Using Natural Language Processing and Neural Network Models to Classify, Cluster, and Organize Software Requirements

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***Abstract*—In order to improve and optimize the requirements gathering phase Machine Learning can be used. By collecting the user input into a meaningful and useful dataset, the power of machine learning, natural language processing, and AI can automate and improve the process of determining the direction for a software development project and the most desired features to focus on.**

***Index Terms*—Software Requirements, Machine Learning, Natural Language Processing, Text Classification, Data-Augmentation**

I. Introduction

As modern software development methods have become standard practice, the adoption of Agile methodologies and fast past development has grown drastically. However, the drawbacks of this approach have become clear, more emphasis is placed upon speedy development rather than methodical project planning and execution. As these drawbacks have become more apparent and as Agile methodologies mature, the needs for a hybrid software development approach are clear to individuals in the industry. The value of proper planning and design has gone to the wayside due to the cost and time it can often take to properly develop and plan software. This time and cost can be greatly decreased and mitigated with the incorporation of Machine Learning and Artificial Intelligence applications, starting at the beginning of the software development process.

Proposed is a methodology for using Natural Language Processing and Machine Learning to reduce the time and cost of software requirements definition, seeking to create an automated process starting at the very beginning of software development. In the beginning stages of a software project user stories and requirements are collected from all stakeholders involved in the project. This can vary from technical to non-technical users and can often grow drastically. These requirements typically are collected in a haphazard fashion with no organization or classification. From here the tedious task of organizing, classifying, and compiling user stories and requirements often falls upon technical team members. This can become a costly process and often leaves requirements undefined or missed due to the large sets of requirements collected.

A solution to this tedious process is the automatic classification and sorting of user stories and requirements using machine learning tools and natural language processing to train classification models to recognize and correctly classify a given requirement. This can serve as the stepping-stone for future software design automation and is the most important initial step. Outlined in this proposal is the methodology to train classification models to label software requirements, cluster related requirements, and prioritize requirements based on classification.

II. Methodology and Dataset

III. PROMISE Dataset of Software Requirements Classification

The *PROMISE dataset* is an open-source collection of software requirements, designed for natural language processing tasks related to software engineering. The dataset contains **925 labeled requirements**, split into two main categories:

- **Functional Requirements (FR):** 444 instances
- **Non-Functional Requirements (NFR):** 481 instances

The **Non-Functional Requirements (NFR)** are further subdivided into 11 distinct subcategories, based on specific characteristics important for software design and performance. These subcategories are as follows:

- **Availability (A):** 31 requirements, focusing on the system's ability to ensure operational continuity under specified conditions.
- **Legal (L):** 15 requirements, dealing with legal obligations, regulatory compliance, and intellectual property considerations.
- **Look-and-Feel (LF):** 49 requirements, concerning the user interface design and the aesthetic aspects of the software.
- **Maintainability (MN):** 24 requirements, focusing on the ease of performing maintenance, updates, and debugging in the software.

- **Operability (O):** 77 requirements, related to the ease of operating and using the software under normal conditions.
- **Performance (PE):** 67 requirements, addressing system performance metrics, such as speed, responsiveness, and resource usage.
- **Scalability (SC):** 22 requirements, focusing on the system's ability to handle increased loads and grow in size without performance degradation.
- **Security (SE):** 125 requirements, dealing with protecting the system from malicious attacks and ensuring data integrity and confidentiality.
- **Usability (US):** 85 requirements, centered on how user-friendly, accessible, and intuitive the software is for its intended audience.
- **Fault Tolerance (FT):** 18 requirements, concerning the system's ability to continue functioning in the presence of errors or failures.
- **Portability (PO):** 12 requirements, which focus on the ease of transferring the software across different environments or platforms.

A. Usage in Project Iteration

In the first iteration of this project, the PROMISE dataset served as the **primary dataset** for classifying software requirements. Since some subcategories of non-functional requirements were underrepresented (minority classes), **data augmentation** techniques were employed to balance the distribution and improve classification performance.

While this dataset was useful in the initial phase, future iterations plan to **expand the dataset** with additional similar datasets and leverage more advanced data augmentation techniques. These improvements will be informed by insights gained from the initial project iteration, aimed at improving classification accuracy, particularly for the minority classes.

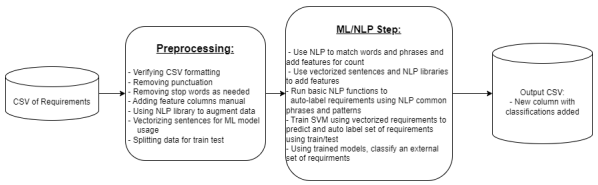

Fig. 1. Methodology Flow Chart

B. Pre-processing

In order to begin training machine learning models to correctly classify non-functional requirements there are necessary steps of data pre-processing that must be completed. These initial steps are standard to natural language processing implementations and allow for proper use of text requirements in machine learning applications [**?**]. These pre-processing steps can be broken down as follows:

- Data Augmentation/Synonym replacement step
- Normalization step
- Natural language manual feature selection
- TFIDF text vectorization Step
- TFIDF feature extraction

Before beginning the remainder of the preprocessing steps, minority classes are determined and synonym replacement used to add requirements and labels to help boost these minority classes. This step enabled drastic improvements in the ML model training and in classifying the minority classes properly. After these extra requirements are added, the dataset is ready for normalization and vectorization. Once the text sentences have been normalized for vectorization and manual features added using features determined to be important, the natural language is processed into numeric vector format using the TFIDF text vectorization library from SkLearn. With the initial pre-processing steps completed the dataset is ready for model training and optimization.

C. Model Selection and Training

After completing the pre-processing steps the model selection and training can begin. For the sake of this implementation four models were chosen:

- Support Vector Classifier
- Multinomial Naive Bayes
- Random Forest Classifier
- Multinomial Logistic Regression

To begin Support Vector Classifier was used as the initial model for training and testing. This involved splitting the dataset into 80 percent for the training dataset and 20 percent for the testing set. Each of the models is initially trained using the non-augmented dataset and the initial 925 requirements to train, test, and evaluate the model's performance using accuracy, recall, and F-1 score. After determining the proper methodology using Support Vector Classifier as the initial model, the process is then applied to the remaining models and the results compared. With the results of the non-augmented models collected and compared, the same process is applied to all four models using the augmented dataset with an increased dataset size from 925 to 1330. The comparison of these results is presented in the following section for analysis.

IV. Past Results and Model Comparison

The results of this work have shown promising results in using different models to classify and label software requirements, with significant improvements made when the dataset was increased in size and augmented. Highlighted in the following section are the results of using a single Support Vector Classifier with the non-augmented dataset and then comparing with the augmented dataset results.

A. Support Vector Classifier without Augmented Data

The results of running a support vector classifier model with non-augmented dataset showed promising results for the properly represented classes but showed poor performance when attempting to classify the minority classes. This can be greatly improved using augmented datasets.

	precision	recall	f1-score
Availability	0.70	0.88	0.78
Fault Tolerance	1.00	0.78	0.88
Functional	0.83	1.00	0.91
Legal	1.00	1.00	1.00
Look & Feel	0.91	1.00	0.95
Maintainability	0.91	0.91	0.91
Operational	1.00	0.80	0.89
Performance	0.89	1.00	0.94
Portability	1.00	1.00	1.00
Scalability	1.00	0.88	0.93
Security	1.00	1.00	1.00
Usability	1.00	0.91	0.95

Fig. 2. Results of SVC without Augmented Data

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As a client, I desire seamless fund transfers between my various accounts within the bank's system. - Predicted: F
As a client, I expect a hassle-free process for paying bills online, ensuring timely payments. - Predicted: F
As a client, I seek timely notifications for significant transactions or any suspicious account activities. - Predicted: F
As a client, I wish to set up automatic transfers or payments to streamline my financial management. - Predicted: F
As a client, I want to have easy access to view my transaction history and download account statements. - Predicted: SE
As a client, I appreciate the convenience of depositing checks using the bank's mobile banking feature. - Predicted: F
As a client, I aim to apply for loans or credit cards online, with a straightforward application process. - Predicted: F
As a client, I need the flexibility to update my contact details and account preferences online. - Predicted: F
As a client, I want a simple procedure to report lost or stolen cards and request replacements. - Predicted: F
As a client, I value the option to chat with a customer service representative online for quick assistance. - Predicted: F
As a client, I prioritize security and desire the ability to temporarily freeze or unfreeze my card. - Predicted: SE
As a bank teller, I require efficient processing of cash deposits and withdrawals for clients. - Predicted: MN
As a bank teller, I need a reliable system to verify client identities and account information accurately. - Predicted: F
As a bank teller, I seek a user-friendly interface to assist clients with their account inquiries and transactions. - Predicted: LF
As a bank teller, I want an easy process to order checks and issue cashier's checks for clients. - Predicted: MN
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Fig. 3. SVC Model Tested on Unclassified Requirements

B. Support Vector Classifier with Augmented Data

As shown in the figure above, after data augmentation and boosting the minority classes the model was able to classify all labels and achieve note worthy F-1 scores for each. This shows that by using even basic data-augmentation methods it is possible to retain all non-functional requirements labels. This is essential for future work and development in leveraging text classification specific to software engineering.

C. Four Model Comparison without Augmented Data

When running the non-augmented data set on four chosen models it was shown that Support Vector Classifier out performs the other models drastically. Multinomial Naive Bayes, however, was not given enough data to begin the classification process and performed poorly. Random Forest Classification was able to begin the labeling steps but did not perform as well as Support Vector Classifier. Finally Multinomal Logistic Regression was able to perform some classification but was inferior to both Random Forest and SVC.

	precision	recall	f1-score
A	0.50	0.50	0.50
F	0.67	0.94	0.78
FT	0.61	0.70	0.65
L	0.87	0.68	0.76
LF	0.88	0.82	0.85
MN	0.63	0.50	0.56
O	0.50	0.86	0.63
PE	0.78	0.64	0.70
PO	0.83	0.91	0.87
SC	1.00	0.33	0.50
SE	0.71	0.38	0.50
US	0.73	0.57	0.64

Fig. 4. Results of SVC with Augmented Data

Random Forest:

	precision	recall	f1-score
A	1.00	1.00	1.00
F	0.66	0.93	0.77
FT	0.00	0.00	0.00
L	1.00	0.50	0.67
LF	1.00	0.29	0.44
MN	0.00	0.00	0.00
O	0.60	0.33	0.43
PE	0.71	0.71	0.71
SC	1.00	0.25	0.40
SE	0.57	0.80	0.67
US	1.00	0.33	0.50

Multinomial Naive Bayes:

	precision	recall	f1-score
A	0.00	0.00	0.00
F	0.49	1.00	0.66
FT	0.00	0.00	0.00
L	0.00	0.00	0.00
LF	0.00	0.00	0.00
MN	0.00	0.00	0.00
O	0.00	0.00	0.00
PE	0.00	0.00	0.00
SC	0.00	0.00	0.00
SE	1.00	0.10	0.18
US	0.00	0.00	0.00

Logistic Regression:

	precision	recall	f1-score
A	1.00	0.50	0.67
F	0.60	0.97	0.74
FT	0.00	0.00	0.00
L	0.00	0.00	0.00
LF	0.00	0.00	0.00
MN	0.00	0.00	0.00
O	0.67	0.22	0.33
PE	0.80	0.57	0.67
SC	1.00	0.25	0.40
SE	0.56	0.50	0.53
US	0.88	0.39	0.54

SVM:

	precision	recall	f1-score
Availability	0.70	0.88	0.78
Fault Tolerance	1.00	0.78	0.88
Functional	0.83	1.00	0.91
Legal	1.00	1.00	1.00
Look & Feel	0.91	1.00	0.95
Maintainability	0.91	0.91	0.91
Operational	1.00	0.80	0.89
Performance	0.89	1.00	0.94
Portability	1.00	1.00	1.00
Scalability	1.00	0.88	0.93
Security	1.00	1.00	1.00
Usability	1.00	0.91	0.95

Fig. 5. Results of Four Model Comparison without Augmented Data

D. Four Model Comparison with Augmented Data

Support Vector Machine:

	precision	recall	f1-score
A	0.500000	0.500000	0.500000
F	0.662162	0.942308	0.777778
FT	0.583333	0.700000	0.636364
L	0.928571	0.684211	0.787879
LF	0.875000	0.823529	0.848485
MN	0.611111	0.458333	0.523810
O	0.500000	0.857143	0.631579
PE	0.777778	0.636364	0.700000
PO	0.833333	0.909091	0.869565
SC	1.000000	0.333333	0.500000
SE	0.714286	0.384615	0.500000
US	0.727273	0.571429	0.640000

Logistic Regression:

	precision	recall	f1-score
A	0.750000	0.500000	0.600000
F	0.573034	0.980769	0.723404
FT	0.681818	0.750000	0.714286
L	0.800000	0.631579	0.705882
LF	0.818182	0.794118	0.805970
MN	0.666667	0.666667	0.666667
O	0.500000	0.428571	0.461538
PE	1.000000	0.363636	0.533333
PO	1.000000	0.909091	0.952381
SC	1.000000	0.166667	0.285714
SE	0.750000	0.230769	0.352941
US	0.800000	0.571429	0.666667

Random Forest:

	precision	recall	f1-score
A	0.285714	0.333333	0.307692
F	0.583333	0.942308	0.720588
FT	0.666667	0.600000	0.631579
L	0.750000	0.789474	0.769231
LF	0.774194	0.705882	0.738462
MN	0.705882	0.500000	0.585366
O	0.428571	0.428571	0.428571
PE	0.777778	0.636364	0.700000
PO	0.846154	1.000000	0.916667
SC	1.000000	0.500000	0.666667
SE	0.600000	0.230769	0.333333
US	0.833333	0.357143	0.500000

Multinomial Naive Bayes:

	precision	recall	f1-score
A	0.666667	0.333333	0.444444
F	0.451327	0.980769	0.618182
FT	0.722222	0.650000	0.684211
L	0.857143	0.631579	0.727273
LF	0.818182	0.794118	0.805970
MN	0.680000	0.708333	0.693878
O	0.666667	0.285714	0.400000
PE	1.000000	0.181818	0.307692
PO	1.000000	0.727273	0.842105
SC	0.000000	0.000000	0.000000
SE	1.000000	0.153846	0.266667
US	1.000000	0.142857	0.250000

Fig. 6. Results of Four Model Comparison with Augmented Data

Running all four models with augmented data yielded surprising results when compared to the non-augmented data results. With the minority classes boosted, all models could perform classification on almost every label and achieve notable F-1 scores. Support Vector was no longer the top performing model, with Random Forest achieving comparable results. This shows that if further data augmentation and dataset improvements could prove drastic improvements to the classification models.

V. Related Works

A. Classifying Functional and Non-Functional Software Requirements

Prior work in requirements engineering has utilized simple word patterns to classify requirements as either functional

or non-functional. These methods typically involve keyword matching or basic rule-based techniques to make binary classifications of the requirements. For instance, functional requirements often describe system behavior, while non-functional requirements focus on constraints such as performance or security. While effective for basic categorization, the major limitation of these approaches is their binary nature, which lacks the depth needed for advanced clustering or more nuanced categorization of requirements. This simplistic methodology is unable to support more granular classification, such as subcategories within non-functional requirements, and fails to address the complexities of real-world requirement sets, which may be ambiguous or overlapping.

Drawback: These methods fail to provide clustering and more advanced classification models, limiting their applicability for large and complex datasets. Furthermore, the reliance on simple word patterns restricts adaptability in diverse projects and introduces limitations in scalability when dealing with mixed and vague requirements [1].

B. NLP Approaches to Requirements Engineering Practice

Natural Language Processing (NLP) techniques have also been employed in requirements engineering (RE) to improve processes. These efforts are generally categorized into six key areas: quality checks, extraction, classification, modeling, traceability, and search and retrieval. Each area addresses different aspects of RE. For example, quality checks use existing NLP models to assess the clarity and completeness of requirements, while extraction focuses on deriving domain-specific information based on predefined patterns. NLP-based classification aims to categorize software requirements for easier management and clustering, while traceability techniques establish links between various requirements to ensure consistency.

Methodology: Most of these approaches utilize pre-trained NLP models and employ a combination of rule-based methods and supervised learning to perform tasks such as extraction and classification. Techniques like Term Frequency-Inverse Document Frequency (TF-IDF) are frequently used for feature extraction and text representation. Despite promising results, the majority of these models are limited by their inability to handle domain-specific language nuances and require significant manual input for model training and feature selection.

Drawback: NLP tools applied to RE are still in their infancy and often fail to handle the domain-specific language of software requirements. Moreover, many of the techniques require manual tuning or domain-specific expertise to achieve meaningful results, limiting their broad applicability [2].

C. Past Project Work

In recent studies, various models were used to classify software requirements with promising results. For instance, a Support Vector Classifier (SVC) was applied to a dataset of labeled software requirements, yielding moderate success. However, without data augmentation, the model struggled to classify minority classes effectively, resulting in poor overall performance. The application of basic data augmentation techniques significantly improved these results by boosting the representation of underrepresented classes. This highlights the importance of data size and quality in NLP-driven models.

Methodology: A Support Vector Classifier (SVC) was utilized on both augmented and non-augmented datasets to observe improvements in classification accuracy. Data augmentation included techniques such as synonym replacement and oversampling of minority classes to balance the dataset. This approach improved F1 scores across the board, showing that even minor augmentations can have a substantial impact on model performance.

Drawback: While the model performed better with augmented data, the reliance on basic data augmentation techniques is a limitation, especially for more sophisticated classification tasks. The model also showed poor generalization when applied to datasets with significant variations in domain or language style [3].

MOTIVATION

The software development landscape has rapidly evolved with the widespread adoption of Agile methodologies, emphasizing speed and iterative development over methodical planning. While this approach accelerates the creation of software, it also introduces challenges in managing and organizing software requirements effectively, particularly in the early stages of development. Requirements gathering from diverse stakeholders often results in large, unstructured data that can be overwhelming to process manually. This disorganization can lead to missed or incomplete requirements, potentially derailing a project's success.

In this context, leveraging Natural Language Processing (NLP) and Neural Networks offers an opportunity to revolutionize requirements engineering (RE) by automating the classification and clustering of requirements. By automatically analyzing and organizing requirements data, machine learning techniques can reduce the burden on human engineers, ensuring that all functional and non-functional requirements are captured, categorized, and prioritized systematically.

The motivation for this research lies in addressing the inefficiencies of manual requirement processing. It aims to streamline the early stages of software development using advanced NLP models and neural networks. This automation not only saves time and reduces costs but also paves the way for more robust and scalable approaches to software development. By improving the accuracy and consistency of requirement classification, the proposed methods will support more informed decision-making in the design and planning phases, ultimately leading to higher-quality software solutions.

VI. Planned Experiment

To improve the classification and prioritization of software requirements using NLP, several enhancements are planned for this experiment. These improvements focus on expanding the dataset, applying more advanced machine learning techniques, and fine-tuning the models to handle domain-specific knowledge.

A. Expanding the Dataset

The current PROMISE dataset, with 925 labeled software requirements, will be expanded by adding more expert-classified requirements. This expansion will address the imbalance in the dataset, particularly for underrepresented categories such as Fault Tolerance and Portability. By increasing the number of training examples, the models will be better equipped to handle a wider range of requirement types.

B. Enhanced Data Augmentation

We will use more advanced data augmentation techniques to further balance the dataset. In addition to basic methods like synonym replacement, we will explore techniques such as back-translation and paraphrasing. This will generate additional training examples, especially for minority classes, improving the models' ability to classify rare requirement types.

C. Neural Network Models

To enhance classification performance, we will introduce neural network-based models, such as Recurrent Neural Networks (RNNs) or BERT, which are well-suited for handling natural language data. These models can capture more complex patterns in the text and are expected to outperform traditional machine learning models like Support Vector Machines and Random Forests. We will compare the performance of these neural models with simpler algorithms to determine their effectiveness.

D. Training on Domain-Specific Knowledge

We plan to fine-tune the models using domain-specific knowledge related to software engineering. This step will involve training the models on additional datasets specific to software requirements, allowing them to better understand and classify technical terms and phrases commonly used in the industry. This is expected to improve classification accuracy, particularly for more specialized requirements.

E. Model Training and Evaluation

The models will be trained on both the expanded and original datasets and evaluated based on metrics like accuracy, precision, recall, and F1-score. We will perform an 80/20 train-test split and use cross-validation to ensure the results are robust. The performance of each model will be compared, focusing on their ability to classify both functional and non-functional requirements accurately.

This experiment will provide valuable insights into how NLP models, especially neural networks, can be improved for use in software requirements engineering. The results will guide future work on automating the software development process, particularly in requirement gathering and classification.

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