



Title of the Final Year Undergraduate Project

An undergraduate project proposal report submitted to the

Department of Electrical and Information Engineering
Faculty of Engineering
University of Ruhuna
Sri Lanka

in partial fulfillment of the requirements for the

**Degree of the Bachelor of the Science of Engineering
Honours**

by

R. Lareef - EG/2021/4644
A. Abekon - EG/2021/4645
B. Safeer - EG/2021/4771

.....
Prof. A.B.C. Dee
(Supervisor)

.....
Prof. A.B.C. Dee
(Co-Supervisor)

Abstract

The growing complexity of modern software systems and the need for effective communication among stakeholders have made Unified Modeling Language (UML) diagrams a vital component of software engineering. However, manually creating UML diagrams from textual requirements is a time-consuming, error-prone process that requires considerable expertise. To address this challenge, this research proposes an AI-driven framework for automatically generating UML class and use case diagrams from natural language software requirements.

The proposed system leverages advanced Natural Language Processing (NLP) and Deep Learning (DL) techniques to interpret unrestricted, ambiguous, and incomplete textual inputs more accurately. By improving grammatical and semantic understanding, the framework aims to produce more reliable and comprehensive UML representations.

The methodology includes both quantitative and qualitative evaluation. Accuracy is measured using standard metrics such as precision, recall, and F1-score, while usability is assessed through feedback from students and industry professionals. A comparative analysis with existing tools demonstrates that the proposed approach offers improved scalability, robustness, and efficiency.

This research contributes to the field of software engineering by reducing manual effort, enhancing design accuracy, and improving collaboration among stakeholders. By automating UML diagram generation, the proposed framework supports more efficient and adaptive software development workflows, benefiting both academic research and industrial practice.

Contents

Acronyms	vi
1 Introduction	1
1.1 Background	1
1.2 Problem Statement	2
1.3 Objectives and Scope	2
2 Literature Review	3
2.1 Previous Work	3
2.2 Gaps in Literature	4
3 Methodology	6
3.1 Research Design	6
3.2 Data Collection	6
4 Timeline and Resource Required	7
4.1 Timeline	7
4.2 Resource Required	7
5 Conclusion	9
References	9

List of Figures

3.1 This is an example image.	6
---------------------------------------	---

List of Tables

4.1 8-Month Project Work Plan	8
---	---

Acronyms

AI Artificial Intelligence

DL Deep Learning

ML Machine Learning

NLP Natural Language Processing

UML Unified Modeling Language

Chapter 1

Introduction

1.1 Background

The rapid growth of technology and the expanding influence of the software and IT industry have significantly transformed how individuals and organizations operate. Software applications now play a central role in driving innovation across domains such as healthcare, education, finance, and entertainment. As software systems become more complex, the demand for efficient, accurate, and collaborative software development processes has increased. Effective communication tools and clear design methodologies are essential to ensure a shared understanding among all stakeholders involved in software projects.

Unified Modeling Language (UML) diagrams are widely used to represent software designs in a standardized and visual manner. They help illustrate system components, interactions, and workflows, making them understandable to both technical and non-technical users. However, creating UML diagrams manually from textual software requirements is a time-consuming and expertise-dependent task. This process often leads to inconsistencies, misinterpretations, and inefficiencies, especially in large-scale projects where speed and accuracy are critical.

Recent advancements in Artificial Intelligence (AI), particularly in Natural Language Processing (NLP) and Deep Learning (DL), provide a promising solution to this problem. NLP enables machines to understand and analyze human language, while DL models can learn complex patterns and generate meaningful outputs. By leveraging these technologies, our project aims to automate the generation of UML diagrams—specifically class diagrams and use case diagrams—from natural language software requirements. This approach seeks to provide a more comprehensive and practical solution for software design automation.

Existing automated systems face several limitations, including the inability to handle incomplete requirement documents, restrictions on sentence structure, and difficulties in understanding grammatical nuances. These issues often result in inaccurate or incomplete UML diagrams. Our proposed system addresses these challenges by supporting unrestricted natural language input, improving grammatical analysis, and handling missing information more effectively.

From a practical and commercial perspective, automating UML diagram generation can significantly reduce development time and cost. It can improve team productivity, enhance collaboration among distributed teams, and ensure consistency in design documentation. By improving efficiency, accuracy, and scalability,

our solution can help organizations gain a competitive advantage in today's fast-paced software industry.

This project proposes a robust AI-driven framework that converts textual software requirements into accurate UML diagrams. By bridging the gap between natural language and visual system models, our work contributes to the integration of AI technologies into the software development lifecycle.

1.2 Problem Statement

Despite the significant role that UML diagrams play in software development, existing tools for generating them from natural language requirements have several limitations. Most current solutions focus primarily on class diagrams, while neglecting other important diagram types such as use case diagrams. Furthermore, these tools struggle with incomplete requirement documents, restricted input formats, and grammatical inconsistencies, which often result in errors and inefficiencies. As a result, considerable manual intervention is required, reducing the scalability, accuracy, and practicality of these systems in real-world software development environments.

1.3 Objectives and Scope

State the objectives of your project clearly.

Chapter 2

Literature Review

2.1 Previous Work

The extraction of UML class diagrams from informal software requirements has traditionally been addressed using Natural Language Processing (NLP) techniques combined with heuristic rules or domain ontologies. Over time, researchers have explored more advanced approaches, including machine learning (ML) and deep learning (DL), to improve automation, accuracy, and efficiency. Existing studies mainly fall into three categories: NLP-based, ML-based, and DL-based approaches [?].

NLP-Based Approaches

Ibrahim and Ahmad introduced the RACE tool, which uses NLP techniques to analyze software requirements and extract UML class diagrams. The process includes structural analysis, refinement of diagram elements, and validation of UML concepts. However, the generated diagrams often lack complete information [?].

Kumar and Sanyal developed the SUGAR tool using the Rational Unified Process (RUP) methodology. It generates UML class diagrams from natural language requirements by first creating use case diagrams and then linking them to class diagram components. This approach supports object-oriented analysis but still relies heavily on predefined structures [?].

Sharma et al. proposed the Functional Design Creation Tool (FDCT), which preprocesses and analyzes requirements to identify model entities and integrate them into high-level class diagrams [?].

Deeptimahanti and Sanyal introduced UMGAR, a semi-automatic system that uses syntactic rules and analysis trees to extract UML elements. Although it can generate multiple UML diagram types, it requires human intervention to refine relationships and remove irrelevant elements [?].

Similarly, the RAPID tool by More and Phalnikar can generate use case, sequence, and collaboration diagrams using an architecture similar to RACE [?].

Shinde et al. developed a system that applies NLP preprocessing and rule-based extraction to generate UML class and sequence diagrams, and even produce Java source code from the extracted models [?].

The UDRA tool by Amune and Naik combines NLP with domain ontologies to

generate various UML diagrams such as class, object, package, and deployment diagrams. It supports relationships like association, generalization, and composition [?].

Other language-specific approaches include the work of Jaiwai and Sammapun, who developed a system for Thai-language requirements, and Utama and Jang, who used SpaCy with linguistic rules to extract UML class diagrams from unrestricted natural language [?].

Abdelnabi et al. proposed an NLP and heuristic-based method for generating class diagrams from informal requirements [?].

Bashir et al. developed the READ tool, which uses the NLTK library and rule-based extraction to automatically identify classes, attributes, and operations. Their results showed improved accuracy compared to earlier tools [? ?].

Machine Learning and Deep Learning Approaches

Although NLP-based systems improved automation, they still struggle with ambiguity, incompleteness, and uncertainty in natural language requirements [?].

Arachchi proposed a hybrid system that combines NLP, machine learning, and deep learning to generate UML class and use case diagrams. The system uses NLP for text processing, Naive Bayes for classification, and RNNs for identifying actors, classes, and relationships [?].

Saini et al. introduced DoMoBOT, which integrates NLP with ML and DL models to generate domain models as UML class diagrams. The system preprocesses text using SpaCy, extracts domain concepts using NLP rules, refines them using trained ML/DL models, and integrates the results into a final UML model [?].

Rigou and Khriss proposed a deep learning-based framework using Bi-LSTM, BERT, and GPT-2 models to extract UML class diagrams from natural language requirements. Their system identifies entities, removes redundant references, and classifies relationships using neural networks. Results showed that larger training datasets improved diagram accuracy [? ?].

2.2 Gaps in Literature

Despite significant progress, several limitations remain in existing UML diagram extraction systems:

- **Limited Diagram Coverage:** Most tools primarily focus on generating UML class diagrams, while other important diagram types such as use case diagrams, sequence diagrams, and activity diagrams receive less attention.
- **Dependence on Rule-Based Systems:** Many approaches rely on fixed linguistic rules and heuristics, making them less flexible when dealing with diverse writing styles, complex sentence structures, or informal requirements.
- **Handling of Incomplete Requirements:** Existing systems struggle to generate accurate diagrams when requirement documents are missing key information, leading to incomplete or incorrect UML models.

- **Grammatical and Semantic Challenges:** Ambiguity, grammatical inconsistencies, and contextual misunderstandings in natural language often cause extraction errors, even in advanced NLP-based tools.
- **High Manual Intervention:** Several systems require human input to refine relationships, remove irrelevant elements, or correct extracted models, reducing scalability and automation.
- **Limited Real-World Scalability:** Many tools are tested only on small datasets or controlled inputs, making their performance in large-scale, real-world projects uncertain.
- **Restricted Input Formats:** Some systems require standardized or structured requirements, limiting their usability with freely written natural language documents.

Chapter 3

Methodology

3.1 Research Design

Describe the research design and methodology. Use diagrams or flow charts to illustrate the methodology.

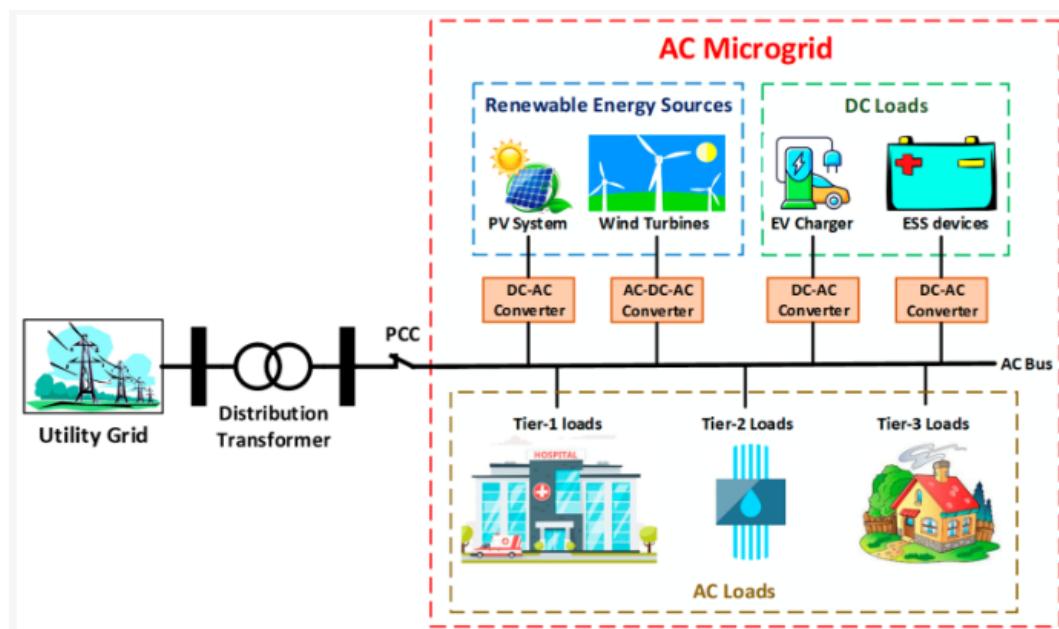


Figure 3.1: This is an example image.

As shown in Figure 3.1, the image is centered and has a caption.

3.2 Data Collection

Explain how data will be collected for the project.

Chapter 4

Timeline and Resource Required

4.1 Timeline

4.2 Resource Required

Time Period	Activities	Deliverables
Month 1–2	<ul style="list-style-type: none"> Conduct literature review on UML automation Study existing NLP and AI-based tools Identify challenges and refine problem statement 	<ul style="list-style-type: none"> Literature Review Report Refined Problem Statement
Month 3–4	<ul style="list-style-type: none"> Prepare training and testing dataset Design preprocessing pipeline (tokenization, POS tagging, parsing) Explore NLP and DL models (BERT, GPT) 	<ul style="list-style-type: none"> Prepared Dataset Preprocessing Pipeline Design
Month 5–6	<ul style="list-style-type: none"> Implement AI-based UML extraction model Train and fine-tune the model Generate UML class and use case diagrams Integrate PlantUML / Graphviz 	<ul style="list-style-type: none"> Working UML Generation System Generated UML Diagrams
Month 7	<ul style="list-style-type: none"> Evaluate using precision, recall, F1-score Compare with existing tools Conduct usability testing 	<ul style="list-style-type: none"> Evaluation Report Performance Comparison Results
Month 8	<ul style="list-style-type: none"> Finalize system Write final report Prepare presentation and documentation 	<ul style="list-style-type: none"> Final Project Report Presentation Slides System Documentation

Table 4.1: 8-Month Project Work Plan

Resource Category	Description
NLP Tools	SpaCy, NLTK, and Coreferee will be used for text preprocessing tasks such as tokenization, part-of-speech tagging, dependency parsing, and coreference resolution. These tools help extract linguistic features required for UML diagram generation.
Deep Learning Frameworks	TensorFlow and PyTorch will be used to develop and train deep learning models. Pre-trained transformer models such as BERT, GPT, or RoBERTa will be used for feature extraction and classification.
Diagram Generation Tools	PlantUML and Graphviz will be used to automatically generate UML class and use case diagrams. These tools support multiple UML diagram types and allow customization according to UML standards.
Data Storage and Management	PostgreSQL or MongoDB will be used to store datasets, training results, and generated UML models in an organized manner.
Hardware Resources	A computer with sufficient processing power (GPU support preferred), at least 8GB RAM, and stable internet access for model training and testing.
Software Tools	Python, VS Code, GitHub for version control, and LaTeX for documentation and report writing.

Table 4.2: Resource Requirements for the Project

Chapter 5

Conclusion

This research proposes a robust AI-driven framework for automating the generation of UML diagrams from natural language software requirements. By addressing key challenges such as ambiguity, incomplete inputs, and grammatical inconsistencies, the proposed system enhances the accuracy and efficiency of software design processes. The integration of advanced Natural Language Processing (NLP) and Deep Learning (DL) techniques enables scalable automation and supports multiple UML diagram types, thereby improving collaboration among stakeholders.

The proposed methodology, supported by rigorous evaluation and validation, ensures that the framework is practical and suitable for real-world software engineering applications. Although certain limitations, including scalability and domain-specific adaptability, require further investigation, this research establishes a strong foundation for incorporating AI-based solutions into the software development lifecycle.

The outcomes of this study have the potential to transform how software designs are documented and communicated, offering significant benefits to both academia and industry. Future work will focus on extending support for additional UML diagram types, enhancing domain adaptability, and refining evaluation methods to further improve the effectiveness of AI-driven software design automation.

References

- [1] A. Jones, *Machine Learning: Theory and Practice*. Tech Publications, 2019.