, we process and save 73 types of information from these reports (such as the author, closer, events, milestones, comments, etc.). Then we perform rigorous text processing techniques on the data.

In the next phase, we train a transformer-based classifier, to predict the objective of an issue. More specifically, we fine-tune RoBERTa (Liu et al. 2019) on our dataset. The three intended categories we use are Bug Report, Enhancement, and Support/Documentation.

In the third phase, we take the information we gathered in the previous phases and employ various NLP and machine learning techniques to train a model based on RF for predicting priority levels of issues. Finally, we use our cross-project trained model to predict the priority of issues in unseen repositories. More specifically, we conducted an experiment for human labeling and evaluation to assess the performance of the proposed model on unlabeled issues from six unseen GitHub projects. In the following sections, we provide

[1] https://github.com/MalihehIzadi/IssueReportsManagement

[2] https://zenodo.org/record/4925855#.YNME2r4zbtQ

[3] https://developer.github.com/v3/

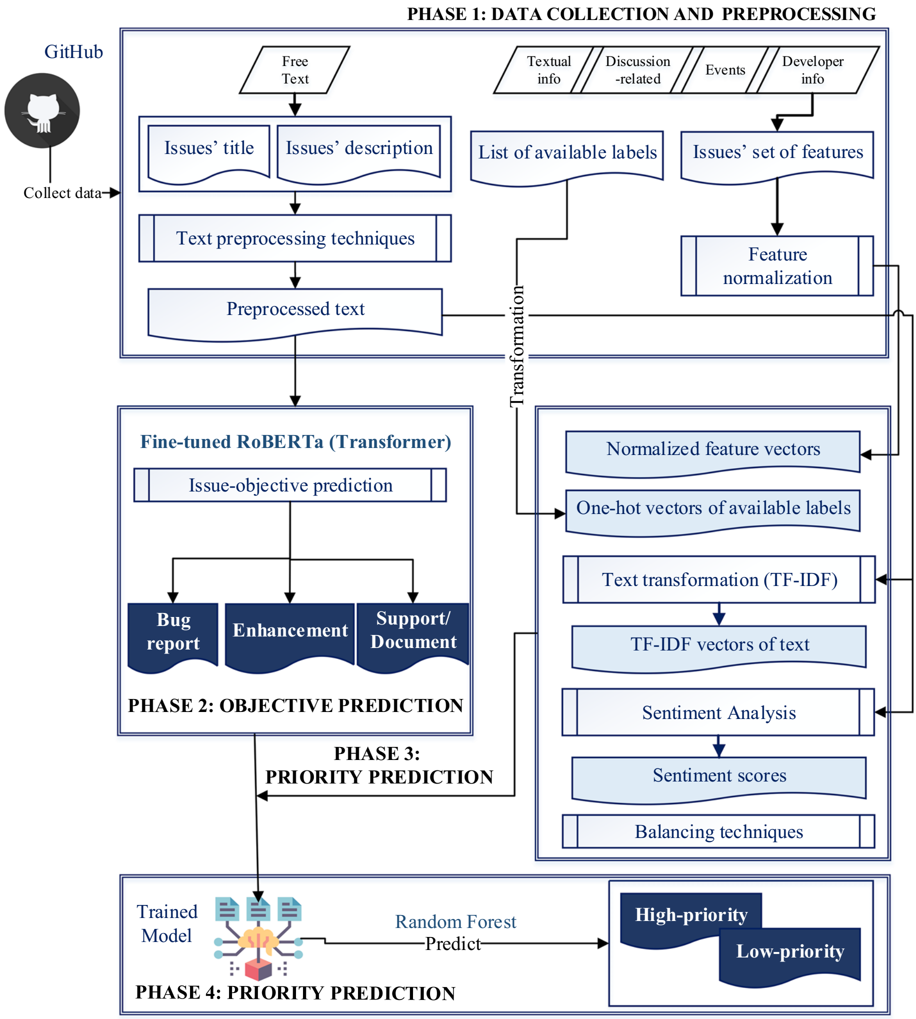


**Fig. 3** Approach workflow

more details for each step of the proposed approach. Figure 3 presents the workflow of our proposed approach with more details.

## 2.2 Label Inspection

GitHub has a set of seven default issue labels, namely `bug`, `enhancement`, `question`, `help-wanted`, `duplicated`, `wont-fix`, and `invalid`. Members can also add or modify labels to adjust to their project's needs.

To obtain a better understanding of which labels we should use for each task (objective and priority prediction), we collected labels used in the top 1000 repositories of GitHub

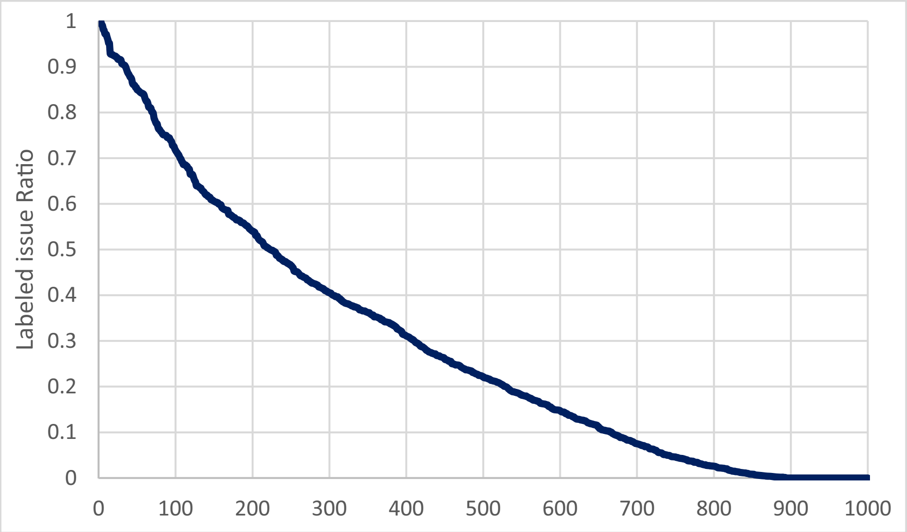


**Fig. 4** Labeled issues ratio per repository (for the top 1000 GitHub repositories)

which had at least 500 stars using the GitHub API.[4] These repositories are ranked based on their number of stars. Then two of the authors analyzed the labels. At the time we collected labels of these repositories, they had 4, 888, 560 issue reports in total, from which 2, 333, 333 had at least one label. This means approximately half of the issues of popular repositories did not have any labels. Furthermore, on average, 71% of all issue reports in each repository were unlabeled. As shown by Figure 4, only 3% of these repositories have labeled most of their issues (above 90% coverage), while about 80% of repositories have labeled less than half of their issues.

Figure 5 shows top 20 labels used in the most popular repositories of GitHub. As expected, most of these repositories already have the above-mentioned seven default labels of GitHub. So the frequency of these labels are much higher than the new customized labels defined by users. We found 6182 distinct labels in the top 1000 repositories. As shown, the frequency distribution has a long-tail. However, labels, like any other tag entity, are written in free format. Thus, the distributed nature of the tagging process results in multiple differently-written labels with a common semantic. For instance, issues opened to report bugs are tagged with labels such as `bug` and `type: bug` or issues for requesting new features are tagged with labels such as `feature`, `feature request`, and `new feature`.

Previous studies have also investigated the main categories for issue objectives (Fan et al. 2017; Kallis et al. 2019; Bissyandé et al. 2013; Cabot et al. 2015). Upon investigating issues of three million repositories, Cabot et al. (2015) concluded the most frequent issue labels in GitHub are `enhancement`, `bug`, `question`, `feature`, `documentation`, `won't fix`, and `task`. In another large-scale study on issue reports, Bissyande et al. (2013) analyzed about 800$K$ issues from which 27% were labeled. They reported that the most frequent labels in their study were `bug` and `feature`. Fan et al. (2017) conducted a study to determine whether issue reports are related to bugs or not. They used

[4] https://api.github.com/search/repositories?q=stars:>500&sort=stars

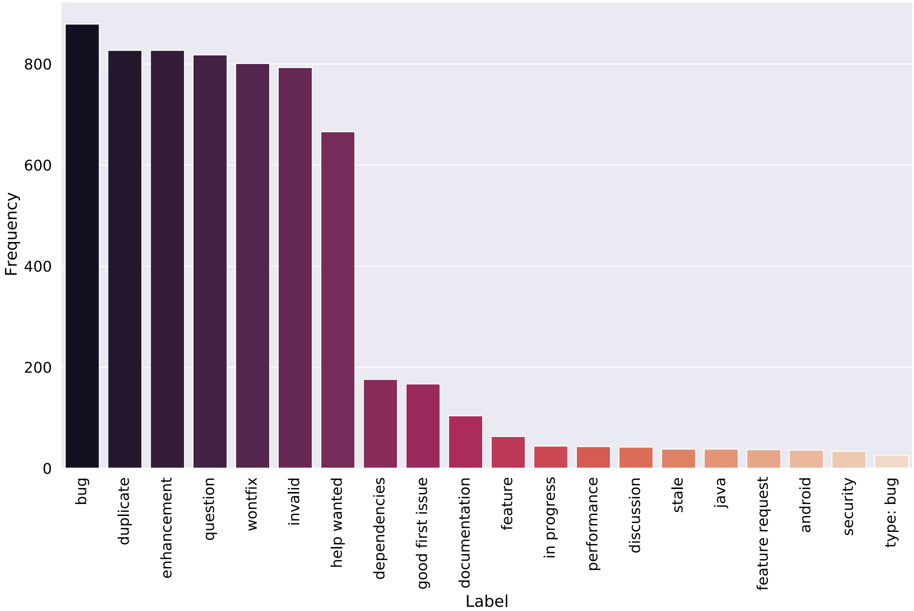


**Fig. 5** Label frequency among the top 1000 GitHub repositories

the dataset provided by Yu et al. (2015) which contained 952K issue reports from 1, 185 GitHub repositories. Among the 7, 793 labels in the dataset, 149 were identified as the labels which indicate the *type* of an issue. Over 252K issue reports (26%) in the dataset were tagged with one of these type labels. Fan et al. (2017) categorized the most frequently-used type labels into two major classes of *bug-related* (52%) and *non-bug related* (38%). The latter consists of the following labels: enhancement, feature, question, feature request, documentation, improvement, and docs. This category can be broken down to two finer categories of *Enhancement* and *Support/Documentation*. Lastly, Kallis et al. (2019) also categorized issue reports into three classes of `bug`, `feature`, and `question`. Therefore, based on our analysis and previous studies, we selected the three most-frequently-used labels for issues' objectives in the top projects as *Bug Report*, *Enhancement* and *Support/Documentation*. Next, two of the authors independently and manually identified the most related but differently-written user-defined labels as these three main objectives. In this process, authors have relied on the definitions provided by GitHub for labels.[5] Then the authors compared the categories and discussed any conflicts to validate the final decision. As a result, we collected issue reports that had at least one of the labels mentioned in Table 1 for each objective category. Note that we only use mono-labeled issues in our dataset. Thus issues tagged with more than one label are removed.

Note that there are other objectives for opening an issue, e.g., for testing, making announcements, or discussing matters in the team. However, there were less frequently used compared to our main selected categories. Moreover, among the most frequent labels, there are also other recurrent labels such as `duplicate`, `wont fix`, `invalid`, `in progress`, `good first issue`, `stale`, `java`, `android`, etc. However, these labels

[5] https://docs.github.com/en/issues/using-labels-and-milestones-to-track-work/managing-labels

**Table 1** Selected labels for each category of objective

| Category | Labels' list |
|---|---|
| Bug report | bug, defect, kind/bug, type: bug |
| Enhancement | enhancement, kind/enhancement, type: enhancement, type: improvement, improvement, feature request, feature, kind/feature, type: new feature, new feature |
| Support/ Documentation | help wanted, status: help wanted, type: support, supports, question, type: question, kind/question, docs, documentation, type: documentation, kind/documentation, information, more info needed, more info required, more-information-needed, need more info, needs info, needs more info, needs-info, needs-details |

do not address the reason behind opening an issue. They are merely other types of metadata for adding extra information. That is why we do not include these labels as issue objective.

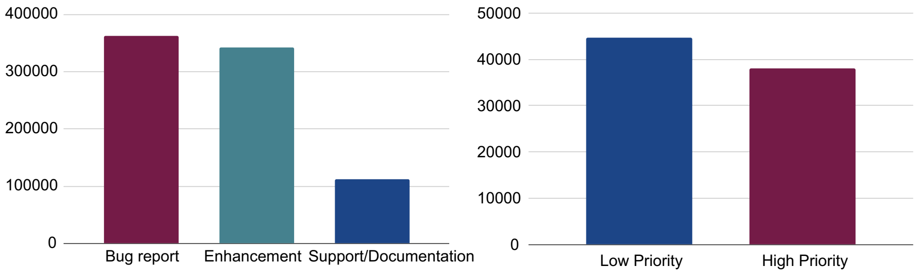
The second task which is prioritizing issues, requires issues with a priority-related label. Therefore, we inspected various priority labels including `blocker-priority`, `critical-priority`, `high-priority`, and `low-priority`. Note that priority labels are also written in different formats. For instance, we found the following labels as indicators of an issue with *critical-priority*: `criticalpriority`, `priority-critical`, `critical priority`, `priority:critical`, `priority critical`, `priority: critical`, `priority - critical`, `critical-priority`, `priority/urgent`, `priority/critical`, `critical`, and `urgent`. Thus, to find these semantically similar labels, we performed the same analysis on priority-related labels explained above, and found semantically similar but differently-written priority labels.

Moreover, in Section 2.7, we report the result of our analysis for extracting other frequent and semantically-similar labels and incorporating them in our proposed approach as an optional feature vector.

## 2.3 Data Collection

For the first task of predicting the objective of an issue, we collected closed issues from GitHub's open-source repositories with Java as their main programming language which were created before April 2021. We used Java as it was used frequently in previous studies and also to limit the number of retrieved issues. We selected three main categories of objectives, namely *Bug Report*, *Enhancement*, and *Support/Documentation* based on the labels presented in Table 1. The initial dataset for the classifying issue objectives contained 1, 096, 704 issues from 79, 729 repositories. Issues are grouped into three categories; 480$K$ bug-related issues, 528$K$ enhancement-related issues, and 173$K$ support-related issues. In the end, after performing all our pre-processing steps reviewed below, there remained 817, 743 issues from 60, 958 repositories. More specifically, we include 362$K$, 342$K$, and 112$K$ pre-processed issues belonging to the bug report, enhancement, and support/documentation categories, respectively. We denote this dataset as the *issue-objective dataset*.

For the second task we collected issues with at least one of the following four priority-related labels: `blocker-priority`, `critical-priority`, `high-priority`, and `low-priority`. We aggregate issues with labels of blocker, critical and high-priority in the same group of the crucial issues. The rest are categorized in the low-priority group.



(a) Objective categories (b) Priority categories

**Fig. 6** Class distribution

In all, we collected 47 synonyms for the two categories of High and Low priority (for the complete list refer to Appendix 1.) In the end, after pre-processing the data, we have a dataset of 82, 719 issues from 70 repositories for this task. The pre-processed dataset contains 44, 733 `high-priority` and 37, 986 `low-priority` issues. We denote this dataset as the *Issue-priority dataset*.

Figure 6 provides the distribution of objective and priority classes after pre-processing in their respective dataset for all projects. Figure 7 presents three box-plots for the number of issues in the 70 repositories of the Issue-priority dataset. HP Issues and LP Issues denote the number of issues with High-Priority and Low-Priority labels, respectively. Figure 8 depicts the ratio of HP to LP labels of issue reports (*HP*/*LP*) per project in this dataset. Although the average *HP*/*LP* ratio is 1.00, this ratio per project ranges from 0.16 to 6.40. That is for some repositories, the HP class is more represented, while for others, the LP class is more supported.

## 2.4 Pre-processing

Each issue has two main textual information sources, namely title and description. To train our models, we create a feature vector for both of them based on the following pre-processing steps.

Filtering and cleaning We first remove issues that have very little (less than three characters) or no text in their title or description. We also remove issues that are tagged as `not an issue` or *duplicate* issue reports to prevent biasing our models. Then, we filter out issue reports that are written in a non-English language (more than 50% of the text). Then, we clean issues' textual information by removing arbitrary digits, non-ASCII characters, and punctuation marks. Note that we retain question marks as they are mainly used in questions and support-related issues. Thus, they can be helpful for predicting this class.

Text normalization Handling large vocabularies is a challenging task in NLP-based researches. Generally, studies limit vocabulary to the most common words and replace out-of-vocabulary tokens with a special unknown token <`UNK`>. To reduce out-of-vocabulary tokens, we normalize issue reports' textual information using several normalization rules. More specifically, we replace *abstract concepts* such as *user-names*, *code snippets*, *function calls*, *markdown* symbols, *emails*, *URLs*, *paths*, *dates*, and *times* using regular expressions. The intuition is that including the exact content of these concepts increases the size of our vocabulary, however, by performing text normalization we can both keep the notion of having e.g., a code snippet in an issue and remove the exact characters of that code snippet to

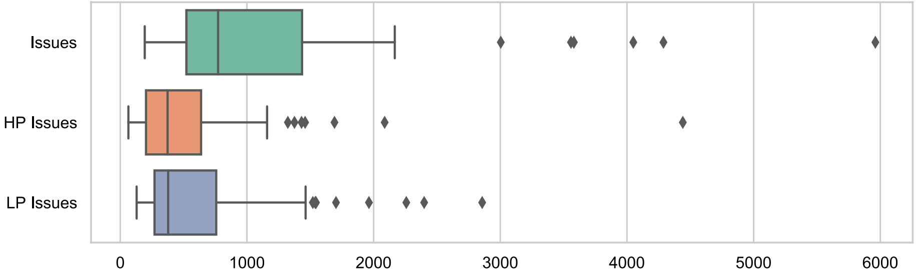


**Fig. 7** Distribution of LP and HP issues among repositories

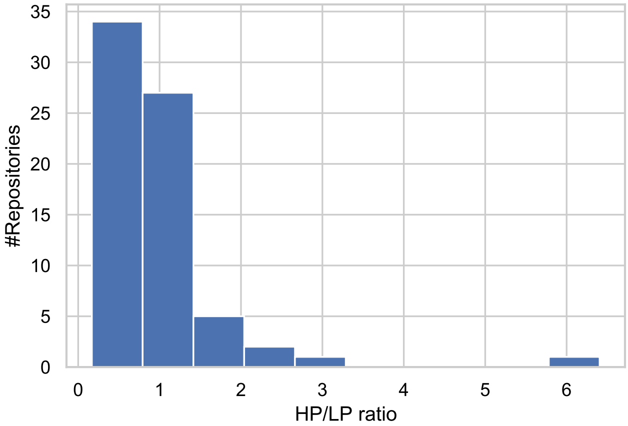


**Fig. 8** Histogram of HP/LP ratio per project

help our models learn better. To achieve this, we replace the content of a code snippet with an abstract token <CODE>. We apply the same technique to the rest of the above-mentioned concepts as well. Text normalization has been used before in pre-processing data for machine learning models (Svyatkovskiy et al. 2020; Izadi et al. 2021).

Tokenization and lemmatization We split tokens based on several naming conventions including SnakeCase, camelCase, and underscores using an identifier splitting tool called *Spiral*.[6] This will also mitigate the out-of-vocabulary problem. Using NLTK library[7], we first tokenize the text of issue reports, then we remove frequently used words in the language called stop-words which do not bring any value to the models. Note that we keep negative words such as NOT and compulsory words such as MUST, which can be useful for the sentiment analysis phase. We then lemmatize the pre-processed text to reduce grammatical forms but retain their correct word formats.

Transformation The final step is to transform the textual information of issues to their mathematical representation that can be fed to the machine learning models. We convert the collection of pre-processed issues' text to a matrix of TF-IDF vectors. More specifically,

[6] https://github.com/casics/spiral.

[7] https://www.nltk.org/

we represent each issue title and description as a vector where each word is a feature. Note that we generate their TF-IDF embedding vectors separately, then we concatenate these two vectors for each issue. The simpler approach would be to first concatenate the text of these two sources and then build the embedding vectors. However, our experiment yielded better results when taking title and description TF-IDF vectors separately. This is probably due to the fact that although both title and description are inherently textual information describing an issue, their abstract level and objective differ. Interestingly, our machine learning models were capable of picking up on this difference. It is worth mentioning we also experimented with Doc2Vec and Word2Vec embeddings. However, TF-IDF vectors yielded the best results, thus we only report them in this work.

## 2.5 First stage: Objective Detection

Previously, we obtained and pre-processed our issue-objective dataset. In this step, we train our classifier for the first stage of our approach. To predict issue objectives (Bug report, Enhancement, or Support/Document), we train a transformer-based model on the issue-objective dataset. We fine-tune the RoBERTa (Liu et al. 2019) on our issue-objective dataset. RoBERTa includes pre-training improvements (compared to the vanilla BERT model Devlin et al. 2018) using only unlabeled text from the web, with minimal fine-tuning and no data augmentation. The authors modified the masked language modeling task of BERT by using dynamic masking based on a new masking pattern generated each time a sentence is fed into training. They also eliminated the next sentence prediction task since Facebook's analysis indicated that it indeed hurts the model's performance. The Input of our model is the concatenated pre-processed word vectors of title and description of issues. In this stage, we feed the models with pre-processed text (word vectors) and the models process them accordingly. The output of the first stage is the probability of an issue to be a Bug report, Enhancement, or Support.

## 2.6 Sentiment Analysis

Sentiment analysis uses computational linguistics and NLP techniques to quantify the intended sentiment of a piece of text. We believe more urgent issues hold more distinct sentiment, and use sentiment analysis methods to extract this information from textual information of issues. We use *SentiStrength* which quantifies the strength of positive and negative sentiment[8] in text. SentiStrength reports two scores in the range of (−1, −5) with −5 for extremely negative sentiment, and (1, 5) with 5 as the extremely positive sentiment. Psychology research claims that we process positive and negative sentiment at the same time. Thus, SentiStrength reports both sentiment scores (positivity and negativity). We apply SentiStrength on both issues' titles and descriptions and analyze these features in our feature selection process.

We also use TextBlob, a library that quantifies sentiment in terms of two measures of subjectivity and polarity.[9] It reports a tuple of *Sentiment*(*polarity*, *subjectivity*). Polarity range is $[-1, 1]$ and subjectivity range is [0, 1] with 0 as completely objective and 1 as

[8] http://sentistrength.wlv.ac.uk/

[9] https://textblob.readthedocs.io/en/dev/

**Table 2** Semantically similar clusters of issue labels

| Representative | Semantically similar labels |
|---|---|
| Duplicate | duplicate, status/duplicate, status: duplicate, status:duplicate, status=duplicate, status-duplicate, type:duplicate, was:duplicate, resolution:duplicate, resolution/duplicate, duplicate issue, t-duplicate, r: duplicate, closed: duplicate, kind/duplicate, type: duplicate |
| Won't fix | won't fix, wont fix, wontfix, wont-fix, status: won't fix, will not fix, resolution:won't fix, status=will-not-fix, closed: won't fix, state:wont-fix, status: will not fix, won't-fix, will-not-fix, cant-fix, cantfix, can't fix |

completely subjective. Same as the above, we use this library on the title and description of issues and use them in the feature selection process.

## 2.7 Label Clustering

Labels are free-format text. Thus, users can use different word formats for semantically-similar concepts. Clustering the morphological synonym labels as a form of issue label management can boost the performance of machine learning models which takes these labels as inputs. However as shown in Section 2.2, the number of distinct user-specified labels is high. To be able to decrease issue labels' space, two of the authors manually analyzed the collected labels from the top 1000 repositories, and found several clusters of semantically similar labels. Based on our investigation, we selected the most 66 frequently-used labels in GitHub and then extracted their synonyms but differently-written labels to build a dataset of clusters of labels. Table 2 shows two sample identified clusters.[10]

We use representatives of these clusters as one of our feature sets. More specifically, we build a one-hot vector with a size of 66, in which each element denotes the presence of one of the label clusters. In the model construction phase, we concatenate this label vector with the TF-IDF embedding vector of textual information of an issue and the selected features' normalized vector and feed the final vector to our model.

## 2.8 Feature Extraction And Categorization

Before training our prioritizer classifier, we performed feature selection. Feature selection is the process of selecting a subset of relevant predictors to feed to the machine learning model. These techniques are usually employed to simplify models, provide better interpretation, avoid overfitting by providing more generalizable models, and achieve a shorter training time (Dash and Liu 1997).

[10] A complete list of these 66 clusters is available in our repository.

**Table 3** Selected features for prioritizing issue reports

| Category | Feature | Description |
|---|---|---|
| Textual information | title-words | Number of words in the title of an issue. |
| | desc-words | Number of words in the description of an issue |
| | code | Number of code snippets in the description of an issue |
| | url | Number of URLs in the description of an issue |
| Discussion | comments | Number of comments in the discussion |
| | cm-mean-len | Average length of comments in an issue |
| | cm-developers-ratio | The ratio of number of comments to number of developers engaged in the discussion |
| | time-to-discuss | The time span of the discussion |
| Events | events | Number of events that happened to an issue[a] |
| | assigned | Is an issue assigned to a team member? |
| | is-pull-request | Is an issue a Pull Request? |
| | has-commit | Does an issue have any referenced commit? |
| | has-milestone | Does an issue have a milestone? |
| | labels | Number of labels assigned to an issue |
| Developer | author-followers | Number of followers of the author of an issue |
| | author-following | Number of GitHub users the author follows |
| | author-public-repos | Number of public repositories of the author of an issue |
| | author-public-gists | Number of gists of the author of an issue |
| | author-issue-counts | Number of issues opened by the author of an issue |
| | author-github-cntrb | Number of contributions of the author of an issue in GitHub |
| | author-account-age | The age of the author's GitHub profile account |
| | author-repo-cntrb | Number of contributions of the author to the current repository |
| | association | Association type of the author i.e., Collaborator, Contributor, Member, Owner, None |
| | same-author-closer | Are the author and closer same people? |
| Sentiment | desc-positivity | Positive sentiment score of the description of an issue |
| | desc-negativity | Negative sentiment score of the description of an issue |

**Table 3** (continued)

| Category | Feature | Description |
|---|---|---|
| | desc-pos-polarity | Positive polarity score of the description of an issue |
| | desc-subjectivity | Subjectivity score of the description of an issue |

[a] A complete list of all issue events is available at https://developer.github.com/v3/issues/issue-event-types/

Two of the authors manually inspected issue reports and extracted a list of 73 potential features which could affect the importance of issue reports. These features included (but are not limited to) information about textual length of an issue, author of an issue, the closer of an issue, were the author and closer the same people, the amount of discussion an issue has attracted, how long the discussions took, the sentiment of the discussions, number of events on the issue, does it have a commit, milestone, or assignee, is it a Pull Request, and many more. Each of these features can potentially affect the outcome. For instance, experienced developers are more likely to report or close important issues. A heated and/or long discussion can be an indication of urgent matters being discussed by the team members. For each opened Pull Requests, an issue is opened automatically (Kalliamvakou et al. 2014). Pull Requests can be considered as important issues. In fact using GitHub API when collecting the dataset, one can choose to retrieve only issues and exclude Pull Requests or retrieve all of them together. Considering the tight relationship of issues and Pull Requests, we decided to keep Pull Requests when collecting the data. Note that Pull Requests can also be investigated separately using their specific features and applications (Gousios et al. 2015; Veen et al. 2015). Therefore, we compute the correlation of these features, draw their heat map (filter-based selection), perform two wrapper-based selection methods, namely backward and recursive feature elimination approaches to analyze these features and remove rudimentary ones. In the end, we choose 28 features and categorize them into five groups of *textual-*, *discussion-*, *events-*, *developer-*, and *sentiment-related* features. Table 3 summarizes these features. Our analysis showed text length and the existence of code snippets and URLs inside the description can help the model. For the discussion-related features, we include four features, namely number of comments, the average length of comments, the ratio of the number of comments to the number of engaged developers in the discussion, and discussion time. For the events-related category, we include six features: the number of all events, the fact that whether this issue is assigned, does it have a milestone already, is it a Pull Request, does any commit reference this issue, and finally, how many labels does it have. For the developer-related category, we use ten features including various information about who has opened the issue, their reputation and number of followers/followings, their experience and contribution to this project and GitHub in general, their association, that is, whether they are a team member or merely a GitHub user, their profile age and whether the author and closer are the same users or not. Because the author and closer information have a high correlation score (above 80%) in our dataset, we do not include *closer information* separately.

## 2.9 Feature Normalization

As the value of our features selected in the previous step vary in degrees of magnitude and range, we perform feature normalization. machine learning algorithms such as Logistic Regression (LR) and Neural Networks that use gradient descent as an optimization technique require data to be scaled. Furthermore, distance-based algorithms like K-Nearest Neighbors (KNN), and Support Vector Machines (SVM) are affected by the range of features. This is because they use distances between data points to determine their similarity. We use the *Min-Max scaling* technique in which values of features are re-scaled to be in the fixed range of 0 and 1 (Al Shalabi et al. 2006). We apply Min-Max scaling using Equation 1 where $X_{max}$ and $X_{min}$ are the maximum and the minimum values of a feature, respectively. We apply this technique to all our selected numerical features from the previous section.

**Table 4** Inputs to our models in both stages

| Stage | Inputs |
|---|---|
| Objective detection | - Word vectors of issue titles,<br>- Word vectors of issue descriptions. |
| Priority prediction | - TF-IDF vectors of issue titles,<br>- TF-IDF vectors of issue descriptions,<br>- Predicted objective of issues from the first stage,<br>- One-hot encoded vector of available labels,<br>- Normalized feature vector (containing five different set of information, namely textual information, discussion-related, developer-related, events-related, and sentiment scores). |

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

### 2.10 Balancing Techniques

A training dataset is considered to be imbalanced if one or more of the classes are represented by significantly less number of samples (issues) compared to other classes. This leads to skewed data distribution between classes and can introduce bias into the model (Weiss and Provost 2001). Therefore, we employ two balancing techniques to improve the performance of our models. We first assign higher weights to the less-represented classes. The classifier is penalized based on these weights when it misclassifies issues. The weight vector corresponding to our classes is calculated using Equation 2, where $N$ is the number of issues in the whole dataset and $frequency_{t_i}$ is the number of issues per class. Second, we use the Synthetic Minority Oversampling Technique (SMOTE) (Chawla et al. 2002) to augment (over-sample) the minority classes.

$$weight_{t_i} = \frac{N}{frequency_{t_i}} \tag{2}$$

### 2.11 Second Stage: Priority Prediction

We train our classifiers for the second stage of our approach. To predict the priority level of issues, we use our issue-priority dataset. The input of the model in this phase consists of three different types of feature sets obtained from previous steps and explained below. Table 4 summarizes the input to our model.

- **Textual Features (TF)**: First part of the input is the concatenated TF-IDF vectors of title and description of an issue. We fit our TF-IDF vectorizer on the training dataset. Later we use the same vectorizer to transform the test dataset. We set the maximum number of features for title and description vectors to 10$K$ and 20$K$. The objective label of an issue which is the output of the first stage of the proposed approach is also included. Moreover, we set ngram range to (1, 2).

- **Labels Features (LF)**: The second feature set is the one-hot vector of available labels for an issue computed in Section 2.7.
- **Normalized Features (NF)**: And the third part of the input is the normalized version of our engineered features obtained in Section 2.9. The complete list of selected features is provided in Table 3. We also include sentiment scores in this set.

We use RF as the selected classifier in this phase. RF has been shown to perform better on tabular data. We configure the model parameters using *Random Search* algorithm (Bergstra and Bengio 2012), that performs an exhaustive search of the hyper-parameter space. The output of the second stage is the probability of an issue being High or Low. Note that we use the two balancing techniques presented in Section 2.10 to improve the performance of our classifier, for the project-based setting, where for some repositories, the ratio of labels is very unbalanced.

## 3 Experiment Design

We conduct various experiments to validate the proposed approach. An experiment is designed to analyze the performance of the issue-objective predictor model. For the priority prediction task, we analyze the model in both project-based and cross-project settings. Our priority prediction model has two applications: (1) to prioritize open or closed issues to facilitate timely task assignment and better project management, (2) to help select important issues for inclusion in the periodic documentation of the project, e.g., to automatically select important changes for inclusion in release notes. It is worth mentioning that all issue features in both experiments of the project-based and cross-project settings for the priority prediction task are calculated after issues are closed. However, a possible future research direction is to design an experiment for training and evaluating the priority prediction model through collecting dynamic features periodically. We also conduct a human labeling and evaluation experiment on unlabeled issues.

We use the datasets presented in Section 2.3. We split them to train, and test sets with ratios of 80%, and 20%. Note that we use stratified sampling on the target value to randomly select these datasets to reduce sampling biases and retain the similar class distribution in train, test, and the whole dataset. On smaller datasets, we also incorporate the cross-validation technique.

We conduct our experiments on a machine with Ubuntu 16.04, 64-bit, GeForce RTX 2080 GPU, Intel(R) Xeon(R) CPU E5-2690 3.00GHz and 64.0GB RAM. Next, we present our Research Questions (RQ) and the performance metrics for evaluating our model on the collected datasets.

### 3.1 Research Questions

In this study, we investigate the following research questions:

- **RQ1**: How accurately our model predicts the objective behind opening an issue? We train a text classifier on a large-scale dataset of 818K issue reports to investigate how accurately we can predict the objective of an issue. The list of objectives that we con-

sider in this phase are among the most-used labels in GitHub, namely Bug, Enhancement, and Support.
- **RQ2**: How accurate is our priority prediction model in a project-based context? We train classifiers for each repository separately. The goal is to predict the importance of an issue. This predicted label can then be used for prioritizing team resources for solving the high-priority issues or used for documentation purposes of the project. One use case of the latter are release notes (or any other types of reports). That is, team managers, tasked with writing reports of each release, can use the model to extract the urgent issue reports addressed by the team for that release.
- **RQ3**: How accurate is our priority prediction model in a cross-project setting? That is how well does our trained classifier performance transfer to other repositories? We investigate the previous research question but in a cross-project setting. We train our model on 80% of repositories and investigate how well this generic model predicts the priority label of issues from other repositories?
- **RQ4**: How does the priority prediction model preform on unlabeled data? We conduct human labeling and evaluation to assess the performance of the priority detection model trained in a cross-project context on unlabeled issues from unseen GitHub projects. Moreover, through an open question, we ask what are the factors participants take into account when categorizing issues into high and low priority.

## 3.2 Evaluation Metrics

We use standard measures for evaluating classifiers, namely *precision*, *recall*, *F1-score*. We also report *accuracy* which is the ratio of correct predictions, both true positives (TP) and true negatives (TN), to the total number of cases examined. TP indicates the number of truly X-labeled issues that are classified as X. FP is the number of truly Non-X issues that are classified as X. True Negative (TN) denotes the number of truly Non-X issues that are classified as Non-X. And False Negative (FN) indicates the number of truly X-labeled issues that are classified as Non-X. Equations 3, 4, 5, and 6 compute the above measures.

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{3}$$

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{4}$$

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{5}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{6}$$

## 3.3 Baselines

For both tasks, we include baselines from a wide range of rule-based and learning-based solutions.

For the first task, objective detection, we train several supervised machine learning-based models on a large-scale dataset of pre-processed 818K issue reports to predict their objective (Bug Report, Enhancement, or Support/Documentation). We use TicketTagger (Kallis et al. 2019; Song and Chaparro 2020) and Intention-mining (Huang et al. 2018) as the baselines for this task. Moreover, we train two more classifiers based on Multinomial Naive Bayes and Bidirectional Long Short Term Memory (BiLSTM) deep neural networks that are usually used for text classification as complementary baselines. The latter is inspired by the study of Li et al. (2019) for tag recommendation in software information sites. Finally, we also implement a keyword-based approach to include simpler rule-based solutions in the experiment. In this baseline, the model looks for specific keywords related to the three categories above and tags them with their respective label. For example, if the issue contains words such as *crash* and *fix*, it will be labeled as a bug report.

For the second task, priority prediction, we include baselines which are all vanilla (standard) versions of classical Machine Learning models, namely KNN, Multinomial NB, Logistic Regression and RF. Furthermore, we add several simpler models based on the date of issues or number of comments to the list of the baselines for this task. For instance, for the “Most Comments” baseline, we calculate the median number of comments for issues. We then proceed to tag those with a higher number of comments than the median value with HP and the rest with LP labels. Finally, we also include the proposed approach by Dhasade et al. (2020), *Issue Prioritizer*, for this task.

### 3.4 Human Labeling And Evaluation: Setup

We designed an experiment to investigate whether the trained model in the cross-context setting can be used successfully for labeling *unlabeled* issue reports. As this experiment is designed to assess the performance of the proposed model on unlabeled issues, we do not have the ground truth labels to compare against. Thus, we employ a *partially objective labeling task* (Alonso et al. 2014), a crowd-sourced labeling task in which the label (High or Low Priority) of a subject (issue report) is determined based on inter-rater agreement among the participants. That is, a given issue report is assigned the label which the majority of raters have given it. We then compare these majority-vote labels with the labels generated by our priority detection model.

We provided general information about each project for the participants to help them make informed decisions. This information includes the project’s goal, description, #stars, #forks, #contributors, #closed and #open issues, and median response time by the developers of the project to its issues. Furthermore, participants were instructed to analyze the assigned repository and its main characteristic to get familiar with the project. We asked the participants to assess ten issues of a given project and assign a High or Low priority label to each one based on the characteristics of the project. Next, with an open question, we asked what factors participants took into account while tagging the issues.

Projects We randomly selected 60 issue reports from six unseen GitHub projects (ten issues per project). The list of projects is as follows. They were selected based on their popularity, and the variety in their sizes. Moreover, all projects’ main programming language is Java.

- **Elasticsearch**: Free and Open, Distributed, RESTful Search Engine,
- **Spring Boot**: Spring Boot makes it easy to create stand-alone, production-grade Spring based Applications that you can just run,

**Table 5** RQ1: objective detection results

| | Evaluation metrics | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Accuracy | Precision | | | Recall | | | F1-score | | |
| Model / Classes | | B | E | SD | B | E | SD | B | E | SD |
| Keyword-based | 26% | 66% | 63% | 26% | 39% | 15% | 19% | 49% | 25% | 22% |
| Multinomial NB | 73% | 79% | 71% | 62% | 75% | 83% | 37% | 77% | 77% | 47% |
| Bi-LSTM | 68% | 71% | 71% | 48% | 77% | 72% | 34% | 74% | 72% | 40% |
| CNN (Huang et al. 2018) | 73% | 74% | 73% | 54% | 80% | 77% | 32% | 77% | 75% | 41% |
| FastText (Kallis et al. 2019; Song and Chaparro 2020) | 76% | 78% | 77% | 67% | 82% | 80% | 46% | 80% | 78% | 54% |
| Proposed approach | **82%** | **84%** | **83%** | **72%** | **86%** | **84%** | **62%** | **85%** | **84%** | **67%** |

- **OkHttp**: Square's meticulous HTTP client for the JVM, Android, and GraalVM,
- **RxJava**: Reactive Extensions for the JVM; a library for composing asynchronous and event-based programs using observable sequences for the Java VM,
- **Retrofit**: A type-safe HTTP client for Android and the JVM,
- **Guava**: Google core libraries for Java.

Participants As we did not have access to the main developers of these projects, we invited 62 software engineers from both industry and academia to participate in this study. Each participant was assigned to the issues of one project. Thirty-four software engineers responded and participated in the study from which 30 responses were valid (25 males and 5 females). Thus our response rate is 48%. All participants have a BSc or MSc in software engineering with an average of 4.8 years of developing experience. They all are proficient with the programming language Java. In addition, on average the participants own or contribute to 6.52 open-source projects on GitHub.

Inter-rater Reliability Measurement Inter-rater reliability is the level of agreement among independent observers who label, code, or rate the same phenomenon (Gwet 2008). Several statistics can be used to measure inter-rater reliability, from which the most common are *Percent Agreement*, *Cohen's kappa* (for two raters), and *Fleiss kappa* as an adaptation of Cohen's kappa for three or more raters (Fleiss and Cohen 1973). To compute the Percent Agreement score among the participants, we create a matrix in which the columns represented the different labelers, and the rows represent issue reports. The cells of this matrix contain the label (category) the labelers entered for each issue. As we only have two labels (High and Low Priority), we fill the cells with either 0 (Low Priority) or 1 (High Priority) For each row, we calculate the Percent Agreement and then report the average. Percent agreement ranges between 0 and 1, with 0 as no agreement and 1 as perfect agreement. Kappa determines the extent to which the observed amount of agreement among labelers surpass the expected value if all labelers tagged issues completely randomly. Two variations of kappa for multi-raters (more than two) are Fleiss' fixed-marginal multi-rater kappa (Fleiss 1971) and Randolph's free-marginal multi-rater kappa (Randolph 2005). Marginal distributions are considered to be *free* when the quantities of cases that should be distributed into each category are not predefined. As our labelers are not forced to assign a fixed number of issues to each label (category) we report Randolph's free-marginal kappa score for this experiment (Brennan and Prediger 1981) Values of kappa can range from

−1.0 (perfect disagreement below chance), to 0 (agreement equal to chance), to 1.0 (perfect agreement above chance). The kappa will be higher when there are fewer categories. Landis and Koch (1977) suggest the following system for interpreting kappa values:

- less than 0 as poor agreement,
- 0.01 − −0.20 as slight agreement,
- 0.21 − −0.40 as fair agreement,
- 0.41 − −0.60 as moderate agreement,
- 0.61 − −0.80 as substantial agreement, and
- 0.81 − −1.0 as almost perfect agreement.

## 4 Experiment Results

In the following, we report the results of our experiments and the answer to our research questions.

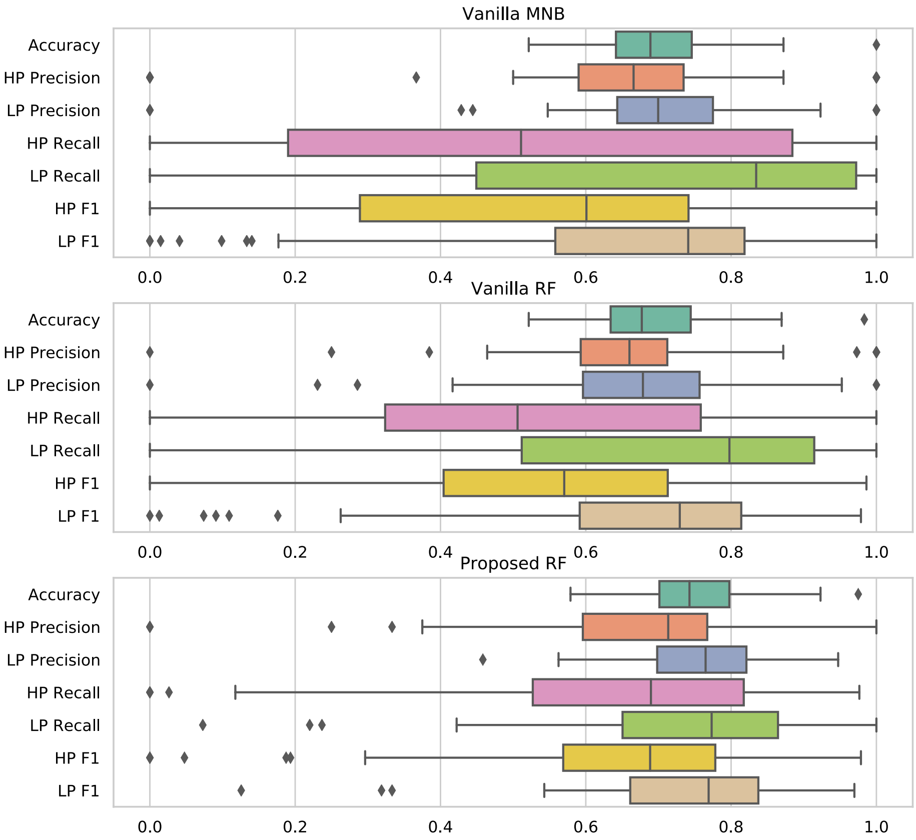
### 4.1 RQ1: Issue Objective Detection

Table 5 reports the results of objective-prediction task. *B*, *E*, and *SD* represent Bug Report and Enhancement and Support/Documentation classes. As presented, our proposed approach indeed has a high accuracy for predicting issue-objective labels. We successfully outperform all the baselines regarding all the evaluation metrics. For instance, regarding the F1-score of the Support class, we outperform BiLSTM, Multinomial NB, CNN (Intention mining), and FastText (TicketTagger and BEE) -based classifiers by 204%, 66%, 43%, 63%, and 24%, respectively. The keyword-based approach does not achieve sufficient accuracy. That is probably because an issue can contain prominent but conflicting keywords. For instance, a user can describe a bug but does not use the bug-related vocabulary explicitly, hence misleading such simple models. Furthermore, although Huang et al. (2018) use a deep model for classification, it is not performing very well in our case as is. The problem can be due to the fact that their model is designed and optimized to predict the goal of each sentence of an issue report separately. As we have not adapted the architecture of their approach to our goal, it may not be suitable for predicting the objective of a complete issue report. However, it can provide preliminary analysis on using different Convolutional deep neural networks in classifying issues. Finally, the BiLSTM-based deep model also does not perform well in our case and it takes a very long time to train as expected when training Recurrent Neural Networks on large datasets. On the contrary, the inherent parallelization of Transformers' architecture allows our proposed approach to be trained much faster along providing better results.

While we outperform all the baselines for all classes, our model too seems to struggle for the *Support/Documentation* class (compared to the other two classes; Bug report, and Enhancement). This is probably due to several reasons including (1) this class is under-presented in our dataset (less number of issues), and (2) the objective behind opening issues in this category is inherently more diverse. As described in Section 2.3, we include various issues tagged by labels such as *question*, *support*, *help*, etc. in the Support/Documentation category. While Kallis et al. (2019) only consider issues tagged with the label *question* as their third class, our goal is to cover a broader range of issue reports in the third class and provide a more generic objective classifier. It is also worth mentioning, usually fixing

**Table 6** RQ2: Project-based priority prediction results

| | Evaluation metrics | | | | | | |
|---|---|---|---|---|---|---|---|
| | Accuracy | Precision | | Recall | | F1-score | |
| Models / Classes | | HP | LP | HP | LP | HP | LP |
| Oldest | 48% | 43% | 52% | 48% | 47% | 44% | 49% |
| Recently updated | 48% | 44% | 53% | 48% | 50% | 45% | 50% |
| Most comments | 50% | 46% | 54% | 64% | 39% | 52% | 44% |
| Issue Prioritizer (Dhasade et al. 2020) | 55% | 58% | 53% | 51% | 61% | 54% | 57% |
| KNN | 67% | 63% | 69% | 64% | 70% | 63% | 68% |
| Multinomial NB | 69% | 68% | 69% | 63% | 77% | 60% | 69% |
| Logistic Regression | 70% | 69% | 71% | 66% | 76% | 64% | 71% |
| Vanilla RF | 69% | 69% | 69% | 65% | 75% | 63% | 70% |
| Proposed approach | **75%** | **73%** | **77%** | **74%** | **78%** | **72%** | **77%** |


Vanilla MNB

Vanilla RF

Proposed RF

**Fig. 9** Distribution of results among 70 repositories for three approaches

existing bugs or implementing requested features are of more value to the community,

**Table 7** RQ3: cross-project priority prediction results

| | Evaluation metrics | | | | | | |
|---|---|---|---|---|---|---|---|
| | Accuracy | Precision | | Recall | | F1-score | |
| Models / Classes | | HP | LP | HP | LP | HP | LP |
| Oldest | 47% | 43% | 51% | 47% | 47% | 45% | 49% |
| Recently updated | 50% | 46% | 54% | 50% | 50% | 48% | 52% |
| Most comments | 50% | 47% | 55% | 53% | 49% | 50% | 52% |
| KNN | 57% | 47% | 63% | 38% | 71% | 42% | 67% |
| SVM | 58% | 47% | 64% | 43% | 68% | 45% | 66% |
| Logistic Regression | 57% | 46% | 64% | 45% | 65% | 46% | 64% |
| Multinomial NB | 62% | 55% | 66% | 40% | 78% | 46% | 71% |
| Issue Prioritizer (Dhasade et al. 2020) | 55% | 55% | 55% | 50% | 60% | 53% | 57% |
| Vanilla RF | 57% | 46% | 63% | 43% | 67% | 44% | 65% |
| Proposed approach | **74%** | **70%** | **75%** | **59%** | **83%** | **64%** | **79%** |

thus, we believe better performance on the first two objectives (bugs and enhancement) is deemed more important. Nonetheless, one can improve these models' performance by collecting more data for this class or narrowing down the objective of this class. It is worth mentioning that we investigated the use of various additional features for this task. As the results did not improve significantly, we decided to keep it simple for the first stage and only incorporate textual information of issues.

## 4.2 RQ2: Project-Based Priority Prediction

In this experiment, we train our proposed approach per repository to predict the priority of their issues. As discussed in Section 2.11, we have three sets of input features, namely TF, LF, and NF and experimented with different combinations of them. For each repository, we take 80% of its issues as the train data and test the model on the remaining 20%.

Table 6 reports the results of the project-based priority-prediction task on these 70 repositories. As mentioned before, *HP* and *LP* represent High-Priority and Low-Priority classes. As there are various feature sets attributed to an issue report, we investigated the use of different variations of these feature sets and report the best case below. The results indicate integrating selected features (refer to Section 2.11) helps training a better model. As shown, our proposed approach based on RF with all the three input feature vectors (NF, LF and TF) outperforms all the baselines. This indicates the benefit of integrating other features, and employing normalization, balancing, and optimization techniques. Lastly, our experiments also show both of the balancing techniques proposed in Section 2.10 perform comparably.

Figure 9 provides three sets of box-plots for three approaches including two baselines and one of our proposed approaches based on RF. The box-plots report the distribution of results per repository and based on all the evaluation metrics. Comparing vanilla Multinomial NB and our approach, it is clear that enriching these classifiers with the advance techniques mentioned in Section 2.11 cause the model to perform more consistently. For instance, take the box-plot for the recall metric (for the HP class) provided by Multinomial NB and our approach. Our approach scores above 50% for all repositories, while the

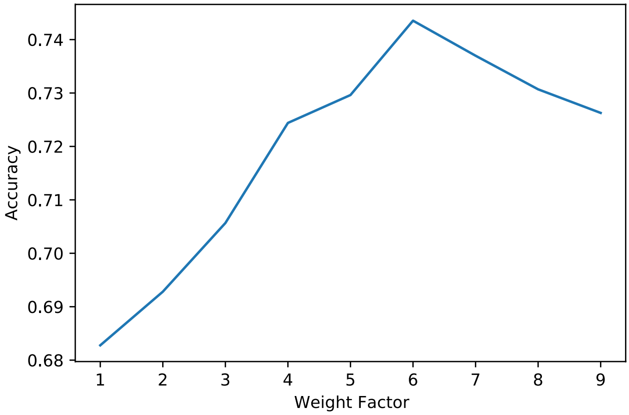
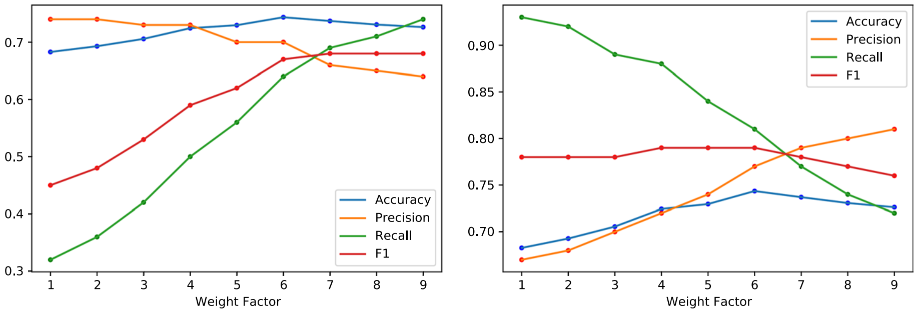


**Fig. 10** The impact of class weights on total accuracy



(a) HP class

(b) LP class

**Fig. 11** The impact of changing class weights per class

Multinomial NB performance fluctuates for different repositories with the first quartile as low as 20%. The first quartile for all the metrics and all the repositories are above 50% in our approach. Moreover, comparing the vanilla RF with our enriched version of RF, one can see that the latter shifts the results of all metrics to higher scores. Therefore, we are able to successfully outperform the baselines regarding different evaluation metrics.

### 4.3 RQ3: Priority Prediction In Cross-Project Context

We also train a generic model on issues from 80% of repositories and evaluate this model on the rest of the repositories. Our goal is to investigate whether a generic model trained in a cross-project setting can perform on par with project-based models. Table 7 reports the results of priority-prediction task in the cross-project context. Based on the results, our proposed approach based on RF with the two feature inputs (NF, and LF) outperforms all other models. This generic model can indeed perform comparably with the average performance of project-based models. Therefore, we can train only one generic model to automatically predict the priority of issues and successfully reuse (and/or retrain) it for unseen repositories or repositories with little historical data. It is worth mentioning that in our case, TF-IDF vectors provide more information to these models compared to Doc2Vec and Word2Vec vectors.

### 4.3.1 Feature Importance

Using RF, we derived the importance of 28 features listed in Table 3 (NF feature vector). The five most important features are *time_to_discuss*, *cm_mean_len*, *desc_words*, *desc_subjectivity*, and *desc_pos_polarity*. The least important five features are *numeric_association*, *code*, *has_commit*, *same_author_closer*, and finally *is_pull_request*. Moreover, the five most important features from the LF feature vector are *bug*, *feature*, *documentation*, *stale*, *usability*, *won't fix*. The least five features from this vector are *weekly-report*, *announcement*, *pinned*, *hard*, *bounty*.

### 4.3.2 High vs. Low Priority

As the impact of misclassifying HP and LP classes differ, they can be treated differently. In this section, we investigated the impact of adding more weights to the HP class to see how it affects the results. To this end, we set the weights to $0.1 \times (10 - i)$ for the LP class, and $0.1 \times i$ for the HP class where $i = [1, 9]$. Figures 10, and 11 depict changes in the total accuracy, and results of different evaluation metrics for HP and LP classes. The results indicate that as the weight of the HP class increases, the scores of recall, F1, and accuracy for HP class and precision for LP class increase. At the same time, the precision of HP class, and the recall of LP class decrease. However, the best overall accuracy of the model based on both classes is achieved when $i = 6$. That means slightly more emphasis on the HP class results in the best overall result. As we have tuned the parameter, this is the setting we have used for the cross-project context as well. That is, the final model puts more emphasis on the HP class to achieve the best overall results. However, in cases where the HP class (or LP) is of much higher importance, one can adjust the weights to get the desired results from the model.

## 4.4 RQ4: Human Labeling And Evaluation: Results

For the first part of this experiment, we asked participants to tag unlabeled issues from six unseen projects. We collected at least 5 votes (priority labels) per issue (300 votes in total).

We initially obtained 34 responses to our questionnaires, from which four responses had major conflicts with others (outliers). We define an outlier labeler as an individual whose tagged labels are different than labels assigned by the majority of other labelers (who tagged the same issues) in more than 50% of cases. To avoid introducing noise, we removed all the labels assigned by such outlier participants and then proceeded to assess the results based on the responses of the remaining 30 individuals. The average outlier percentage for the remaining 30 labelers, is 19%. That is, on average, a labeler, has assigned similar labels to what others tagged for the same issues in more than 80% of cases.

The model achieves 90% overall accuracy. Moreover, accuracy per project ranges from 80% to 100%. Weighted precision, recall, and F1 scores for the two classes of HP and LP are 92%, 90% and 91%, respectively. The results indicate the model is capable of predicting unseen issues successfully. Note that the above accuracy is achieved using the cross-project-based priority prediction model. We believe adding historical data of projects in GitHub and training project-based models can further improve these results.

To measure the inter-rater reliability among the 30 participants, we use two measures, *Percent Agreement* and *Randolph's free-marginal multi-rater kappa*. We achieve 85.3% overall Percent Agreement and 0.71 Kappa. For the latter, based on Landis and Koch's interpretation system (Landis and Koch 1977), the achieved score translates to *substantial agreement* among the labelers. Thus, our labelers substantially agree according to this measure. We also compute these measures per project. Percent Agreement among the six projects varies between 76% to 96%. Moreover, for two out of six projects (ElasticSearch and Retrofit), kappa is above 0.81 which translates to *almost perfect agreement* among labelers for these projects. Considering the diversity among participants, the large number of labelers, and the inherent subjectiveness when prioritizing issues, we believe the assigned labels have good quality and the labelers are mostly in agreement with each other. However, the exact same results may not be replicated using another set of labelers or issues.

In the second part of this experiment, we asked the participants what factors they take into account when determining the importance of issue reports. In the following, we have summarized their free-format answers in several major groups to provide insights for future work. Two of the authors were involved in the process of analyzing the free-format answers. We used the *open coding* technique for this process by breaking issues into discrete parts and creating codes to label them (Khandkar 2009). Each author separately labeled each sentence of a free-format answer for all participants. We used concise summarization of a sentence's goal in the labeling process. If sentences were compound, authors separately labeled the goal of each phrase. Then, for each participant, the two authors compared the goal category for each sentence/phrase. In the end, we accumulated the categories, clustered them, and reported on the largest clusters existing in the data of this experiment. While we have exploited some of these factors (e.g., issue type, discussion magnitude, roles, etc.) in this study, other interesting factors such as the required effort and estimated impact can be also utilized to further improve the proposed model.

- **Issue type**: Many participants indicated that they first look for the type of issue, whether it is a bug report, a feature request, a question, etc. Then they go deeper, if it is a bug, what kind of a bug it is, e.g., is it security related?
- **Content**: Is it related to the core features of the project?
- **Impact**: Is the reported issue blocking other functionalities of the project? Is it affecting many users? Which one can potentially cause more problems?
- **Discussion/Reaction magnitude**: How large is the discussion around the reported issue? How many comments has it attracted? How many users are participating in the discussion? What are the emojis used?
- **Labels**: What are the labels assigned to the issue, e.g., duplicate, invalid, etc?
- **Roles**: Who has opened the issue? What is their experience level? Which team members are participating in the discussion?
- **Required effort**: How much effort is required to solve the issue?
- **Dates**: How long ago has it been reported?

### 4.5 Applications

The proposed models in this work can be integrated into online platforms such as GitHub and help software teams automatically and instantly tag their issues with the correct label. One can also use the models dynamically to assign new priority labels. That is, teams can use the model periodically (e.g., at a specific hour each day) and re-assess the importance of issues based on the updated features (e.g., new discussions among team members, labels being added/removed, etc.). Moreover, previous work has shown that properly tagged issues are easier to manage. For instance, based on the determined objective (Bug report, Enhancement, support/Documentation), bug triaging can be facilitated and more important issues are assigned earlier to proper team members. Finally, major and important issue reports can be automatically selected to be included in software teams' periodic reports (such as release notes).

### 4.6 Threats to Validity

In this section, we discuss the potential threats to the validity of our findings and how we address or mitigate them.

Internal validity Internal validity threats are related to our implementation and results, labels analysis, and human bias in manual processes. Although we have tried to thoroughly check our implementation, there still may be missed mistakes. To mitigate this, we have made our code and data publicly available in our repository for replication and use by other researchers.[11] Moreover, the parameters used in this study can pose potential threats. To mitigate this we have tried to optimize all models and explicitly reported the values of parameters in each experiment separately. Any unmentioned parameter is set to the default value of the corresponding library. The set of synonym but differently written labels also poses a risk. To mitigate this risk, two authors independently assessed these labels, then compared the results, and resolved any case of conflict. Moreover, in this process, both authors adhered to the labels' definitions provided by GitHub. These measures increase our confidence in the manually created label sets.

As the main goal for the human labeling and evaluation task is to showcase the ability of the model when prioritizing unlabeled issues, we were not able to compare against the ground truth labels in this experiment. To mitigate this we employed a partially objective labeling task and took the majority vote for each label as its ground truth. As prioritizing issues is a subjective task, biases and different opinions cannot be avoided. A factor that is important for an individual is not necessarily considered important for another person. Thus, the problem of prioritization is inherently subjective and biased. We took several measures to mitigate such biases, including selecting matured projects, randomly selecting issues from these projects, inviting a large number of professional developers and software engineers to participate in our experiment (diversity), providing labelers with important information of projects, and instructing them to get to know the project and its type of issues (awareness and knowledge). We also assigned each labeler only to one project. Moreover, we computed two inter-rater reliability measures, Percent Agreement and Randolph's free-margin multi-rater kappa. The results indicated that there is a substantial level of agreement among labelers for all projects. Furthermore, for two projects there are

[11] https://github.com/MalihehIzadi/IssueReportsManagement

perfect agreements. On one hand, the key limitation of Percent Agreement is that it does not account for the possibility that labelers may guess the labels, so it may overestimate the true agreement (McHugh 2012). As our labelers are experts in the software engineering domain and are instructed to make well-informed decisions, little guessing is likely to exist, minimizing this risk. On the other hand, due to some of the kappa's assumptions, it can underestimate the agreement among labelers (McHugh 2012). That is why we have included both of these measures in this study. Moreover, participants' level of carefulness and effort can also affect the validity of the experiment's results. To mitigate this risk, we recruited participants who expressed interest in our research and double-checked the results to make sure there is no error. For instance, we removed outlier labelers to avoid introducing noise by including people who had responded with low-quality labels (more than 50% inconsistency with others). In the end, it is worth mentioning, due to the inherent subjectiveness of the prioritization task, the results of this particular experiment may not be completely replicable using another set of labelers or issue reports.

External validity These threats are related to the generalizability of our work. To address this issue, in both tasks we train our models on large-scale datasets. For the objective-prediction task, we use over $818K$ issue reports collected from approximately $61K$ repositories. Furthermore, for the second, priority-detection, we also have trained a generic model in a cross-project context. We have shown that our model can successfully predict priority of issue reports for unseen repositories.

Construct validity Threats to construct validity relates to the suitability of the evaluation metrics used in this study. We use a set of standard evaluation metrics, namely precision, recall, F1-score, and accuracy which are all employed in previous work (Kallis et al. 2019; Song and Chaparro 2020; Huang et al. 2018) in the field. However, more clusters and/or synonym labels can be found and used in the future. Another threat is the choice of classifiers and the list of feature sets that we feed our models. It is possible that using different features sets (and models) result in different findings. To address this issue, we thoroughly inspected issue reports and collected a large set of features. Then we performed feature engineering methods to identify the most important ones. We also used normalization techniques on numerical features. Furthermore, we experimented with different Machine Learning models to find the best algorithm that fits our case. To obtain more stable results for smaller datasets, we used the cross-validation technique. However, random selection does not preserve chronology and ignores possible dependency between issue reports that may influence the trend of issues' category and importance in practice. To mitigate this problem, the blocked version of the cross-validation technique through adding margins can be used.

## 5 Related Work

In the following, we review studies related to two phases of our proposed approach in the categories of collective knowledge in SE, issue report classification, issue report prioritization, and cross-project models.

### 5.1 Collective Knowledge in Software Engineering

Collective knowledge accumulated on software-related platforms has been exploited in various studies to help improve the software development process by introducing new techniques or providing empirical evidence. Various types of collective knowledge have provided the means to perform studies on empirical studies on such knowledge acquired from Stack Overflow, GitHub, and App store (Baltes et al. 2019; Wu et al. 2019; Hu et al. 2019; Zeng et al. 2019), investigating, utilizing, and improving crowd-sourced knowledge in Stack Overflow (Zhang et al. 2015; Tavakoli et al. 2020), usage of collective knowledge in a cross-platform setting (Baltes and Diehl 2019). Vasilescu et al. (2013) studied the relationship between Stack Overflow activities and the development process in GitHub through analyzing the available crowd-sourced knowledge. They claimed the Stack Overflow activity rate correlates with the code changing activity in GitHub. For instance, active committers tend to provide more answers on Q&A websites. In another work, Vasilescu et al. (2014) studied the evolution of mailing list participation after the lunch of StackExchange. They showed that the behavior of developers has been impacted by the emergence of these platforms, e.g., users are motivated to provide faster answers on StackExchange than on `r-help` mailing list due to its gamified environment.

There are also numerous studies on providing automatic and intelligent solutions for various SE problems through exploiting these sources of collective knowledge such as source code summarization (Wan et al. 2018; Aghamohammadi et al. 2020), automatic tag (topic) recommendation in Stack Overflow and GitHub (Wang et al. 2018; Izadi et al. 2021) and more. For instance, Zhou et al. (2020) through acknowledging the voluntary nature of open source software and the difficulty of finding appropriate developers to solve difficult yet important issue reports studied monetary rewards (bounties) to motivate developers and help the evolution of the project. They found the timing of bounties is the crucial factor affecting the likelihood of an issue being handled. In another work, Chen et al. (2021) performed an empirical study on the user-provided logs in bug reports to investigate the problems that developers encounter and how to facilitate the diagnosis and fixing process. Da Costa et al. (2018) conducted a comparative study on traditional and rapid release cycles to grasp the effect of rapid release cycles on the integration delay of fixed issues by analyzing 72K issue reports from the Firefox project.

Our work is similar to the above in the context that we too try to exploit collective knowledge to address SE problems and provide efficient and automatic solutions. However, we specifically aim at addressing the management of issue reports as an important source of such knowledge to further facilitate and support the evolution of software projects. We employ advanced Machine Learning techniques to address issue reports from two aspects of objective and priority and help team managers make better decisions. In the following, we review the literature on issue report classification and prioritization.

## 5.2 Issue Report Classification

Bug report categorization using Machine Learning techniques has received increasing attention from the software research community. Antoniol et al. (2008) used three Machine Learning algorithms, namely Naive Bayes, Decision Trees, and Logistic Regression to determine whether the text of their manually-labeled bug reports is enough to classify them into two distinctive classes of bugs or non-bugs. They found the information included in an issue can be indeed used to classify them. However, they only investigated three projects of Mozilla, Eclipse, and JBoss projects from Bugzilla. In the past years, there have been more researches on categorizing bug reports using text mining, topic modeling (Pingclasai et al. 2013; Limsettho et al. 2016) and classification techniques (Sohrawardi et al. 2014; Zhou et al. 2016; Terdchanakul et al. 2017; Pandey et al. 2017) in bug tracking systems such as Bugzilla and Jira.

The main focus of the previous work has been on distinguishing *bug* from *non-bug* reports for the purpose of bug triaging. Moreover, most of these studies only investigate a few projects and rely only on a limited set of projects and their data for training separate models. There is no proof whether they are suitable from a large-scale perspective. Therefore, in the issue-objective prediction phase of our proposed approach, we perform a large-scale analysis of issue reports in GitHub issues to classify them into three coarse-grained classes of Bug, Enhancement, and Support using state-of-the-art transformer-based techniques.

To the best of our knowledge, there are two papers with the same focus (similar issue classes, GitHub as the common platform, large-scale) as the issue-objective prediction phase of our proposed approach. In 2019, Kallis et al. (2019) proposed *TicketTagger*, a tool based on FastText for classifying issues to three categories of `Bug`, `Enhancement` and `Question`. These categories are among the default labels of the GitHub issue system. They trained their model on the text (title and description) of 30*K* issue reports from about 12*K* GitHub repositories. Their evaluation reports 82%, 76%, and 78% of precision/recall scores for three classes of Bug, Enhancement, and Question, respectively. Recently, BEE was proposed by Song and Chaparro (2020), which uses the pre-trained model of TicketTagger to label issues. Then it proceeds to identify the structure of bug descriptions from predicted reports that are predicted to be a bug in the issue-objective prediction phase. Furthermore, Huang et al. (2018) proposed a model based on convolutional neural networks (CNN) to classify issue report sentences. They manually labeled 5408 issue sentences from four GitHub projects and categorized them into seven groups based on their intentions. These intention categories include Problem Discovery, Feature Request, Information Giving, Information Seeking, Solution Proposal, Aspect Evaluation and finally, Meaningless. Our objective categories overlap with theirs, however, they extract issue sentence intention while we classify the whole issue. We not only classify issue reports and outperform these baselines, but also use these probabilities as one of the input features in the second stage of our proposed approach which is the prioritization of said issues. This is because the priority of issues is largely sensitive to their actual objective. Although answering users' questions and helping them are important tasks, fixing bugs and adding new features are probably assigned higher ranks of importance. Pull Requests are intertwined with issue reports (they usually try to address open issues), and this notion is confirmed by Gousios et al.'s (2015) findings as well. They reported that software project integrators tend to prioritize contributions (pull requests) to their projects by considering the criticality of bug fixes, the urgency of new features, and their size. Furthermore, to the best of our knowledge, we are the first to use transformer-based classifiers to manage issue reports. We finetune RoBERTa, a pre-trained model on our large-scale dataset and achieve higher accuracy (outperforming all the baselines by large margins). We also apply more rigorous text processing techniques and we employ a much larger dataset incorporating more labels to train a more generic model. More specifically, we collect and process over one million issue reports from 80*K* repositories. We include 818*K* pre-processed issues from about 61*K* repositories, while Kallis et al. (2019) use only 30*K* issues from 12*K* repositories.

### 5.3 Issue report Prioritization

Researchers have been studying bug report prioritization avidly (Uddin et al. 2017). Kanwal and Maqbool (2012) proposed a bug priority recommender using SVM and NB classification techniques. Alenezi and Banitaan (2013) tried to predict bug priority using three classifiers, namely NB, DT, RF on two projects of Firefox and Eclipse. Tian et al. (2013)

proposed *DRONE* for Eclipse projects. They investigated the effect of multiple factors, namely temporal, textual, author, related-report, severity, and product features of bug reports on their priority level in the five-category ranking system of the Bugzilla's Bug Tracking System (BTS). Kikas et al. (2016) proposed an approach to predict the lifetime of an issue and whether it can be closed in a given period, using dynamic and contextual features of issues. There are also other studies on prioritizing pull requests (PRioritizer) (Veen et al. 2015), and prioritizing user-reported issues through their relations with app reviews and ratings (Gao et al. 2015; Noei et al. 2019, 2019; Di Sorbo et al. 2020). For instance, Noei et al. (2019) proposed an approach to identify issues that need immediate attention through matching them with related user reviews in several apps. They suggested software teams should first address issues that are mapped to the highest number of reviews. By doing so, their app rating can be positively affected.

Although there are several studies on prioritizing bug reports on Bugzilla, the scope and features available in these systems differ. For instance, Bugzilla is primarily designed for bug report management and has a predefined set of five priority labels, thus it has more training data available. In these studies, the focus is on bug reports and predicting whether a report is a bug or non-bug, while we train a model to detect the objective behind opening issues. It also includes information regarding the severity which previous work has greatly exploited. A recent study proposed by Dhasade et al. (2020) has addressed the need for priority prediction models in GitHub. However, they use LDA to identify the categories of issues, then train a classifier to predict the hotness of issue reports on a daily basis. On contrary, our model uses classification models to label issues with two straightforward labels (High/Low). The model can be used on both open and closed issues. And it can be utilized both for prioritizing tasks plus resource allocation and also for documentation purposes such as writing reports, delivering release notes, and highlighting the most important closed issues in a release.

The mentioned studies mostly try to prioritize bug reports in various ITS and BTS systems such as Bugzilla, Jira, and GitHub using different Machine Learning techniques. However, to the best of our knowledge, there is no prior work on supervised models for issue reports of GitHub similar to ours. Our work differs from bug prioritizing approaches since we address all issues and not just bugs. Furthermore, BTS systems have readily available metadata which are unfortunately missing in GitHub. Merten et al. (2016) empirically analyzed four open-source projects from GitHub and Redmine and found projects' metadata can improve classifier performance. Therefore, we also conduct feature engineering techniques on metadata of issue reports and extract the salient features from GitHub which have not been utilized before. On the other hand, approaches based on linking app's user reviews and issues from GitHub do not take into account various important factors such as author information, the amount of discussion happening in the report, issue lifetime, issue category, etc. In addition to utilizing the metadata of reports, we predict the objective of issue reports and then feed the predicted probability to our classification model for prioritizing. We also perform sentiment analysis and include the outcome in our prioritizer model. Moreover, we train both project-based and cross-project models. And finally, we also conducted a human labeling and evaluation task to assess the performance of the proposed model on unseen data and provided developers' insights for future studies as well.

### 5.4 Cross-project Models

Peters et al. (2013) claimed project-based predictors are weak for small datasets. Also, Kitchenham et al. (2007) found that relying on project-based datasets is problematic due to

**Table 8** Selected labels for each category of issue priority

| Priority | Labels' list |
|---|---|
| High-priority | p0, priority: p0, p1, priority 1, priority: p1, priority 2, critical, criticalpriority, priority-critical, critical priority, priority:critical, priority critical, priority: critical, priority - critical, critical-priority, priority/critical, urgent, priority/urgent, priority/blocker, priority: blocker, important, priority/important, priority: major, highpriority, priority-high, high priority, priority:high, priority high, priority: high, priority - high, high-priority, priority/high, is:priority |
| Low-priority | p3, priority: p3, priority 4, priority: minor, lowpriority, priority-low, low priority, priority:low, priority low, priority: low, priority - low, low-priority, priority/low, is:no-priority |

the challenging task of collecting just enough project data to train models properly. Cross-project classification is a realistic solution for training a generic model from the data of a large number of different projects. The trained model then can be successfully used for projects that have little to no data available for training. In this field, a few studies have been conducted in the cross-project context. Yu et al. (2018) conducted an empirical study to identify the factors that affect the performances of transferring reusable models across projects in the context of issue classification. They extracted 28 attributes grouped into four dimensions. Sharma et al. (2012) evaluated different Machine Learning models for predicting priority of new issues in five datasets of Open-Office and Eclipse projects. Our work complements these studies by analyzing factors affecting issue reports in GitHub from both aspects of issue objective and priority.

## 6 Conclusions and Future Work

An issue report can be opened due to several reasons including reporting bugs, requesting new features or merely for seeking support from the software team. Naturally not all issues are equally important. Some may require immediate care, some may need to be included in the documentation reports of the project, while others are not as urgent. In this study, we proposed a two-stage approach to predict both objective and importance of issue reports posted on software repositories. We defined three sets of features related to issue reports and exploited state-of-the-art text classifiers to achieve our goal. According to the evaluation results, our models outperform the baselines in both project-based and cross-project settings with 82% and 75% accuracy for objective and priority prediction, respectively. Furthermore, we showed that our proposed priority prediction model in the cross-project setting performs on par with the project-based models. Moreover, we conducted a human labeling and evaluation task to use the proposed priority detection model on unlabeled issue reports from six unseen projects with the help of 30 software engineers. The results indicate that the model is capable of predicting priority of unseen data with high accuracy (90%). Therefore, our proposed model can be used for other unseen projects successfully without the need for extra training.

In the future, we plan to work on finer-grained categories of both objectives and priority levels. Moreover, based on the results of our human labeling and evaluation experiment, we plan to investigate more features that can affect the importance of an issue from software engineers' perspectives. For instance, many participants considered the *bug type* and the degree of its *impact* as an important factor while prioritizing issue reports. Finally, adding more projects from other programming languages can also help the generalizability of the proposed approach.

## Appendix: Priority Labels

Table 8 presents the list of manually extracted labels from top GitHub repositories (most star) for categories of high and low priority issues.

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## Authors and Affiliations

**Maliheh Izadi[1] · Kiana Akbari[1] · Abbas Heydarnoori[1]**

✉ Maliheh Izadi
maliheh.izadi@sharif.edu

Kiana Akbari
kakbari@ce.sharif.edu

Abbas Heydarnoori
heydarnoori@sharif.edu

[1] Intelligent Software Engineering Lab, Sharif University of Technology, Tehran, Iran