Multifaceted Hierarchical Report Identification for Non-Functional Bugs in Deep Learning Frameworks

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Abstract—Non-functional bugs (e.g., performance- or accuracy-related bugs) in Deep Learning (DL) frameworks can lead to some of the most devastating consequences. Reporting those bugs on a repository such as GitHub is a standard route to fix them. Yet, given the growing number of new GitHub reports for DL frameworks, it is intrinsically difficult for developers to distinguish those that reveal non-functional bugs among the others, and assign them to the right contributor for investigation in a timely manner. In this paper, we propose MHNurf — an end-to-end tool for automatically identifying non-functional bug related reports in DL frameworks. The core of MHNurf is a Multifaceted Hierarchical Attention Network (MHAN) that tackles three unaddressed challenges: (1) learning the semantic knowledge, but doing so by (2) considering the hierarchy (e.g., words/tokens in sentences/statements) and focusing on the important parts (i.e., words, tokens, sentences, and statements) of a GitHub report, while (3) independently extracting information from different types of features, i.e., content, comment, code, command, and label.

To evaluate MHNurf, we leverage 3,721 GitHub reports from five DL frameworks for conducting experiments. The results show that MHNurf works the best with a combination of content, comment, and code, which considerably outperforms the classic HAN where only the content is used. MHNurf also produces significantly more accurate results than nine other state-of-the-art classifiers with strong statistical significance, i.e., up to 71% AUC improvement and has the best Scott-Knott rank on four frameworks while 2nd on the remaining one. To facilitate reproduction and promote future research, we have made our dataset, code, and detailed supplementary results publicly available at: https://github.com/idea-lab/APSEC2022-MHNurf.

Index Terms—Bug Report Analysis, Deep Learning, Natural Language Processing, Software Maintenance, Performance Bug

I. INTRODUCTION

Deep learning (DL), which is a kind of machine intelligence algorithms that mimics the workings of the human brain in processing data [1], has been gaining momentum in both academia and industry [2, 3, 4, 5, 6]. As such, several well-known DL frameworks (e.g., TensorFlow, Keras, and PyTorch) were created and maintained on GitHub, aiming to provide effective and readily available API for seamlessly adopting the DL algorithms into real-world problems.

Despite the success of DL frameworks, they inevitably contain bugs, which, if left unfixed, would propagate issues to any applications that were built on top of them [7]. Among other bugs, there exist non-functional bugs that have no explicit symptoms of exceptions (such as a Not-a-Number error or the program crashes), i.e., they cannot be judged by using a precise oracle. For instance, common examples of non-functional bugs are performance- or accuracy-related bugs (which is the focus of this work), since from the perspective of the DL frameworks, it is typically hard to understand how “slow” or how “inaccurate” the results are would be considered as a bug without thorough investigation, therefore they are more challenging to be analyzed. However, those non-functional bugs tend to cause some of the most devastating outcomes and hence are of great concern [8, 9]. Indeed, according to the U.S. National Transportation Safety Board (NTSB), the recent accident of Uber’s self-driving car was caused by a non-functional bug of their DL framework, which classified the pedestrian as an unknown object with a slow reaction1.

To deal with bugs, it is a normal Software Engineering practice for DL frameworks to allow users to submit a report on repositories like GitHub, which would then be assigned to a contributor for formal investigation with an attempt to fix the bug, if any [10]. Identifying whether a report is non-functional bugs related (among other functional counterparts) is a labor-intensive process. This is because firstly, the number of new reports increases dramatically. For example, there are around 700 monthly new GitHub reports for TensorFlow in average2, including bugs related ones and those for other purposes, such as feature requests and help seeking. Secondly, GitHub reports can be lengthy, e.g., it could be up to 322 sentences per report on average [11]. Finally, given the vague nature of non-functional bug, it is fundamentally difficult to understand if the related reports really reflect bugs. The above mean that, when assigning or prioritizing the GitHub reports, it can take a long time for developers to read and understand the bug reports, hence delaying the potential fixes to the destructive non-functional bugs, especially when some of the key messages are deeply hidden inside.

In light of the above, the problem we focus on in this paper is the following: given a GitHub report for DL framework,

1https://tinyurl.com/ykuufbpe
2https://github.com/tensorflow/tensorflow/pulse/monthly
can we automatically learn and identify whether it is a non-functional bug related report? Indeed, many existing classifiers on bug report identification can be directly applied. For example, those that identify a particular type of bug report [12] (e.g., long-lived bugs); those that predict whether a bug report is bug-related [13]; and those that classify reports based on labels [14, 15, 16]. However, in addition to the fact that these works do not target the level of DL frameworks, they have failed to handle some or all of the following challenges, which are important in the report identification:

- **Semantics matter**: Depending on the context, the same words or code tokens in the GitHub reports can have different meanings. Existing classifiers using statistical learning algorithms [12] could fail to handle this polysemy.

- **Multiple types of features exist**: While most existing classifiers consider the content (title and description) of a GitHub report [12, 13, 14, 15, 16], other types of features may also provide useful information, such as the accumulated comments made by the participants before a contributor is assigned to the report. Further, the mix of code and natural language in a report can pose additional challenge.

- **Not all parts are equally relevant**: Given a lengthy GitHub report, not all of the words and sentences are important in identifying the non-functional bug related reports. Yet, existing work has often ignored such a fact [14, 15, 16].

In this paper, we propose **Multifaceted Hierarchical Non-functional Bug Report Identification**, dubbed MHNurf — an end to end tool for automatically identifying non-functional bug related reports for DL frameworks. Its core component is a newly proposed Multifaceted Hierarchical Attention Network (MHAN) in this work, which extends the Hierarchical Attention Network (HAN) [17].

**Contributions**: To better identify non-functional bug related reports for DL frameworks, our contributions include:

- **MHNurf** learns the semantic knowledge by considering the hierarchy and discriminating important and unimportant parts in GitHub reports.

- The MHAN in MHNurf considers multifacetedness in GitHub reports, i.e., it learns up to five types of feature (content, comment, code, command, and label) independently.

- By using a dataset of 3,721 GitHub reports from five DL frameworks (i.e., TensorFlow, PyTorch, Keras, MXNet, and Caffe), the experiment results confirm that the title and description, which are fundamental parts of a GitHub report, needs to be considered together as part of the content feature.

- We also found that the combination of content, comment, and code give the best result in MHNurf. Notably, the multifacetedness in MHNurf has also helped to considerably improve the prediction against the vanilla HAN in MHNurf.

II. PROBLEM CONTEXT AND CHALLENGES

A. Context

DL frameworks hosted on GitHub allows participants and users to submit issue reports, whose purpose includes, but not limited to, bugs, pull request, feature request, and others. Among those, the GitHub reports that are bug-related are often of high importance to the community, especially the non-functional bug related reports. Here, we distinguish two types of users/developers on GitHub:

- **Contributors**: who are assigned to a report so that the formal investigation starts.

- **Participants**: who have not been assigned to a report, but are free to make comments on it.

Most commonly, after assignments, those GitHub reports need to be reviewed by the contributors who will pick the most important ones to investigate and fix when necessary.

As shown in Figure 1, apart from the normal content (title and description), a GitHub report may likely be commented on by different participants before being assigned to a contributor. Further, a label may also be added by the automatic bot or by a contributor based on his/her first impression. A formal investigation begins when the report is assigned to someone.

Our work here is to automatically identify those GitHub reports that are non-functional bug related for a DL framework. This need not have to be done immediately when a report is submitted but also can be achieved in a short period of time after submission, as long as it is before the assignment. This can then provide useful information for the bot (or human) who assigns the GitHub reports in terms of which contributor to assign and how to prioritize them, hence saving more
maintenance efforts and mitigating the consequence of truly devastating bugs.

In this regard, we are dealing with a binary classification problem: a GitHub report can be either describing a non-functional bug (e.g., performance and/or accuracy related) or not, which may be a functional bug report or reveal no bug at all (e.g., it is a feature request, API misuse, or merely a false alarm).

B. Key Challenges

Here we describe the key challenges identified about the GitHub reports for DL frameworks, which motivate our designs of MHNurf.

Challenge 1: Semantics matter. GitHub reports for DL frameworks also contain strong semantic information, especially for non-functional bugs. For example, in report #26736 for TensorFlow, words like ‘slow’ is the key to indicate that it is a (performance) non-functional bug related report. However, this does not mean that any report with a term ‘slow’ is non-functional bug related, as the context and semantic information are also important. In another example — report #63854 for PyTorch — the ‘slow’ merely means a particular mode under which a logical bug was explored.

The above are common examples where the semantics matter for identifying non-functional bug related reports for DL frameworks.

Challenge 2: Multiple types of features exist. As shown in Figure 1, a report for DL frameworks on GitHub consists of different types of features, which we summarize as follows:

- **Content:** This is the fundamental feature for a report on GitHub, which includes both title and description. They are often the most important source of information in non-functional bug related report identification.
- **Comment:** For GitHub reports, comments from the participants may be accumulated before a contributor is assigned.
- **Code:** Code for reproduction is also a common feature in the description of a GitHub report. In particular, here we refer to the problematic code, test code, the results returned, and the stack traces that are quoted in the code blocks as part of the description.
- **Command:** This is the code snippet that is not part of the code block but is mixed with the texts in the description.

Challenge 3: Not all parts are equally relevant.

Another intuition we found is that not all parts in the GitHub report are equally important for identifying whether it is related to non-functional bugs. For example, in Table I, only the highlighted sentence provides the most important information for one to understand whether the corresponding report is non-functional bug related or not. The words ‘speed’ and ‘slowed’ imply more about a performance problem, hence it should be related to non-functional bugs.

```
with tf.Session() as sess:
    start = time.time()
    for i in range(10):
        sess.run(c)
    t = (time.time()-start)/10.
    print(t, 'sec', tflops, 'TFlops')
```

Fig. 2: Code snippet extracted from non-functional bug related report #33430 for TensorFlow. The red sentence gives strong meaning of a non-functional bug report while the blue words ‘speed’ and ‘slowed’ contribute the most therein.

Similarly, for code, as shown in Figure 2, the statements _start = time.time()_ and _t = (time.time() - start)/10_ indicate that it is important to record running time in the code snippet, which is a clear indication that performance is of great concern in the report. In particular, the token _time_ is what contributes more clues for one to confirm whether the report is non-functional bug related — a strong sign that this can be a non-functional bug related report.

As a result, appropriate attention needs to be paid to different parts and their hierarchy in the report for identifying non-functional bug-related ones in DL frameworks.

III. MULTIFACETED HIERARCHICAL ATTENTION NETWORK

In this section, we elaborate on the key component underpins MHNurf, namely Multifaceted Hierarchical Attention Network (MHAN), which modifies the Hierarchical Attention Network (HAN) [17]. The idea is to adopt multiple attention mechanisms to learn the semantic knowledge collaboratively (Challenge 1). This is achieved by independently extracting the rich semantic information in different feature types of the DL GitHub reports (hence handling the multifacetedness in Challenge 2) while paying hierarchical attention to the important words and sentences (or tokens and statements) within each (hence tackling the unequal importance and information hierarchy in Challenge 3). These independent pieces of information would then be concatenated to make a prediction.

As shown in Figure 3, we design a flexible structure of MHAN such that different feature types of the DL GitHub reports can be easily appended or removed. That is, MHAN can be built by simply considering one type of feature or anything up to all the five feature types we discussed in Section II-B. In Section VI-B, we will empirically identify the best combination of feature types for MHNurf.

### Table I: Texts from the content of non-functional bug related report #33430 for TensorFlow. The red sentence gives strong meaning of a non-functional bug report while the blue words ‘speed’ and ‘slowed’ contribute the most therein.

| Texts | Feature Type | Importance |
|-------|--------------|------------|
| ‘slow’ | Code | High |
| ‘time’ | Command | High |
| ‘speed’ | Content | High |
| ‘TFlops’ | Comment | High |

The prediction speed is slowed down after model.compile(). Predict function is used by users assuming that it will work fast because we use it all the time in production. It should not cause surprise to users.
Suppose that a feature has \( L \) sentences/statements and each of them, denoted as \( s_i \), contains \( T_i \) words/tokens. \( w_{ij} \) is the \( j \)th word/token in the \( i \)th sentence/statement and we have the corresponding word vector as \( w_i = \{ w_{i1}, w_{i2}, \ldots, w_{iT} \} \) for a sentence/statement of \( T \) length. An example could be: “the error is too high” is treated as \( w_1 = \{ \text{'the'}, \text{'error'}, \text{'is'}, \text{'too'}, \text{'high'} \} \). Note that for code and command features, we use tokenization to extract the tokens, e.g., code snippet model compile(loss='crosentropy') can be represented as \( w_i = \{ \text{'model'}, \text{','}, \text{'compile'}, \text{'(','}, \text{'loss'}, \text{'='}, \text{'<STR_LIT'>}' \} \). In what follows, we will present the internal details of MHAN.

A. Word and Token Level (First Hierarchy)

1) Encoder: The first step in our MHAN is to embed the words/tokens of the sentences/statements in a feature type into numeric vectors for straightforward computation. In this work, we utilize GloVe [19] instead of the commonly used word2vec [20], for two reasons: (1) it has fewer parameters; (2) it has been reported to be better on tasks with analogy and related reports. Similarly, from Figure 2, the token time would get higher weights, as they are more semantically correlated to the contexts of model and prediction, which helps to identify DL non-functional bug related reports. Similarly, from Figure 2, the token time would have higher weight in the contexts of Session and run, which is important to the identification.

B. Sentence and Statement Level (Second Hierarchy)

1) Encoder: For the label feature, MHAN only allows for one hierarchy since it can be considered as a special case where a sentence has exactly one word. However, for the other feature types, more semantic information can be extracted at the sentence and statement level. Given the vector for sentence/statement \( s_i \), its annotation \( h_i \) can be encoded by using the bi-directional GRU:

\[
h_i = h_i^t \oplus h_i^l = GRU(V_i)(s_i) \oplus GRU(V_i)(s_i)
\]

where all other notations are the same as Equation 1.

2) Attention: Similar to the previous hierarchy, the sentences/statements that provided more information to the prediction are rewarded using the following:

\[
u_i = \tanh(W_u h_i + b_u)
\]

\[
\alpha_i = \exp(u_i^T u_a) \sum_j \exp(u_j^T u_a)
\]

\[
o = \sum_i \alpha_i h_i
\]
where \( u_k \) is a sentence/statement level context vector; \( o \) is the vector that represents the information of a given feature type, including the attentions to both word (token) and sentences (statements). In this way, the important sentence from Table I and the important statements from Figure 2 would contribute more in \( o \).

C. Multifaceted Hierarchy

In MHAN, we design the above two levels of hierarchy for every feature type of GitHub reports we consider, except for the label, which only has the word level. As a result, the above hierarchical learning process is conducted for each feature type independently. Since according to Equation 8, each feature would output a vector, representing the semantic information extracted (the label feature would output a vector representation using Equation 4), on top of that, we concatenate them to form the final vector \( v \):

\[
v = \sum_{i=1}^{k} o_i
\]

\[
y = \text{softmax}(v)
\]

where \( k \) is the number of feature types \( 1 \leq k \leq 5 \) and \( \sum_{i=1}^{k} o_i \) denotes repeated concatenation. For example, if the content, comment, and code are considered in MHAN, then we have \( v = o_{\text{content}} \oplus o_{\text{comment}} \oplus o_{\text{code}} \). Finally, \( y \) serves as the input to a softmax function, which predicts \( y \), indicating a given GitHub report for the DL frameworks is a report related to a non-functional bug or not.

IV. MHNurf: An End-to-End Tool

MHNurf was designed as an end-to-end tool that can be applied directly to a DL framework hosted on GitHub. As illustrated in Figure 4, to deploy MHNurf, there are four key phases: data preparation, data preprocessing, training, and prediction, each of which is outlined below. Note that MHNurf only needs to train once (or as needed thereafter), and it can then identify newly submitted reports.

A. Data Preparation

In this work, we use the dataset collected by Long and Chen [24] and we pick the top 5 DL frameworks with the largest number of reports. To further enrich the dataset, we extend the samples by including those reports that are not relevant to non-functional bugs following the same protocol. Table II summarizes the collected total of 3,712 GitHub reports for our experiments. They also allow us to conduct a pilot study that motivates some of the designs of MHNurf.

B. Data Preprocessing

We preprocessed all collected reports via the steps below:

1) **Case Conversion:** All upper case texts are converted into lower case ones.

2) **Tokenization:** Sentences/statements are split into word tokens before embedding with GloVe. In this work, we use the Tokenizer\(^3\) in Keras.

3) **Stop Words Removal:** Stop words, such as "the" and "is", are removed. They appear frequently in natural language but with little contribution to semantic meaning.

4) **Symbols Removal:** HTML tags and punctuation marks that appear in the GitHub reports are also removed.

C. Training MHAN

In MHNurf, the MHAN is trained using a stochastic algorithm called Adam [25] with \( \beta_1 = 0.9, \beta_2 = 0.98 \) and \( \epsilon = 10^{-9} \), as recommended by Vaswani et al. [26]. For the structure of MHAN, we follow the values used by Yang et al. [17]: a batch size of 64 with training epochs of 25; while the size of GRU layer and the embedding dimension are both 100. Since the report identification for non-functional bugs in DL frameworks is a binary classification problem, we use the binary cross-entropy as the loss function in the training:

\[
\mathcal{L} = -\frac{1}{n} \sum_{i} y_i \cdot \log y_i + (1 - y_i) \cdot \log (1 - y_i)
\]

where \( n \) represents the number of training samples; \( y_i \) denotes the prediction given the \( i \)th sample, where each sample refers to a GitHub report in this work.

D. Prediction

MHNurf can benefit from those datasets as an initial starting point and be used in practice, since it learns the semantic information of GitHub reports; it can be further

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\(^3\)https://tinyurl.com/wbx7ede
TABLE III: Aliases for different combinations of feature types in MHNurf. MHNurf\(_A\) essentially uses the classic HAN. The content feature is handled by the best scheme from RQ1.

| Alias | Feature Types |
|-------|---------------|
| MHNurf\(_A\) | content |
| MHNurf\(_B\) | content, comment |
| MHNurf\(_C\) | content, code |
| MHNurf\(_D\) | content, command |
| MHNurf\(_E\) | content, label |
| MHNurf\(_F\) | content, comment, code |
| MHNurf\(_G\) | content, comment, command |
| MHNurf\(_H\) | content, comment, label |
| MHNurf\(_I\) | content, code, command |
| MHNurf\(_J\) | content, code, label |
| MHNurf\(_K\) | content, command, label |
| MHNurf\(_L\) | content, command, command, label |
| MHNurf\(_M\) | content, comment, command, code |
| MHNurf\(_N\) | content, comment, code, label |
| MHNurf\(_O\) | content, command, code, label |
| MHNurf\(_P\) | content, comment, command, code, label |

consolidated as more data is collected and labeled. Therefore, the training only happens once or as needed, but the learned knowledge can then be generalized for new reports. This ensures the scalability of MHNurf.

V. EVALUATION

Here, we specify the research questions and settings.

A. Research Questions

We seek to answer four research questions (RQs):

- **RQ1:** How title and description can be best handled as part of the content feature?
- **RQ2:** What is the generally best combination of feature types for MHNurf?
- **RQ3:** How effective is MHNurf against the state-of-the-arts in identifying non-functional bug related reports for DL frameworks?
- **RQ4:** Why does MHNurf work?

Since the title and description are both the fundamental sources of information in the content feature type of a GitHub report (and are used in existing work [12, 13, 14, 15, 16]), we ask RQ1 to study what is the best scheme to handle them. To that end, we compare three schemes:

- **MHNurf\(_{title}\):** only title is considered.
- **MHNurf\(_{desc}\):** only description is considered.
- **MHNurf\(_{title+desc}\):** both title and description are concatenated together as part of the content feature.

To eliminate unnecessary noise, we study RQ1 by using the variant of MHNurf where only the content feature is considered.

We ask RQ2 to understand whether all (or some) of the feature types identified in Section II-B can be useful for MHNurf. To this end, we compare the variants of MHNurf under all possible combinations of the feature types combination, as shown in Table III. Since the content is the most fundamental feature type, it is always considered, and we make use of the best variant from RQ1 as the default treatment for the content feature. In this way, RQ2 also enables us to confirm whether the extended multifacetedness in the MHAN can be helpful, as we consider MHNurf with only the content feature (i.e., MHNurf\(_A\)), which essentially uses the classic HAN. Note that, when a GitHub report does not contain data for certain types of features, e.g., one without any code, we build a dummy vector with only 0 for such a feature type in the underlying MHAN of MHNurf.

To verify the effectiveness of MHNurf, in RQ3, we compare the best variant of MHNurf (from RQ2) against nine state-of-the-art classifiers from the literature, including deep learning-based classifiers such as LSTM and TextCNN, as shown in Table IV.

B. Experiment Procedure

For MHNurf (and variants) and other compared classifiers under a DL framework, our experiment follows the practice of bootstrapping (without replacement) [31], which consists of the steps below:

1) Randomly split the dataset into 80% for training and 20% for the holdout testing.
2) Train the classifiers with the training data. If a classifier under training comes from a state-of-the-art tool, conducting hyperparameter tuning.
3) Evaluate the performance over the testing data.
4) Repeat from step (1) for 30 runs.

All the experiments in this work are implemented with Python 3.7 using the API from Keras, and run on a machine with 2.2GHz CPU, 12GB RAM, and a NVIDIA 16GB GPU.

C. Metric

In this work, the area under the receiver operating characteristic (ROC) curve, i.e., AUC [32], is mainly applied as the performance metric to measure the effectiveness of a classifier over the holdout testing data. Because AUC does not require a particular threshold [33], which is difficult to tweak in order to carry out an unbiased assessment. Besides, it has been shown that the AUC is not sensitive to imbalanced data [34, 35, 36], which is the case for this task (Table II). Moreover, we also apply the precision, recall and F-measure to evaluate the performance of a classifier on difference aspects.

TABLE IV: The state-of-the-art classifiers compared. TF-IDF represents term frequency–inverse document frequency. Note that all classifiers were designed to consider title and description in their original work.

| Classifier | Description | Used By | Year |
|------------|-------------|---------|------|
| TF-IDF/ANN | TF-IDF with k Nearest Neighbors | [12, 27] | 2018-2021 |
| TF-IDF/MLP | TF-IDF with Multi-layer Perceptrons | [12] | 2021 |
| TF-IDF/NB | TF-IDF with Naive Bayes. | [12, 28, 29] | 2018-2021 |
| TF-IDF/RF | TF-IDF with Random Forest | [12, 28] | 2021 |
| TF-IDF/SVM | TF-IDF with Support Vector Machine. | [12, 28, 29] | 2018-2021 |
| TextCNN | A convolutional neural network for text. | [14] | 2020 |
| LSTM | Long short-term memory networks. | [15, 29, 30] | 2018 |
| fastText | A text classification tool from Facebook. | [16] | 2019 |
| auto-fastText | fastText with auto-parameter tuning. | [13] | 2020 |


D. Statistical Test

To ensure the comparisons are statistically meaningful, we apply Scott-Knott test [18] on all comparisons of the AUC over 30 runs. As a widely-used test in Software Engineering [37], Scott-Knott sorts the list of treatments (the classifiers) by their median AUC values. Next, it splits the list into two sub-lists with the largest expected difference [38]. Formally, Scott-Knott test aims to find the best split by maximizing the difference $\Delta$ in the expected mean before and after each split:

$$\Delta = \frac{|l_1|}{|l|} (\bar{t}_1 - \bar{t})^2 + \frac{|l_2|}{|l|} (\bar{t}_2 - \bar{t})^2$$  \hspace{0.5cm} (12)

whereby $|l_1|$ and $|l_2|$ are the sizes of two sub-lists ($l_1$ and $l_2$) from list $l$ with a size $|l|$. $\bar{t}_1$, $\bar{t}_2$ and $\bar{t}$ denote their mean AUC.

During the splitting, we apply a statistical hypothesis test $H$ to check if $l_1$ and $l_2$ are significantly different. This is done by using bootstrapping and $A_{12}$ [39] (a non-parametric effect size metric). If that is the case, Scott-Knott recurses on the splits. In other words, we divide the classifiers into different sub-lists if both bootstrap sampling and effect size test suggest that a split is statistically significant (with a confidence level of 99%) and not a small effect $A_{12} \geq 0.6$. The sub-lists are then ranked based on their mean AUC.

Therefore, when we say $A$ is better than $B$, their difference is indeed statistically significant.

VI. RESULTS

We now present and discuss the experimental results.

A. Schemes for Title and Description

To answer RQ1, Table V shows the results and statistics when comparing the three schemes mentioned in Section V-A. Clearly, we see that MHNurf$_{title+desc}$ significantly outperforms the other two by being consistently ranked as the sole best over the DL frameworks. In particular, the magnitudes of improvements are considerably high, as we can see from the AUC distributions.

An interesting finding is that, when considering only description (MHNurf$_{desc}$), the performance drops significantly. This means that even the title is generally a much shorter piece of text than the description, it is important to take it into account when identifying non-functional bug related reports for DL frameworks. This makes sense, as the title can often provide some of the most important words that can help MHNurf to learn the overall semantic information.

Therefore, for RQ1, we say:

To RQ1: Concatenating title and description in the content is the most effective scheme for MHNurf.

B. Variants of MHNurf

Table VI illustrates the results for RQ2, from which we can see that some of the variants perform much better than the others. Overall, the variant MHNurf$_F$, which considers the feature content, comment, and code is the most promising one, suggesting that those feature types, when being independently considered together, are more likely to offer unique information for learning semantic knowledge. In particular, MHNurf$_F$ has been ranked the 1st for three DL frameworks and 2nd for two, leading to a total rank of 7. It is interesting to see that, as opposed to our initial intuition, using all five types of feature perform badly, producing a total rank of 15. This is indeed possible, because certain feature types may often contribute to a considerable amount of redundant information, leaving the useful knowledge blurred and hence increasing the difficulty of learning. Hence, we say:

To RQ2: Using content, comment, and code (MHNurf$_F$) are generally the most promising feature combination for MHNurf. The extended multifacetedness in MHN of MHNurf can indeed help to considerably improve the result.

C. MHNurf against State-of-the-arts

The results for RQ3 have been shown in Table VII, from which we see that, clearly, MHNurf is able to considerably outperform the state-of-the-art counterparts by having a total rank of 6. In particular MHNurf has been ranked as the 1st for 4 out of the 5 DL frameworks (three of them are the sole best classifier) with up to 71% AUC improvement (e.g., compared with TF-IDF/SVM on TensorFlow), which is a remarkable result. The magnitudes of improvements are also significant since the median and IQR are often much better than the others overall. Further, the result with difference metrics in Table VIII also shows that MHNurf performs better than the state-of-the-art counterparts. In summary, we say:

TABLE V: Scott-Knott rank and AUC on the schemes for title and description in MHNurf. “Med” denotes median AUC over 30 runs; shows the 25%, 50%, and 75% AUC percentiles. Rows are sorted from the best based on rank, median, and then IQR.
TABLE VI: Scott-Knott rank and AUC on the variants of MHNurf (with the best scheme from RQ1). blue highlights the overall best variant. Formats are the same as Table V.

| Variant | Rank | Med | IQR |
|---------|------|-----|-----|
| MH | 1 | 0.857 | 0.025 |
| MH | 1 | 0.853 | 0.040 |
| MH | 2 | 0.858 | 0.045 |
| MH | 2 | 0.857 | 0.042 |
| MH | 2 | 0.854 | 0.036 |
| MH | 2 | 0.854 | 0.043 |
| MH | 2 | 0.849 | 0.035 |
| MH | 2 | 0.845 | 0.040 |
| MH | 3 | 0.852 | 0.035 |
| MH | 3 | 0.847 | 0.044 |
| MH | 3 | 0.846 | 0.031 |
| MH | 3 | 0.845 | 0.025 |
| MH | 3 | 0.845 | 0.061 |
| MH | 3 | 0.843 | 0.050 |
| MH | 3 | 0.842 | 0.041 |


| Variant | Rank | Med | IQR |
|---------|------|-----|-----|
| MH | 2 | 0.788 | 0.194 |
| MH | 2 | 0.787 | 0.158 |
| MH | 2 | 0.782 | 0.348 |
| MH | 2 | 0.778 | 0.199 |
| MH | 2 | 0.768 | 0.187 |
| MH | 2 | 0.769 | 0.355 |
| MH | 2 | 0.768 | 0.349 |
| MH | 2 | 0.775 | 0.251 |
| MH | 2 | 0.766 | 0.308 |
| MH | 2 | 0.761 | 0.371 |
| MH | 2 | 0.750 | 0.232 |
| MH | 3 | 0.768 | 0.339 |
| MH | 3 | 0.74 | 0.350 |

(a) TensorFlow
(b) PyTorch
(c) Keras

TABLE VII: Scott-Knott rank and AUC on comparing MHNurf (the best variant from RQ2) with the state-of-the-art classifiers. The rows for MHNurf are highlighted in blue. Formats are the same as Table V.

| Classifier | Rank | Med | IQR |
|------------|------|-----|-----|
| TF-IDF/MLP | 2 | 0.796 | 0.023 |
| auto-fastText | 3 | 0.786 | 0.039 |
| TF-IDF/NB | 4 | 0.771 | 0.055 |
| TextCNN | 5 | 0.700 | 0.070 |
| LSTM | 6 | 0.681 | 0.102 |
| TF-IDF/RB | 7 | 0.653 | 0.043 |
| TF-IDF/SVM | 9 | 0.586 | 0.148 |
| fastText | 9 | 0.500 | 0.000 |

(a) TensorFlow
(b) PyTorch
(c) Keras

D. Why MHNurf Works

To answer RQ4, we look into the actual GitHub reports in the testing data for which MHNurf classifies correctly but all other state-of-the-art ones made mistakes. The following Case I is a false positive case study for most other state-of-the-art classifiers but has been classified by MHNurf correctly.

Case 1: Report #6688 for Keras

| Title | Kerascast accuracy is not increasing
| Description | I tried different optimizers, activation functions, number of layers, but the accuracy is reaching
| Comment | You need to take care of input numerical scale. Try to normalize every feature dimension into...
TABLE VIII: Average recall, precision and F-measure score for all classifiers over five projects. The best is in blue.

| Classifier | Recall | Precision | F-measure |
|------------|--------|-----------|-----------|
| MHNurf     | 0.763  | 0.804     | 0.771     |
| TF-IDF/NB  | 0.721  | 0.617     | 0.750     |
| TF-IDF/MLP | 0.661  | 0.745     | 0.679     |
| auto-fastText | 0.634 | 0.759     | 0.659     |
| TF-IDF/SVM | 0.554  | 0.551     | 0.537     |
| TF-IDF/ANN | 0.536  | 0.671     | 0.526     |
| TF-IDF/RP  | 0.572  | 0.717     | 0.578     |
| LSTM       | 0.551  | 0.559     | 0.536     |
| TextCNN    | 0.571  | 0.616     | 0.586     |
| fastText   | 0.500  | 0.425     | 0.459     |

comment from a participant implies that the issue can be in fact due to misuse of the code (which is indeed confirmed to be true thereafter). This indicates the importance of considering the right multifaceted information that is available.

Yet, in another case study below (Case 2), MHNurf classifies it correctly but this becomes the false negative for most other state-of-the-art classifiers.

| Case 2: Report #19277 for Tensorflow |
|------------------------------------|
| Title: SSD model execution is slower w/ MKL |
| Description: w/ MKL, benchmark_model got 18.796 FLOPs/second, w/o MKL, it got 26.51B. From the benchmark_model results, we could see that MklConv2DWithBias is the culprit... |

While the title has the word ‘slower’ which may be helpful, the description, however, contains unusual terms and mixed meaning, leading to strong noises which confuse the state-of-the-art classifiers to make a wrong prediction. In contrast, thanks to the hierarchical attentions, MHNurf is able to focus on the most important part of the GitHub report and ignore the other noises, which correctly identifies it as a non-functional bug related report.

Overall, we answer RQ4 as:

**To RQ4:** The effectiveness of MHNurf is the result of better semantic information handling via hierarchical attentions and the multifacetedness, which are precisely the challenges we seek to tackle in this work.

VII. THREATS TO VALIDITY

Threats to internal validity can be related to the parameters. To mitigate such in this work, we set the parameters of MHNurf as default values or according to existing work [17, 26]. For state-of-the-art classifiers, we tune their hyperparameters in each run whenever possible. Construct validity may be subject to threats due to the metrics used in the evaluation. We use AUC — a robust metric — to assess the performance of classifiers on 30 repeated runs in this work. To ensure statistical significance, Scott-Knott test (underpinned by hypothesis test and $A_{12}$) is used to further verify the results. To mitigate threats to external validity, we conduct experiments on five popular DL frameworks with in-depth ablation analysis for MHNurf, including different schemes to handle the content feature and the best combination of them for considering the multifacetedness. We have also compared MHNurf with nine other state-of-the-art classifiers in the field. However, we agree that more subject and DL frameworks may prove fruitful.

VIII. RELATED WORK

Here, we discuss the related work in light of MHNurf.

**Bug report identification with statistical learning.** Traditional statistical learning has been widely applied for bug report identification [27, 40, 41, 42, 43, 44, 45, 46, 47], such as identifying long-lived bug reports [12], configuration bug reports [45], security bug reports [41, 48, 49, 50], high impact bug reports [51, 52, 53, 54], or whether a report is bug-related [27, 40, 42, 43, 44, 46, 47].

However, a major limitation with those works is the inability to handle semantic information, which is an important aspect to consider in bug report identification. This is one of the challenges we seek to overcome with MHNurf.

**Bug report identification with deep learning.** More recently, deep learning based classifiers have been proposed to tackle the limitation of semantic learning [13, 14, 15, 16, 28, 29, 30, 51, 55]. Nevertheless, the above did not consider the fact that different parts of the reports contribute differently in identifying the report, and that multifaceted types of features exist in a GitHub report.

**HAN in software data analytic.** HAN has been deemed as an effective model for different software engineering tasks, e.g., learning the representation of code methods [56], code summarization [57], and defect prediction [58].

Our work differs from all the above as we focus on non-functional bug related report identification for DL frameworks, with specific consideration of the challenges and characteristics of the problem contexts, which motivates the design of MHNurf and MHAN therein.

IX. CONCLUSION

In this paper, we propose MHNurf, an end-to-end tool for automatically identifying non-functional bug related reports for DL frameworks. By extending HAN, MHNurf is underpinned by MHAN that tackles three unresolved challenges: (1) learning the semantic knowledge in the identification and doing so by (2) taking the hierarchy of GitHub reports into account and discriminating the most important part; while (3) considering the multifacetedness of feature types.

We verify MHNurf over a dataset of 3,712 GitHub reports from five popular DL frameworks. The results reveal that:

- The title and description of a GitHub reports should be concatenated together as part of the content feature.
- The content, comment, and code is the best combination for MHNurf and they are considerably better than the classic HAN where only the content is used.
- MHNurf significantly outperforms state-of-the-art classifiers.

In future work, we plan to look into multi-label classification of the GitHub reports for DL frameworks and extend MHNurf to consider more structural information of the provided code in a report, e.g., its Abstract Syntax Tree.
