

**UTILIZING REVERSE-STEMMING AND OTHER
TECHNIQUES TO DEVELOP A DATA ANNOTATION
TOOL FOR CODE-MIXED TEXT DATA FOR
EFFICIENT CUSTOM ENTITY TAGGING**

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The dissertation was submitted in partial fulfilment of the requirements for the B.Sc.
Special Honours degree in Information Technology

Department of Computer Systems Engineering


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ABSTRACT

Named entity recognition is a key component in conversational AIs. It helps conversational AI to identify the key elements in a given text, as an example names of people, places, brands, monetary values etc. This process is done by artificial neural networks or statistical methods. Annotated text data is a vital requirement to train a name entity recognition model. therefore. Training a name entity recognition model requires considerable amount of annotated text dataset. Text annotations is a tedious task because it requires domain knowledge and human interaction for each word. Therefore, few tools are available for text data annotation for make the process easier, but there is no optimized tool for Sinhala - English code-switching text data annotation. Sinhala is a native language in Sri Lanka which is being used by approximately 19 million people. Most of the Sinhalese use Sinhala - English code-switching typing style when they are typing. This paper presents a methos to increase the efficiency of text annotation task by providing name entity suggestions during the Sinhala-English code-switching text data annotation.

Keywords: custom named entity tagging, text annotating, named entity recognition, code-switching text data

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LIST OF ABBREVIATIONS

The list of all the abbreviations used in this report is in the following table.

Abbreviation	Description
AI	Artificial intelligence
AIML	Artificial Intelligence Mark-up Language
CLI	command line interface
CNN	Convolutional neural network
GUI	graphical user interface
LSTM	Long short-term memory
ML	Machine learning
NER	named entity recognition
NLP	Natural language processing
NLU	Natural language understanding
RNN	Recurrent Neural Network
XML	Extensible markup language
CDD	Conversation Driven Development
CaaS	Chatbot as a service

1. INTRODUCTION

1.1 Background & Literature survey

Humans are daily engaging with various kinds of data types to fulfil their requirements. As an example, text data when reading news and magazines, audio data when listening to music or radio, images when watching pictures, and videos when watching films. These observations are interpreted by the human brain to extract the required information to guide our actions or feelings. Text data represents the human languages which are used to speak and write human thoughts. Since humans are social creatures text data is one of the most popular forms of media among others. As a result of advancements in machine learning technologies, there are many machine learning techniques and models specially designed for text data. Before feeding text data into machine learning models there are some pre-processing steps to follow such as lower casing, removal of punctuations, removal of emojis, removal of stop words, stemming, lemmatization and stop word removal. These techniques are used to enhance the results. Text annotation also can be considered as a pre-processing task. A metadata tag is provided during the annotation process to provide features to text data. This information provides tags that indicate criteria like words, phrases, and feelings. This helps to understand the meanings or emotions behind human speech during training an NLP model. The objective is to improve the NLP model's understandability of spoken or written language. Large volumes of annotated data are used by NLP algorithms and AI models. Therefore, text annotation must be done accurately and completely due to its widespread use. This allows computers to read, comprehend, evaluate, and produce text in ways that are useful for technological interactions with people more effectively. According to the 2020 State of AI and Machine Learning report [2], 70% of businesses are using text as a type of their AI products. This allows businesses to cost savings and revenue generation across all industries.

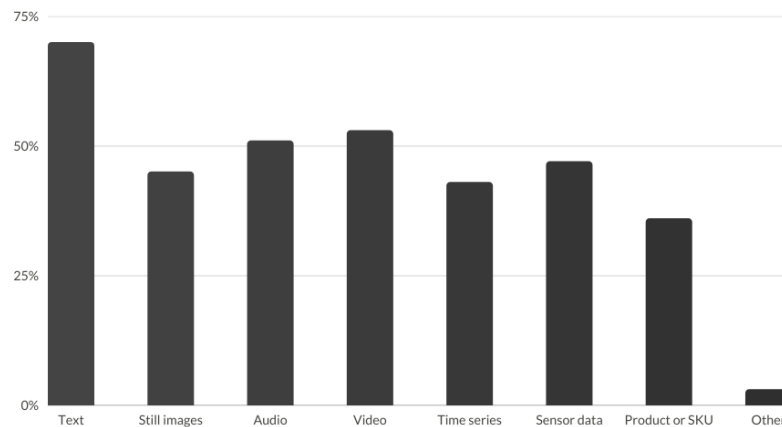


Figure 1.1. 1. 2020 State of AI and Machine Learning report – Data type usage in businesses

The significance of model training with high-quality text data is significantly important for machines to become more adept at understanding human language. In all circumstances, accurate, thorough text annotation is the first step in the creation of accurate training data. AI models will perform poorly with grammatical flaws or issues with clarity, understanding the context, and misinterpretations because of poorly done text annotations. If AI models train on correctly annotated text data, AI models will learn to perform effectively enough for the natural language. [3] These models can handle the more routine and repetitive tasks that are handled by people such as digital customer assistance, intelligent help desks, call centre management, language assistants, machine translators, customer feedback analysis, and more. This enables a business to concentrate on more strategic goals by freeing up time, money, and resources. Additionally, this will increase customer satisfaction as well, because of the quick responses and all-day availability. According to the survey most people tend to use conversational AIs to archive their goals.

Do you prefer to find Information using chatbots or by surfing the internet? (for example: finding available degrees at SLIIT) 🌐
110 responses

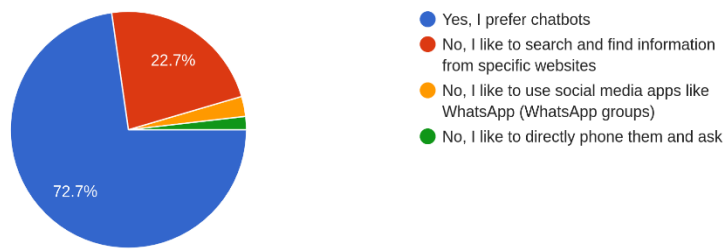


Figure 1.1. 2. Responses for do you prefer to find information using chatbots or by surfing the internet? (For example: finding available degrees at SLIIT)

Do you think using conversational AIs / Chatbots / Digital Assistants is a waste of time? 🤖
110 responses

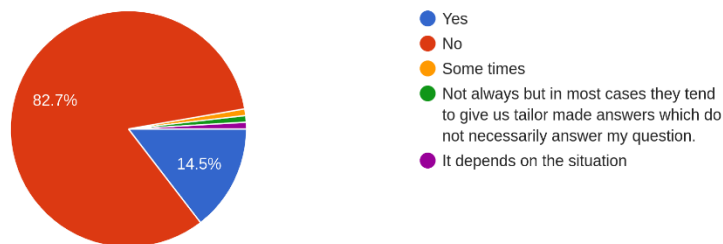


Figure 1.1. 3. Responses for do you think using conversational AIs / Chatbots / Digital Assistants is a waste of time?

For organizations in every domain, the ability to simplify processes by using high-quality text data is having a significant impact on customer satisfaction and financial performance. Text annotations can be of many different forms, sentiment annotation, intent annotation, semantic annotation, and relationship annotation. These annotation types are applied to many different human languages. Sentiment Annotation classifies text as positive, negative, or neutral after evaluating the attitudes and feelings by understanding the context. Text underlying need or desire of the meaning, analysed by intent annotation. Which divides it into various categories. As an example, request, command, or acknowledgement. Semantic text annotation is given additional tags that refer to numerous concepts and entities. As an example, persons, locations, or subjects. The relationship annotation aims to depict various connections between various elements of the document. Resolving dependencies and coreferences are examples of

relationship annotation. These text annotation techniques are applied to conversational AIs as well, also known as chatbots.

Conversational AI is software that simulates human conversations. Through the advancement of NLP and ML technologies, chatbots can understand human needs through textual inputs.[3] Therefore, chatbots can be used to increase customer service and satisfaction at anything by placing a chatbot when customer interaction happens with the business. When a user asks a question from a chatbot it needs to understand the input text. This process is called natural language understanding (NLU). The named entity recognition (NER) approach can be used for NLU tasks. [4][5] There are neural network-based models (Bidirectional LSTM, and Bidirectional LSTM-CNNs) and statistical models such as conditional random field to identify name entities. In this research, only neural network-based models are considered. Neural network-based models require a considerable amount of training data to converge by adjusting weights. Usually, when building a Conversational AI, it should focus on a domain, otherwise, chatbots will not perform well according to business requirements. Therefore, the data set should be created according to the selected domain, by covering the domain-specific vocabulary.

As previously mentioned, [6] adding linguistic information to a corpus is called text annotation or named entity tagging. Named entity tagging is responsible for indicating the classes of words in a corpus. As an example, named entities are predefined categories of real-world things, such as a person, location, time, expressions, organization, and product. Also, it can be a domain-specific class of words. If the corpus contains an enormous number of words, it takes a considerable amount of time to do the tagging process. Because every word in the corpus should be read and identified by the person who is doing the annotation task. Therefore, creating data sets for named entity recognition models is a very time-consuming task and it requires expert knowledge.

Table 1.1. 1. Examples for domain specific named entities

Domain	Name entity	Example words
Biological domain [7]	virus	Coronavirus, Cocksackievirus, Dugbe
	bacteria	Hafnia spp, Escherichia coli, Citrobaacter koseri
Commerce domain	Currency type	Yen, LKR, USD (United States Dollar), ₹
	payment method	visa card, master card, PayPal, crypto

Named entity recognition helps to determine the most suitable intent for a given text. This is done by the intent classification component of the chatbot. In this case, the text is the user's question, the intent is the chatbot's reply. If the chatbot does not have an ability to identify name entities chatbot will work in form filling way as shown in Figure 1.1. 5

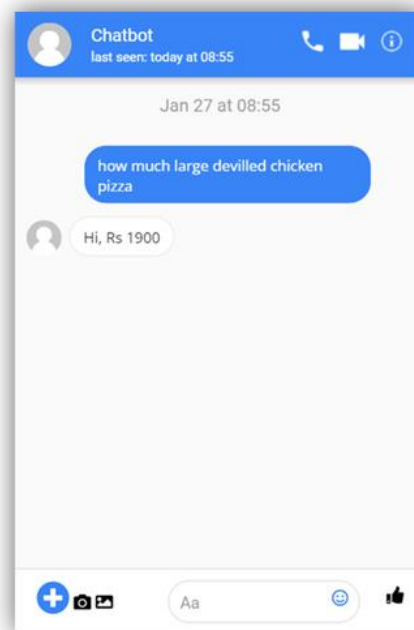


Figure 1.1. 4. Chatbot with named entity identification

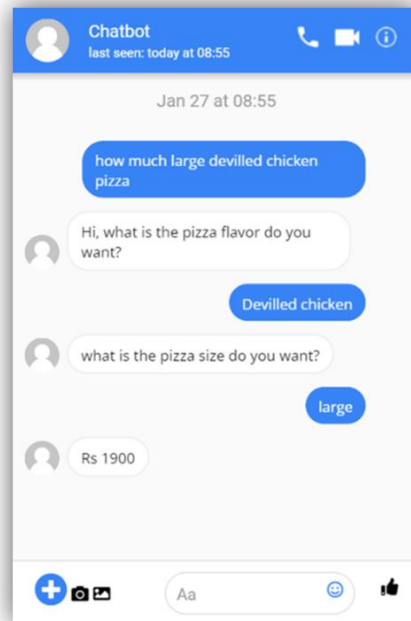


Figure 1.1. 5. Chatbot without named entity identification

As shown in Figure 1.1. 5 when the user asks, “how much large, devilled chicken pizza,” the chatbot failed to identify the size and flavour of the pizza. If the chatbot could be able to identify named entities, the chatbot can provide the price of the pizza in the first reply by understanding flavour type and the size of pizza as shown in Figure 1.1. 5. According to the survey results, most of the people like to interact chatbots with automatically identifying name entities instead of form filling style.

Do you prefer if chatbots can identify Dates / Names / Registration numbers / Places / Lecture Halls and other similar data automatically or do you prefer filling forms instead?
110 responses

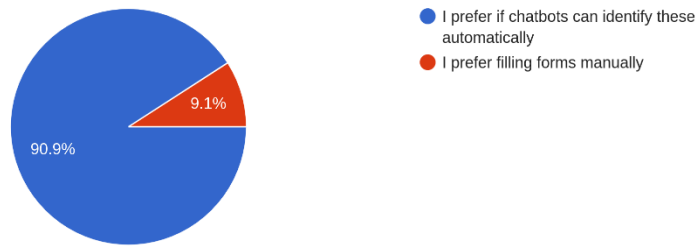


Figure 1.1. 6. Responses for do you prefer if chatbots can identify Dates / Names / Registration numbers / Places / Lecture Halls and other similar data automatically or do you prefer filling forms instead?

1.2 Research Gap

Researchers in named entity recommendation area are used diverse kinds of approaches to implement automated and semi-automated text annotation tools. [8] BRAT is a web-based annotating tool that has a named entity recommendation system using statistical method. It uses a semantic class disambiguation system with numerous outputs and probability estimations to reducing ambiguity of auto annotation. Additionally, it has rich collection of search features which enables users to conduct document, annotations, relations, event structures, and plain text searches. [9] GATE is a multi-role web-based annotation environment, and it facilitates unique text annotation processes and offers methodological and tool assistance to the many hierarchies of team roles. It fully supports every stage of an annotation project's lifecycle. It mainly focused on collaborative annotation because of the time taken to text data annotation and user experience. However, collaborative annotation is not focused on this paper. Additionally, it has feature to auto annotate previously annotated words when user provides a partially annotated document. [10] YEDDA offers a complete range of features for text annotation as well as administrator assessment and analysis. It provides a graphical user interface and command line interface as well as powerful shortcut keys that can be configured with custom labels to annotate entities,

it improves the ineffectiveness of conventional text annotation with these features. By providing pre-annotated text, YEDDA also can provide recommendations by using by Maximum Matching algorithm which is a text segmentation algorithm. [11] ANEA tool uses Wiktionary to make a connection between words in a given text. Wiktionary is an online dictionary it contains details and explanations about the word. Therefore, ANEA recognises entity groupings automatically by identifying Wiktionary descriptions and performing a search of relevant terms. It performs a double optimization task by calculating Cross-similarity and maximizations of words within an entity group and their average similarity to determine candidate labels. The drawback of this approach is if Wiktionary does not contain the required word this tool will not be able to guess the word entity. The lack of Sinhala words in Wiktionary affects negatively to Sinhala text data annotation using this approach.

Since all the previously mentioned text annotation tools are not providing name entity suggestions by considering variations of the base words, SIENA provides name entity suggestions by considering variations of the base words. SIENA tool is specially designed for Sinhala English code-switching text annotation tasks. It can identify variations of Sinhala and English words. By using the SIENA tool, text annotating persons can do their task effectively on Sinhala English code-switching corpus when they require a domain adaptation of named entity recognition.

Table 1.2. 1. Comparison with existing research related to text annotation tools

Tool name	Collaboration features	Name Entity recommendations	Sinhala word variation identification
ANEA	no	yes (<i>via external knowledge source</i>)	no
BRAT	no	yes (<i>via semantic class disambiguation</i>)	no
GATE	yes	no	no
YEDDA	no	yes (<i>via maximum matching algorithm</i>)	no
SIENA (<i>This research component</i>)	no	yes	yes

2. RESEARCH PROBLEM

With the advancement of technology, machine learning models are becoming more complex and denser, because of that the amount of data they needed to train is increasing, therefore a large amount of text data is required to prepare for the model training. As an example, spacy name entity recognition AI model is trained by 741 MBs of text data.[12] NCBI-Disease, BC5CDR and DFKI are popular datasets that used to train name entity recognition models which has large number of word count. Training chatbot components also required a large corpus because of that annotating a such large data set is a very tedious task. As well as when the dataset or the corpus contains enormous number of words, it takes a considerable amount of time to do the tagging process because every word in the corpus should be read and identified by the person who is doing the annotation task. Therefore, annotating data sets for named entity recognition models is a very time-consuming task. Name entity tagging requires domain knowledge as well because the person who does the annotation needs to read the whole text and understand the meaning, therefore it requires expert knowledge regarding the domain. Finding people with domain knowledge is also a challenging task. Also, there is a chance they are not able to do the text annotation due to their lack of technical knowledge.

In this research, only Sri Lankan people are focused, therefore most Sri Lankans are using the Sinhala-English code-switching language style when they interact with a chatbot. This statement is proven by the survey. [13] Sinhalese language, also known as Sinhala (සිංහල) is one of the two official languages of Sri Lanka, with about 16 million speakers out of the total population of 21 million also Sinhala is not a worldwide spread language like English. Due to those reasons, there is a lack of NLP tools and Sinhala specified name entity tagging tools designed for the Sinhala language. Therefore, Sinhala English mixed data annotation is even time consuming due to the absence of Sinhala English code-mixed annotation tools and technologies.

What languages would you prefer to use the most for chatting if you had to interact with a chatbot?



110 responses

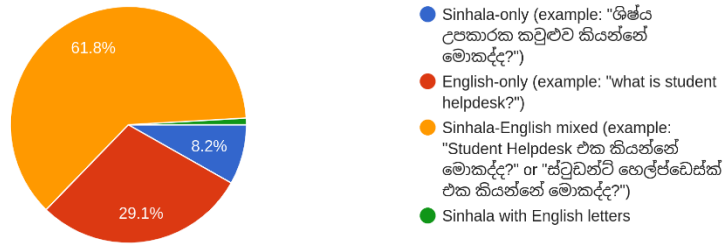


Figure 2. 1. Responses for What languages would you prefer to use the most for chatting if you had to interact with a chatbot?

3. RESEARCH OBJECTIVES

3.1 Main Objectives

The main objective of implementing the SIENA tool is to increase the efficiency of the text annotation process for the Sinhala-English code-switching corpus by providing accurate name entity recommendations and auto annotation.

3.2 Specific Objectives

To archive the main objective, the specific objectives that need to be fulfilled are identified as follows

1. Implement name entity suggestion algorithm

SIENA shows the name entity suggestion list according to the descending order of similarity score when the user selects a phrase.

2. Implement auto annotation algorithm

An algorithm to annotate all variations of phrases at once by selecting a base word of a phrase.

3. Make SIENA compatible with frameworks

After annotation is done. The tool should be able to export data with the compatibility of famous libraries which are used to build NER models. For this research component Rasa NLU data format was selected.

4. Develop visualizations technique to provide user friendly suggestions

Name entity suggestions will appear as a sorted list according to the similarity score below to the user selected phrases. Therefore, the user can easily select the most appropriate name entity.

5. Implement knowledge base as a portable component

Users can import or export knowledge base from or into SIENA. Therefore, users can share the knowledgebase which includes data for name entity suggestion and auto annotation algorithms among other instances of SIENA.

4. METHODOLOGY

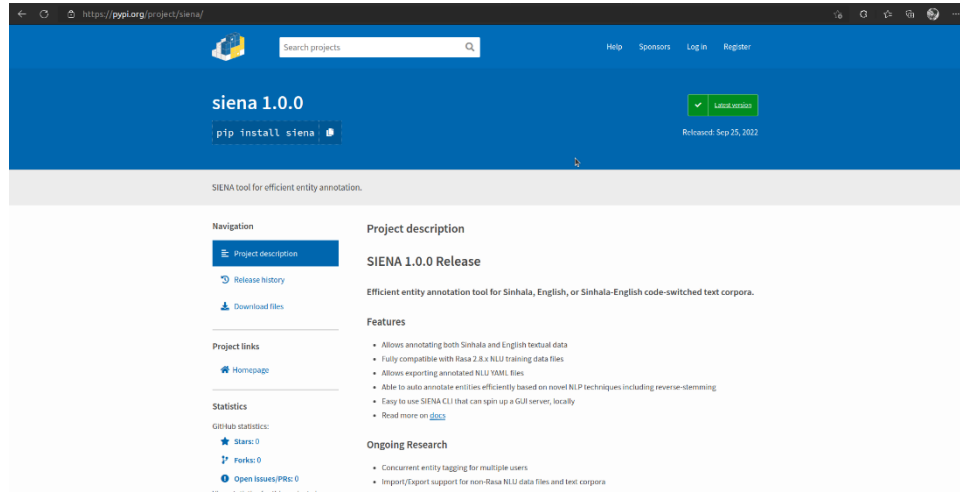


Figure 4. 1. SIENA python package

The requirements-gathering phase of SIENA tool done by studying existing research on name entity annotation and related products. All the functional and non-functional requirements are covered by implemented SIENA tool as described in above and later sections of this paper and mentioned in Table 4. 1. SIENA¹ is a text annotation tool specially designed for Sinhala – English text data. This tool helps the user to annotate text more effectively by providing suggestions and auto annotation. SIENA can install as a python package, and it supports rasa NLU data format for the annotation.

Table 4. 1. Functional and non-functional requirements

Functional requirements	Non functional requirements
Recommend and auto annotate name entities	Maintainability
Import / Upload corpus into SINEA	Security
Export annotated text from SIENA	Reliability
Import / Export knowledge base into SINEA	Portability

¹ <https://pypi.org/project/siena>

```
version: '2.0'
nlu:
  - intent: greet
    examples: |
      - hey
      - hello
      - hi
      - hello there
      - good morning
      - good evening
      - moin
      - hey there
      - let's go
      - hey dude
      - goodmorning
      - goodevening
      - good afternoon
```

Figure 4. 2. Sample NLU file format

SIENA tool can start with the command “siena server” inside the RASA bot folder. SIENA will search all the NLU files inside the “data” folder and shows those files inside the SIENA tool’s files section area.

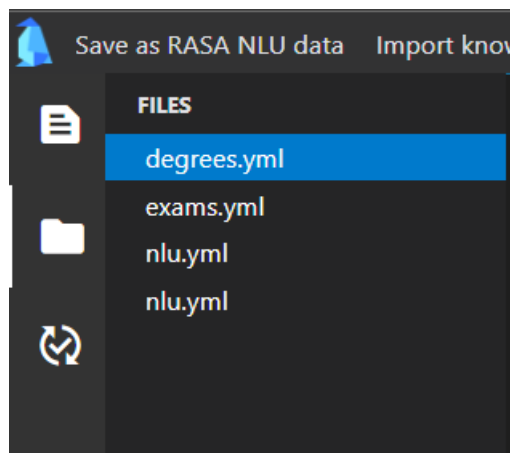


Figure 4. 3. NLU file list

As well as user can define the name entities using the tool and entered name entities will appear in the “entities” section.

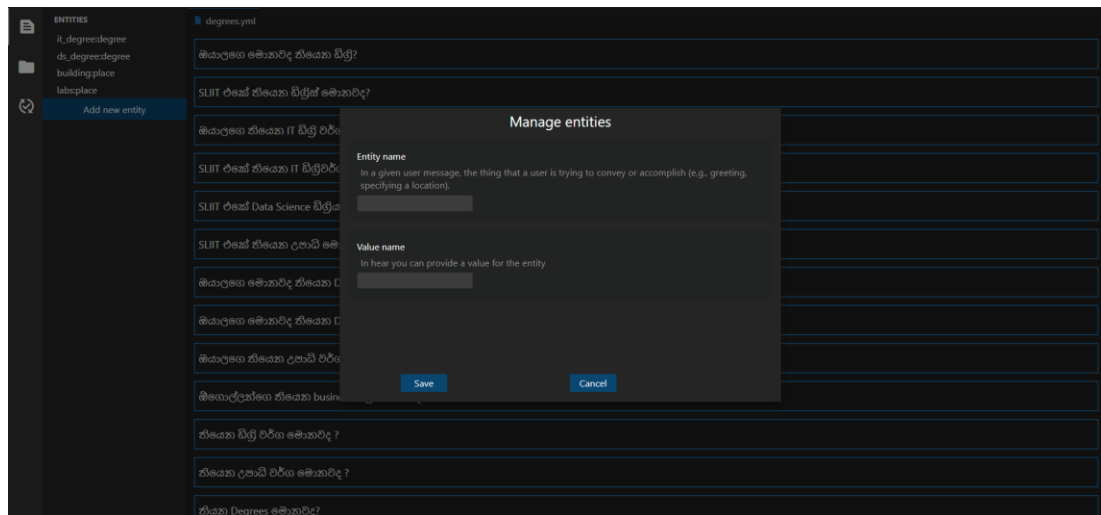


Figure 4. 4. Insert name entities to SIENA

Once the user annotates a named entity, SIENA keeps the annotated name entity and the base form of the phrase inside the knowledge base. Deriving base words is done by the stemming algorithm described in section 4.2. When the user selects a phrase for the annotation, SIENA converts it to its base form and calculates similarity scores against all the base word entries in the knowledge base. To calculate similarity between base forms SIENA uses a text similarity algorithm as described in section 4.1. Then SIENA will sort name entities according to descending order of calculated score and show the sorted list of name entities to the user.

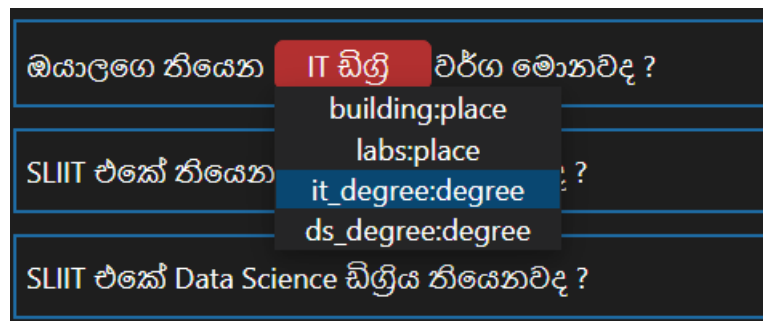


Figure 4. 5. Initial name entity suggestion list order

As an example, Figure 4. 5 shows the initial state of the entity list before annotating “IT ඩිග්‍රි” word. After user annotate it as “it_degree:degree” and select “IT ඩිග්‍රිවර්ග”,

SIENA rearrange the entity list according to the similarity results of the knowledge base entries as shown in Figure 4. 6.

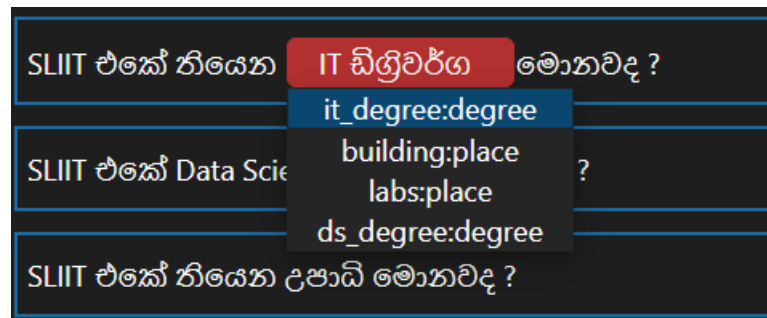


Figure 4. 6. Sorted name entity suggestion list

SIENA support auto annotation through the reverse stemming approach which is described in section 4.3. this allows user to assign same name entity to all the variations of the base word by clicking the base word in the “Knowledge” section of SIENA tool. SIENA shows a mapped name entity to each base word as a tooltip to improve user experience.

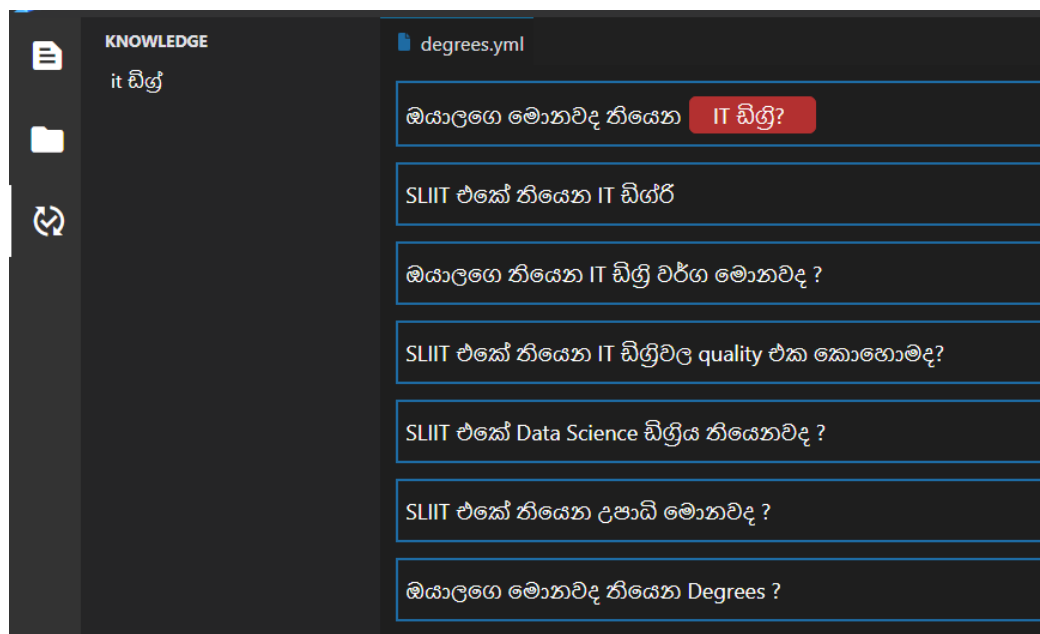


Figure 4. 7. Before auto annotation

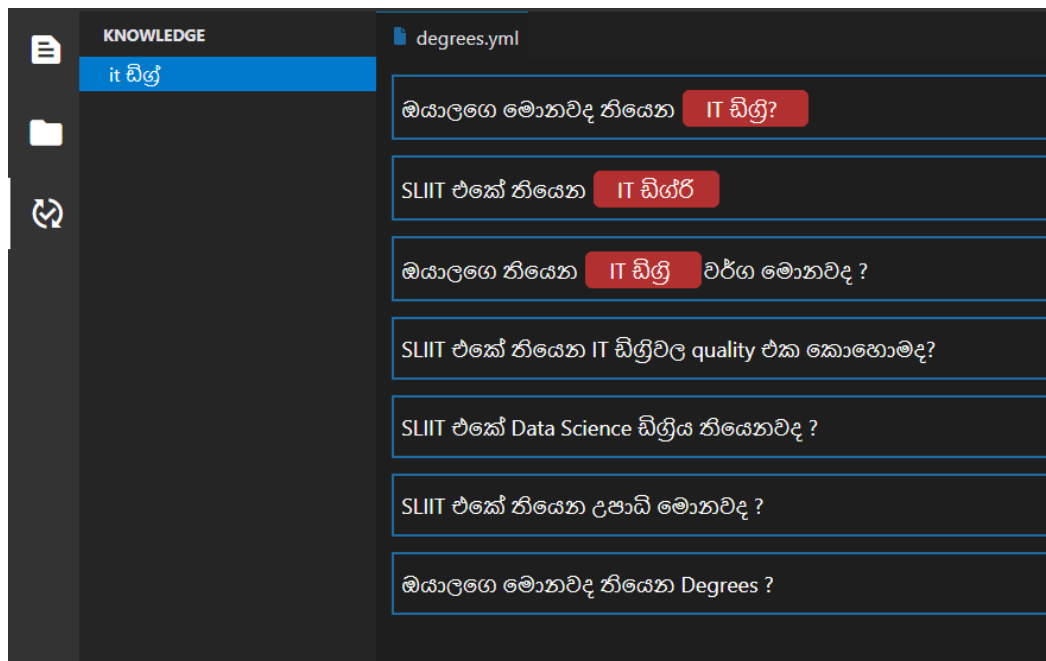


Figure 4. 8. After auto annotation

As well as SIENA can share gathered knowledge among other SIENA instances through the portable knowledge base component.

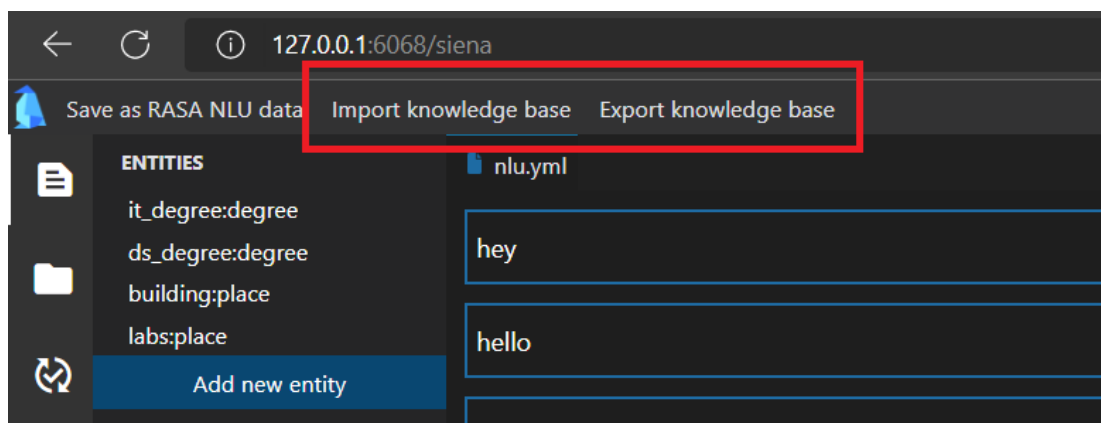


Figure 4. 9. Import or export knowledge base

4.1 Text Similarity Algorithm

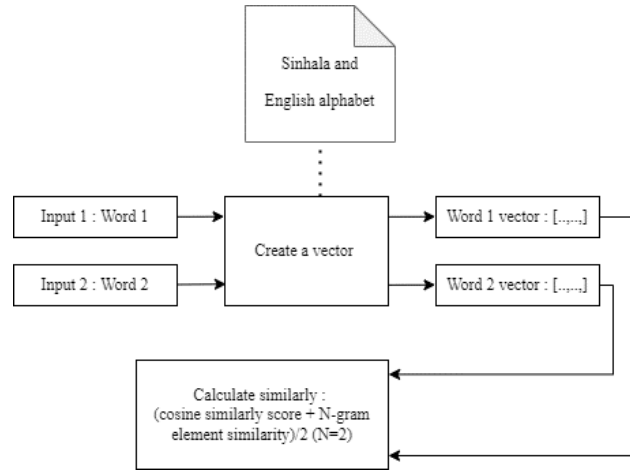


Figure 4.1. 1. Text similarity algorithm

This algorithm is used to measure the similarity between two given phrases. Since this research only focused on Sinhala and English, this similarity algorithm will calculate similarity only for Sinhala and English data. Out of scope languages are ignored without throwing an error. As the first step two given phrases are converted into two vectors. To vectorise the phrase, this algorithm counts all the English and Sinhala letters in given phrases against each letter of the Sinhala and English alphabets. The Sinhala alphabet contains 1001 letters, and the English alphabet contains 26 letters. Therefore, this will produce a 1027-letter long vector for each phrase. To calculate the similarity between two vectors, this algorithm takes cosine similarity. Then it calculates bigram letter wise similarity and provides an average value of bigram similarity and the cosine similarity as the final similarity score. To calculate bigram similarity, it breaks down phrases into a sequence of neighbouring pairs of letters. As an example, word “ABCD” will break into “AB”, “BC”, and “CD”. Then it calculates the proportion of the matching elements.

4.2 Stemming Algorithm

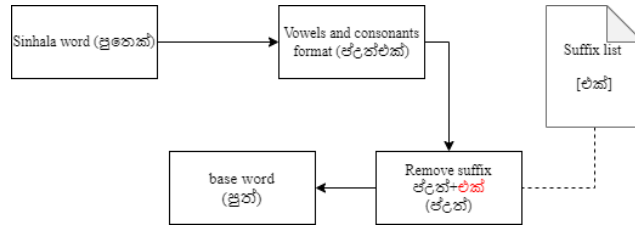


Figure 4.2. 1. Stemming algorithm

This algorithm is used to derive the base form of a given word without considering its morphological information.[14] In the Sinhala language, it is possible to construct words by joining prefixes, root words, and suffixes in a meaningful manner according to the නාම වර්තනීයමය: Sinhala noun declension rules. A combination of prefixes and base words can have multiple suffixes. But prefixes significantly change the meaning of the word, unlike suffixes. For example, the Sinhala word පොත (book) can have multiple representations in terms of noun declension, such as පොත් (The books), පොතක් (a book), පොතට (To the book), පොතකට (To a book), පොතෙන් (From the book), and පොතකින් (From a book) which have the same base form පොත් combined with various suffixes. These combinations have almost the same meaning from the perspective of entity annotation. Therefore, the next section of this paper will propose a method for annotating entities by assigning entity types to the base form of a specified word. To remove suffixes, Sinhala words are converted into vowels and consonant formats. It makes it easy to separate suffixes from a given word because of the Sinhala word conjugation rules. The converted text was then cross checked with a Sinhala suffixes list which is also in vowels and consonants format. Then suffix is removed after the identification. Then remaining word is converted into normal form by combining vowels and consonants. As an example, word “ඇත” (Tusker) need to be converted into “ඇත්” therefore, this algorithm will convert into its vowels and consonant format “ඇත්ආ” then tool looks longest suffix that can be removed from given phrase by checking suffix list which also converted into vowels and consonant format. In this case, the selected suffix will be “ආ” and its vowels and consonant format also “ආ”. Then word “ඇත්” is remains. Then “ඇත්” need to be converted to its

normal form. In this case vowels and consonant format of the word “ඇ” is same as its normal form.

4.3 Reverse Stemming Algorithm

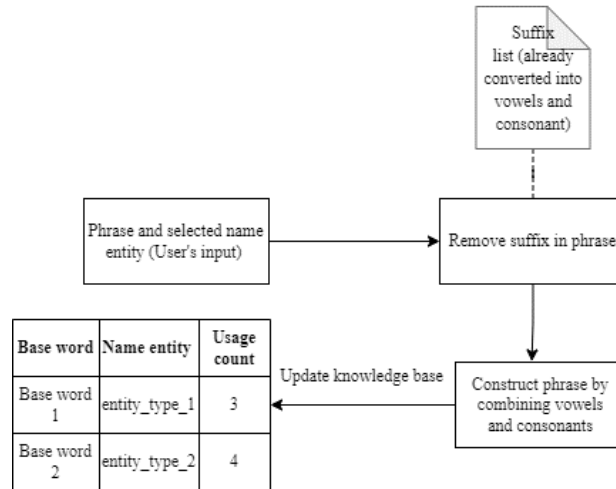


Figure 4.3. 1. Reverse stemming algorithm – inserting to knowledge base

This algorithm is used to perform auto-annotation tasks based on previously annotated data. Unlike stemming algorithms, this is used to create a connection between base words and their original phrases. Therefore, when a user initially assigns a name entity to a phrase, this approach converts that phrase into base form and saves it inside the knowledge base with the name entity that was provided by the user. SIENA also saves the usage count for each entry in the knowledge base. When user selects a phrase SIENA converts it to its base form and searches for it in the knowledge base. If it finds a base word inside the knowledge base, the algorithm will assign it to all the variations of that base word. To find the base word variations, SIENA counts the number of words inside the user selected phrase and creates groups of words by preserving the sequence of sentences also each group consists of same count of words. Then SIENA iterate over all groups and converts to base form and checks if it matches with the user selected base form. If it matches SIENA will assign selected base word’s name entity to that group and reconstructs the sentence from groups of words.

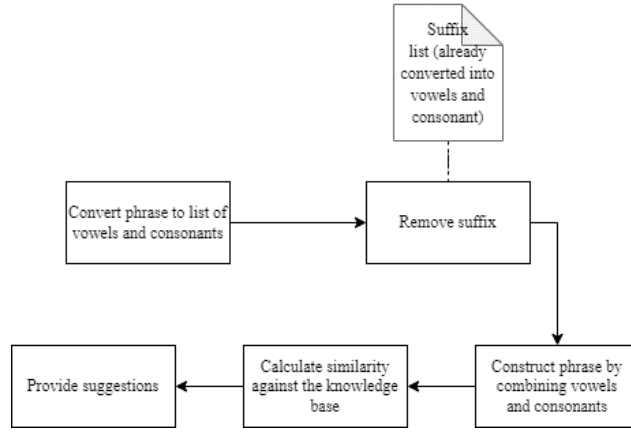


Figure 4.3. 2. Reverse stemming algorithm - Providing suggestions

4.4 Preparation of Datasets

4.4.1 General dataset for algorithm evaluation

[15] To create the general dataset for algorithm evaluation and NLP text pre-processing tasks, used a publicly available Sinhala English newspaper dataset. It consists of Sinhala and English word mixed data. To do the user testing portion of 4.4.2 domain specific dataset is used.

4.4.2 Domain specific dataset for conversational AI training

The second domain specific dataset for text annotation with the SIENA tool is made using manually created Sinhala-English code-switched text. This dataset should be appropriately prepared as it will be used as a training dataset for conversational AI's intent classification challenge. There will be roughly seventy-eight intents (78 classes), seven hundred examples (1700 data points) and each class have minimum of ten examples in each class as a standard. It is important to note that enhancing the overall effectiveness of conversational AI is dependent on the data set. Therefore, chatbot developers can change the number of question examples per intent at any time to improve conversational AI's overall performance and the domain adaptation.

4.5 Individual Component Architecture

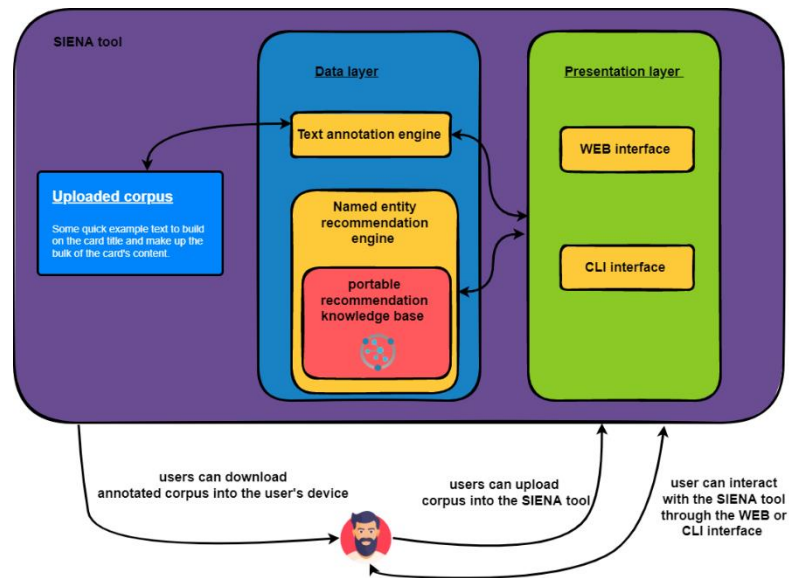


Figure 4.5. 1. Individual Component Architecture

SIENA tool consists of two subcomponents data layer and presentation layer. Data layer is responsible for auto annotation, name entity suggestions and other visualisations, presentation layer is responsible for provide interface to user interaction. SINEA tool will be used to annotate corpus which is used as training data by custom name entity recognition model in RASA NLU pipeline as shown in Figure 4.5. 2 and Figure 4.5. 3.

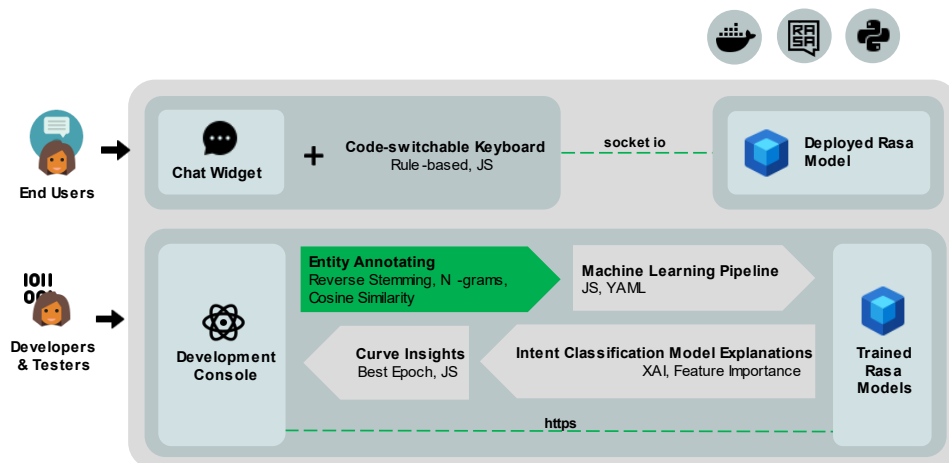


Figure 4.5. 2. Overall system flow

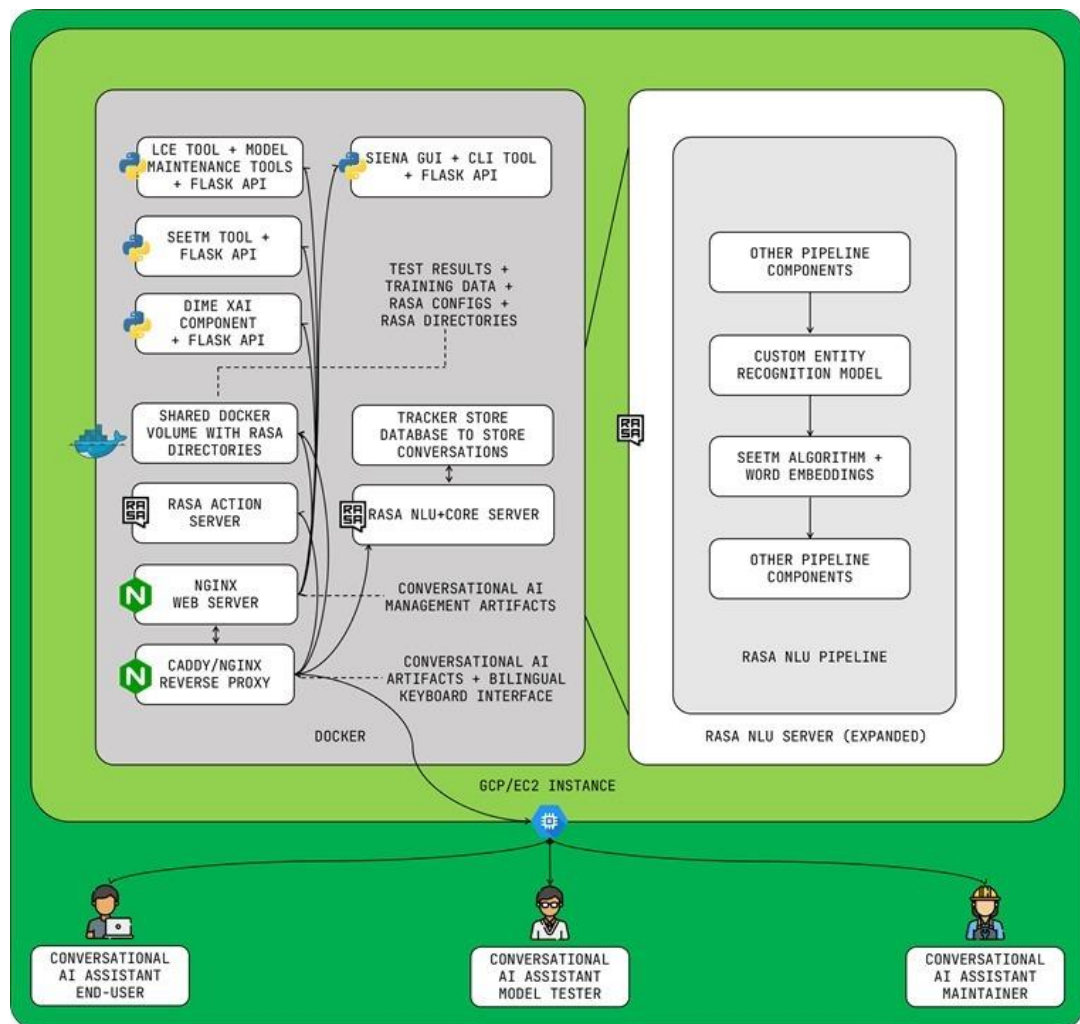


Figure 4.5. 3. Overall system architecture

4.6 Tools and Technologies

SIENA tool was developed using Python 3.8 with the help of Pandas, and NumPy packages. SIENA will be deployed as a flask app inside a docker container. With the help of Microsoft Azure as the cloud hosting service. As well as SIENA was released as a python package available in “pip”. SIENA version controlling is done by GitLab and GitHub. The integrated product version is controlled by GitLab, and the pip package’s version control is done by GitHub.

Table 4.6. 1. Tools and technologies

Task	Tools to be used
Algorithm Implementation and SIENA tool development	Python 3.8, NumPy, Pandas, PyCharm, Visual Studio Code, Google CoLab
Server development as a standalone frontend for the SIENA UI	Flask, JavaScript, CSS
Cloud Infrastructure management	Microsoft Azure
Conversational AI development by Integrating all research components (Backend)	Rasa 2.8.8, Gensim, spaCy, Docker
Conversational AI frontend development	React JS, Bootstrap, socket.io, JavaScript
Overall system deployment	Caddy 2, NGINX, Git, Docker, docker-compose

4.7 Commercialization Aspect of the Product

SIENA is a subcomponent of Kolloqe. Kolloqe is a chatbot development tool which aims to code less chatbot development and maintenance service and it will provide the service as a CaaS. Kolloqe consists of four main components, training data annotation is done by SIENA tool. Chatbot model training configuration and model evaluation, portable Sinhala typing keyboard and token mapping, and provide chatbot model explanation. Since SIENA is text annotation tool kolloqe uses SIENA to annotate Rasa NLU text files efficiently. Business can purchase CaaS to reduce their chatbot development cost and the chatbot maintenance cost. Kolloqe provides several subscriptions by applying different limitations. Therefore, subscription fee is the main income of kolloqe. As well as kolloqe provides one time purchase on premises solution.

5. TESTING & IMPLEMENTATION RESULTS & DISCUSSION

5.1 Results

The main objective of implementing SIENA is reduce the time taken to text annotation. To achieve the main objective SIENA consists of name entity suggestion feature (shown in Figure 4. 6), auto annotation feature (shown in Figure 4. 8) and portable knowledge base component (shown in Figure 4. 9) To test the effectiveness of SIENA tool, provided seventeen lines of text document which contained sentences related to SLIIT degrees. This document provided text dataset to four users and recorded time taken to annotate with SIENA tool and the manual annotation method. SIENA tool achieved 54.7% average effectiveness when compared to manual annotation as shown in the Table 5.1. 1.

Table 5.1. 1. SIENA user testing results

User	Time taken to annotate using SIENA (seconds)	Time taken to manual annotating (seconds)	Time efficiency percentage (%)
User 1	135	184	36.3
User 2	114	178	56.1
User 3	106	181	70.7
User 4	125	195	56.0
Average	120	184.5	54.7

5.1.1 Text similarity algorithm results

The following matrix shows how the combined similarity algorithm works with different words.

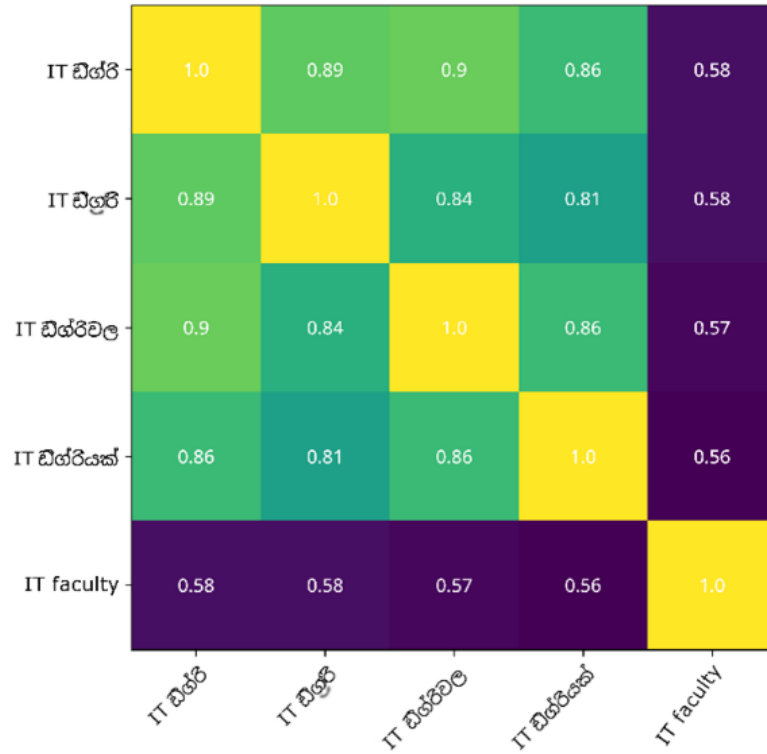


Figure 5.1.1. 1. Text similarity algorithm results

5.1.2 Stemming algorithm results

Since the stemming algorithm and reverse stemming approach shares same accuracy, results are mentioned in the section 5.1.3. The following table shows the stemming algorithm works with different words.

Table 5.1.2. 1. Stemming algorithm results

Word	SIENA base word
IT ඩිජිටල්	it ඩිජිටල්
IT ඩිජිටල්	it ඩිජිටල්
IT ඩිජිටල්	it ඩිජිටල්
IT ඩිජිටල්	it ඩිජිටල්

IT ඩිග්‍රි	it ඩිග්‍රි
IT ඩිග්‍රිවල	it ඩිග්‍රි
IT ඩිග්‍රිය	it ඩිග්‍රි

5.1.3 Reverse stemming results

Evaluation of the SIENA reverse stemming (base word mapping) technique performed using the conversational AI training dataset yielded an average accuracy of 57.1%. this is calculated by getting the percentage of number of correctly identified base words over the total number of variations of the base words for a given phase.

5.1.4 SIENA test results

SIENA tool was tested by performing unit testing and integration testing. Unit tests are done by the python inbuilt keyword “assert”. “test_yaml_file_ext” and “test_csv_file_ext” are file extension validators for YAML NUL and CSV files. “test_stem_word” is the function of the stemming algorithm.

$$Accuracy = \frac{\text{Number of correctly identified base words}}{\text{Total number of base words for given phase}} \times 100\% \quad (1)$$

```

cli_siena > siena > test > functions.py > test_yaml_file_ext
You, 13 seconds ago | 1 author (You)
1  from siena.core.actions import (
2      allowed_file_nlu,
3      allowed_file_knowledge,
4  )
5  from siena.core.similarity import(
6      si_stemmer_sentence_custom
7  )
8
9  def test_yaml_file_ext():
10     assert allowed_file_nlu("test.yaml") == True, "It should be True"
11     assert allowed_file_nlu("test.exe") == False, "It should be False"
12
13  def test_csv_file_ext():
14     assert allowed_file_knowledge("sample.csv") == True, "It should be True"
15     assert allowed_file_knowledge("sample.ccv") == False, "It should be False"
16
17  def test_stem_word():
18     assert si_stemmer_sentence_custom("අශ්වයානි") == "අශ්වය", "It should be අශ්වය"

```

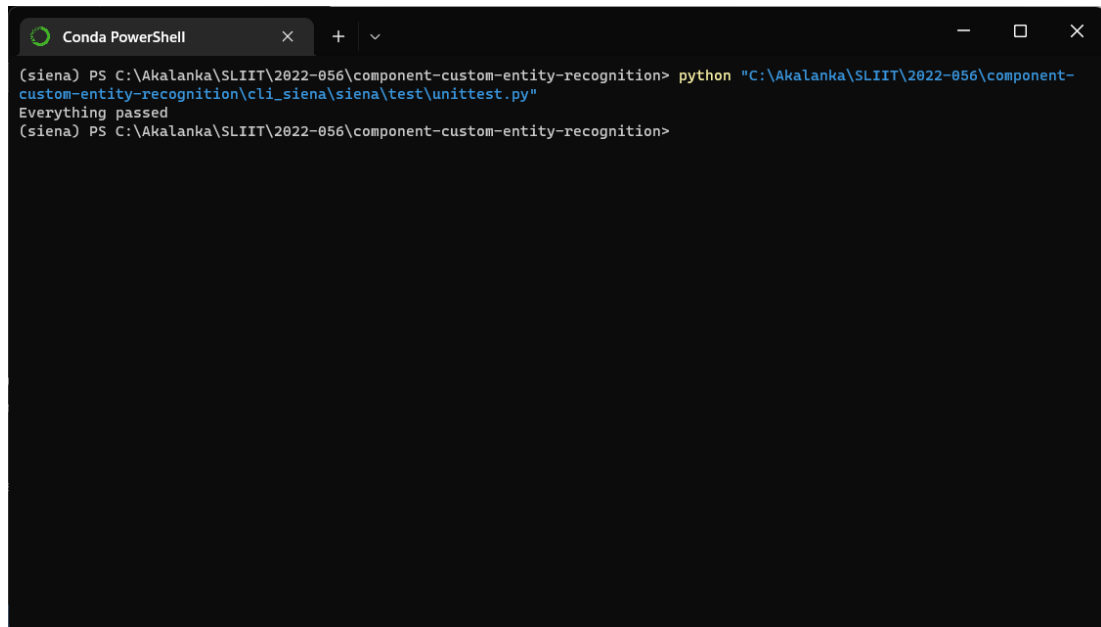
Figure 5.1.4. 1. Unit tests

```

cli_siena > siena > test > unittest.py
You, yesterday | 1 author (You)
1  from siena.test.functions import (
2      test_yaml_file_ext,
3      test_csv_file_ext,
4      test_stem_word,
5  )
6
7
8  if __name__ == "__main__":
9      test_yaml_file_ext()
10     test_csv_file_ext()
11     test_stem_word()
12     print("Everything passed")

```

Figure 5.1.4. 2. Unit tests



```
(siena) PS C:\Akalanka\SLIIT\2022-056\component-custom-entity-recognition> python "C:\Akalanka\SLIIT\2022-056\component-custom-entity-recognition\cli_siena\siena\test\unittest.py"
Everything passed
(siena) PS C:\Akalanka\SLIIT\2022-056\component-custom-entity-recognition>
```

Figure 5.1.4. 3. Unit tests

Integration testing is done with the help of all the team members by testing each other's individual components. After the testing was completed. SIENA and other components are deployed into a Microsoft Azure virtual machine instance.

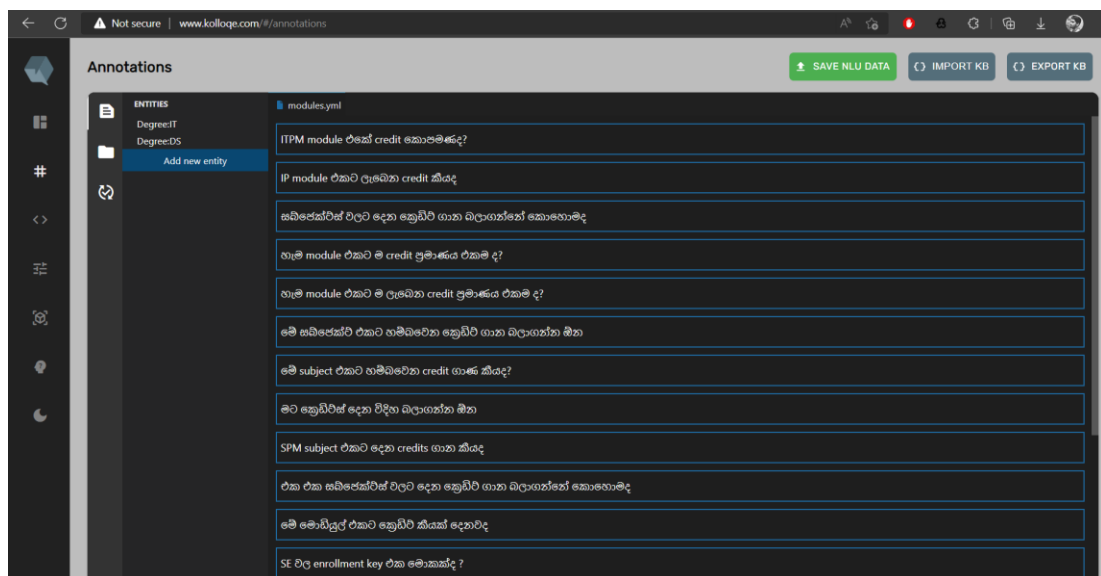


Figure 5.1.4. 4. SIENA integrated into kolloqe

To analyse security issues SIENA is continuously scanned by a popular vulnerability scanning tool “snyk”. It provides suggestions to improve security. As well as It notifies vulnerabilities in third party packages used in SIENA tool.

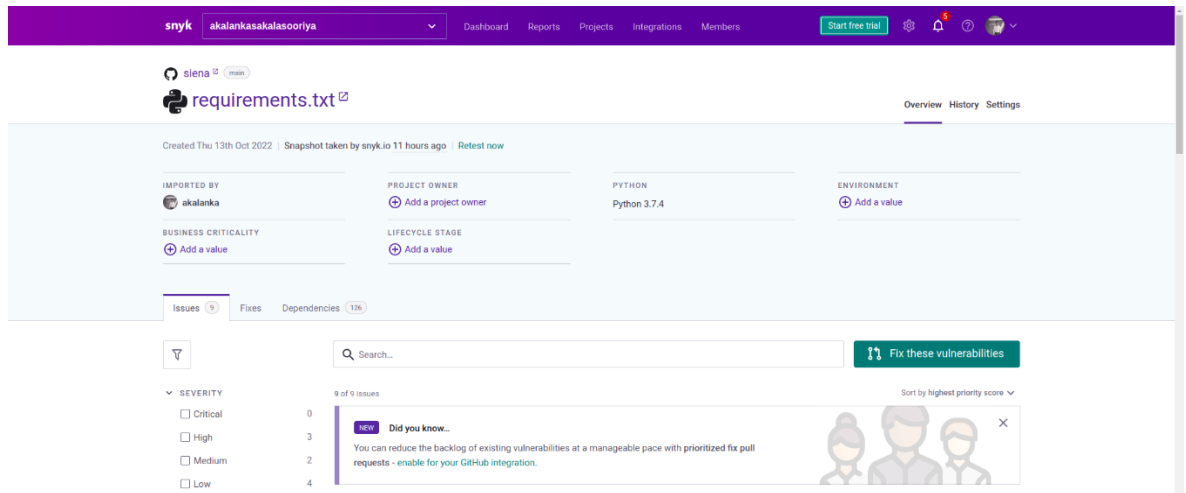


Figure 5.1.4. 5. Results of snyk vulnerability analysis tool

SIENA tool’s main functionalities are test by using the following test cases.

Table 5.1.4. 1. Test case 001

Project ID: 2022-056-IT19051208					
Project Name: SIENA					
Project Function: Name entity suggestions					
Test case ID: 001			Test case designed by: ID No: IT19051208 Name: Sakalasooriya S.A.H.A.		
Test Priority (High/Medium/Low): Medium					
Test Description: The name entity suggestion list should be rearranged once user annotate a similar phrase.					
Prerequisite: User should enter list of name entities to SIENA tool using the entity management window.					
Test Steps: Step 1: Load a file to start the annotation Step 2: Highlight first word Step 3: Click on a name entity from the list (near to the highlighted area) Step 4: Highlight similar word (used in step 2) Step 5: Observer the order of name entity suggestion list.					
Test ID	Test Inputs	Expected Outputs	Actual Output	Result (Pass/Fail)	Comments

001	Input: Selected “IT ವಿಕ್ರಿ” as the first word and assigned “degree_type” as the name entity. Selected “IT ವಿಕ್ರಿಯೆ” as the second word	Entity list rearrange by coming up “degree_type” as the first in the entity list	Entity list rearranged by coming up “degree_type” as the first in the entity list	pass	Entity suggestion function is working properly.
-----	---	--	---	------	---

Table 5.1.4. 2. Test case 002

Project ID: 2022-056-IT19051208					
Project Name: SIENA					
Project Function: Auto annotation					
Test case ID: 002			Test case designed by: ID No: IT19051208 Name: Sakalasooriya S.A.H.A.		
Test Priority (High/Medium/Low): Medium					
Test Description: Auto annotate all the variation of base word when user selects a base word from auto annotation menu.					
Prerequisite: User should annotate at least one name entity to appear base word in auto annotation windows.					
Test Steps: Step 1: Load a file to start the annotation Step 2: Click on base word list icon Step 3: Click on base word Step 4: Observer the auto annotation					
Test ID	Test Inputs	Expected Outputs	Actual Output	Result (Pass/Fail)	Comments
002	Input: Selected “it ವಿಕ್ರಿ” as the base word.	Auto annotate all the identified variations of the selected base word.	Auto annotated all the identified variations of the selected base word.	pass	Auto annotation function is working properly. Auto annotation success notifications works properly

Table 5.1.4. 3. Test case 003

Project ID: 2022-056-IT19051208					
Project Name: SIENA					
Project Function: Exporting knowledge base					
Test case ID: 003			Test case designed by: ID No: IT19051208 Name: Sakalasooriya S.A.H.A.		
Test Priority (High/Medium/Low): Medium					
Test Description: Export knowledge base as a CSV file.					
Prerequisite: User should annotate at least one name entity to contain details inside the exported knowledge base.					
Test Steps: Step 1: Click on export knowledge button Step 2: Save the downloaded file.					
Test ID	Test Inputs	Expected Outputs	Actual Output	Result (Pass/Fail)	Comments
003	Input: No inputs	Web browser ask to save the knowledge base file.	Web browser asked to save the knowledge base file.	pass	Knowledge base export function works properly. Knowledge base export notification works properly.

Table 5.1.4. 4. Test case 004

Project ID: 2022-056-IT19051208	
Project Name: SIENA	
Project Function: Auto annotation	
Test case ID: 004	Test case designed by: ID No: IT19051208 Name: Sakalasooriya S.A.H.A.
Test Priority (High/Medium/Low): Medium	

Test Description: Auto annotate all the variation of base word when user selects a base word from auto annotation menu.					
Prerequisite: User should have up and running SIENA instance.					
Test Steps: Step 1: Click on import knowledge base button Step 2: Find previously exported knowledge base file Step 3: Upload selected file					
Test ID	Test Inputs	Expected Outputs	Actual Output	Result (Pass/Fail)	Comments
004	Input: Navigate to previously exported knowledge base file and select it in file selection dialog box.	Update current knowledge base	Updated current knowledge base	pass	Knowledge base import function works properly. Knowledge base import notification works properly.

5.2 Research Findings

Initially, SIENA used cosine similarity to calculate word similarity, since cosine similarity results are right-skewed and provide close scores to 100%. As well as cosine similarity algorithm does not care about the sequence of the letters when calculating similarity. As an example, cosine similarity provides 100% similarity for word “ABC” and word “CBA”. Therefore, text similarity measurement approach employed by the SIENA tool provides the average of cosine and bi-gram element similarity scores. It makes results nearly symmetrical distribution as shown in the Figure 5.2. 1. These similarity results are taken by cross-calculating randomly selected 1000 words from Sinhala newspaper corpus [15]. The bi-gram similarity algorithm is more sensitive to character variations when compared to the cosine similarity algorithm. As well as the bi-gram similarity algorithm adds a sequential feature to the combined algorithm because the cosine similarity algorithm does not care about positional information of letter in each phrase.

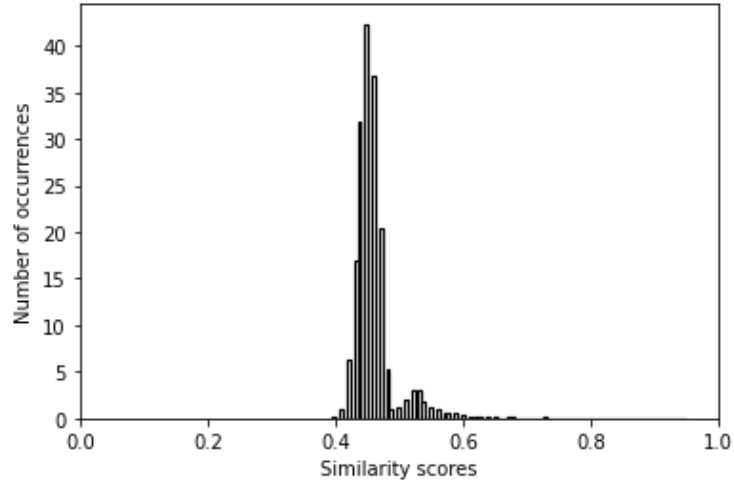


Figure 5.2. 1. Combined text similarity algorithm

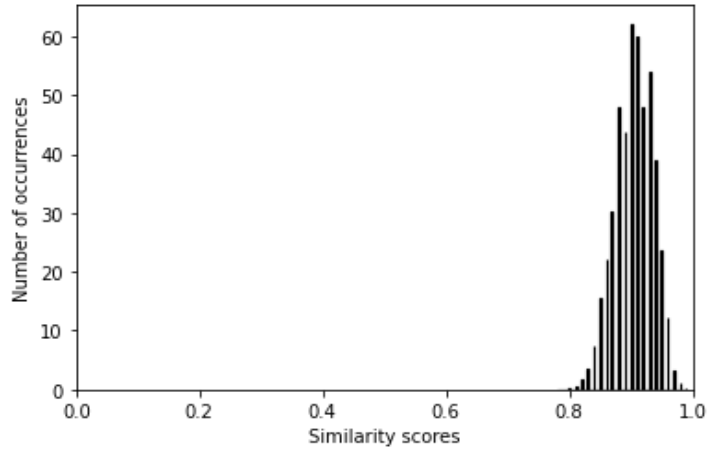


Figure 5.2. 2. Cosine text similarity algorithm

5.3 Discussion

Since SIENA could be able to find the variations of base words, SIENA can auto annotate name entities when there is an already name entity assigned to the base word. But as mentioned in the results section the accuracy of the auto annotation is low due to the problems that occurred in the stemming algorithm. As shown in table 5.3.1 both “IT පිළියක” and “IT පිළි” words should be mapped into a single base form. But the current Sinhala stemming algorithm is not much advanced and depends on a rule-based suffix removal approach, in some cases stemming algorithm cannot cover some Sinhala word conjugation rules. Because of this auto annotation algorithm will not be

able to find all the variations of base words. To overcome this situation stemming algorithm needs to be improved further. Currently SIENA stemming algorithm only supports English and Sinhala languages. This same approach can be used to stem Tamil word as well because Tamil letters are also construed with vowels and consonants like in Sinhala.

Table 5.3. 1. SIENA stemming issues

Word	SIENA base word
IT ඩිග්‍රියක	it ඩිග්‍රිය
IT ඩිග්‍රි	it ඩිග්‍රි

5.4 Contribution

SIENA is an open-source project available on GitHub² and anyone can read, distribute, and modify the source. SIENA is released as a python package which is available on PyPI. Therefore, SIENA can install on any platform that Python supports. Since SIENA is an open-source tool, the transparency of the tool is achieved. As well as developers can further improve the SIENA tool as a community driven project. This will motivate developers to implement or improve Sinhala language focused NLP tools further.

² <https://github.com/orgs/siena-nlp/repositories>

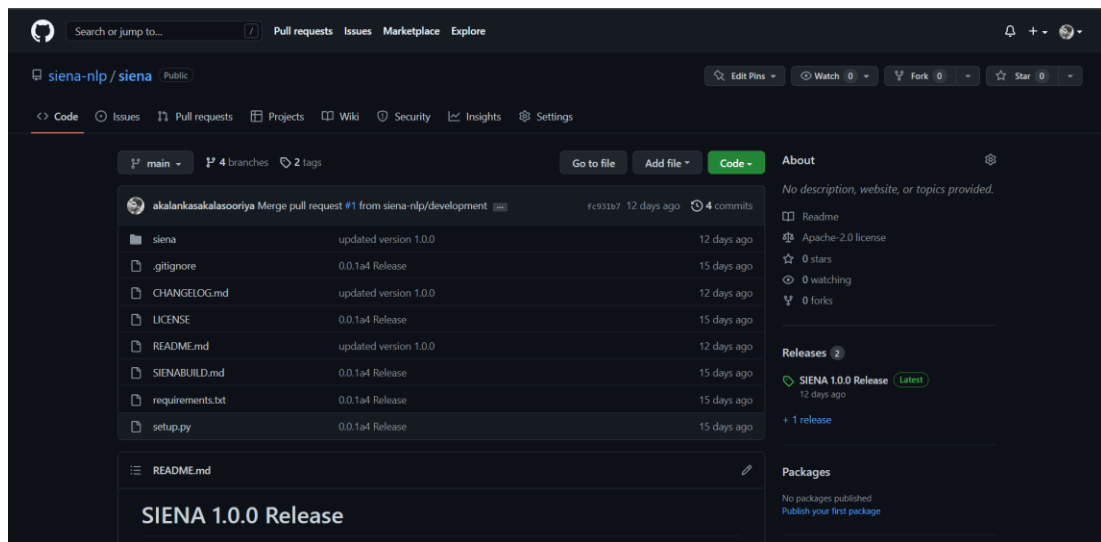


Figure 5.4. 1. SIENA GitHub page

6. CONCLUSION

Text data annotation is time consuming task, and it requires human interaction and domain knowledge. There are several text annotation tools are available but none of them are not specially enhanced for Sinhala and English code-mixed data annotation. Unlike other text data annotation tools SIENA can identify variations of Sinhala base words and auto annotate all the variation at once. By using SIENA tool, users can effectively annotate Sinhala and English text data. Currently, SIENA only accepts Rasa NLU data format because SIENA is a part of a chatbot creation and evaluation tool kolloqe which is a Rasa oriented tool. Since SIENA is a python web-based application it can use any operating system which supports python. SIENA tool was tested on Microsoft Windows, Mac OS, and Linux operating systems. Also, SIENA has name entity suggestion and auto annotation feature which reduce the time taken to annotate. The knowledge base is another vital component which helps to name entity suggestions and auto annotation. Since the knowledge base component is a portable component, it can export its content to another instance of SIENA by exporting the knowledge base and SIENA can import external knowledge as well. Therefore, SIENA can share the gathered knowledge among other instances as needed. This feature is helpful to increase the efficiency when annotating same domain data because it can provide better suggestions and accurate auto annotation at the beginning of the annotation. Therefore, SIENA tool can be used to annotate Rasa NLU text files and it makes it easier to develop Rasa chatbots with the support of Sinhala English code-mixed conversations. Therefore, businesses tend to use chatbots with Sinhala English support as their business interface, this will enhance the most of Sri Lankan customer experience and business growth.

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GLOSSARY

Term	Definition
Artificial Intelligence (AI)	Artificial intelligence is intelligence demonstrated or acquired by machines
Machine Learning (ML)	Machine learning is an area of research focused on comprehending and developing "learning" techniques, or techniques that use data to enhance performance on a certain set of tasks.
Natural Language Processing (NLP)	A branch of linguistics, computer science, and artificial intelligence called "natural language processing" is concerned with how computers and human languages interact.
Convolutional Neural Network (CNN)	A CNN is a particular type of network design for deep learning algorithms that is utilized for tasks like image recognition and pixel data processing.
Long short-term memory (LSTM)	An artificial neural network called long short-term memory is utilized in deep learning and artificial intelligence and it has feedback connections.
Named-entity recognition (NER)	NER is a subtask of information extraction which looks for named entities mentioned in unstructured text.
Natural-language understanding (NLU)	NLU is the understanding of the meaning and structure of human language by computers.

APPENDICES

Appendix A: Survey Form

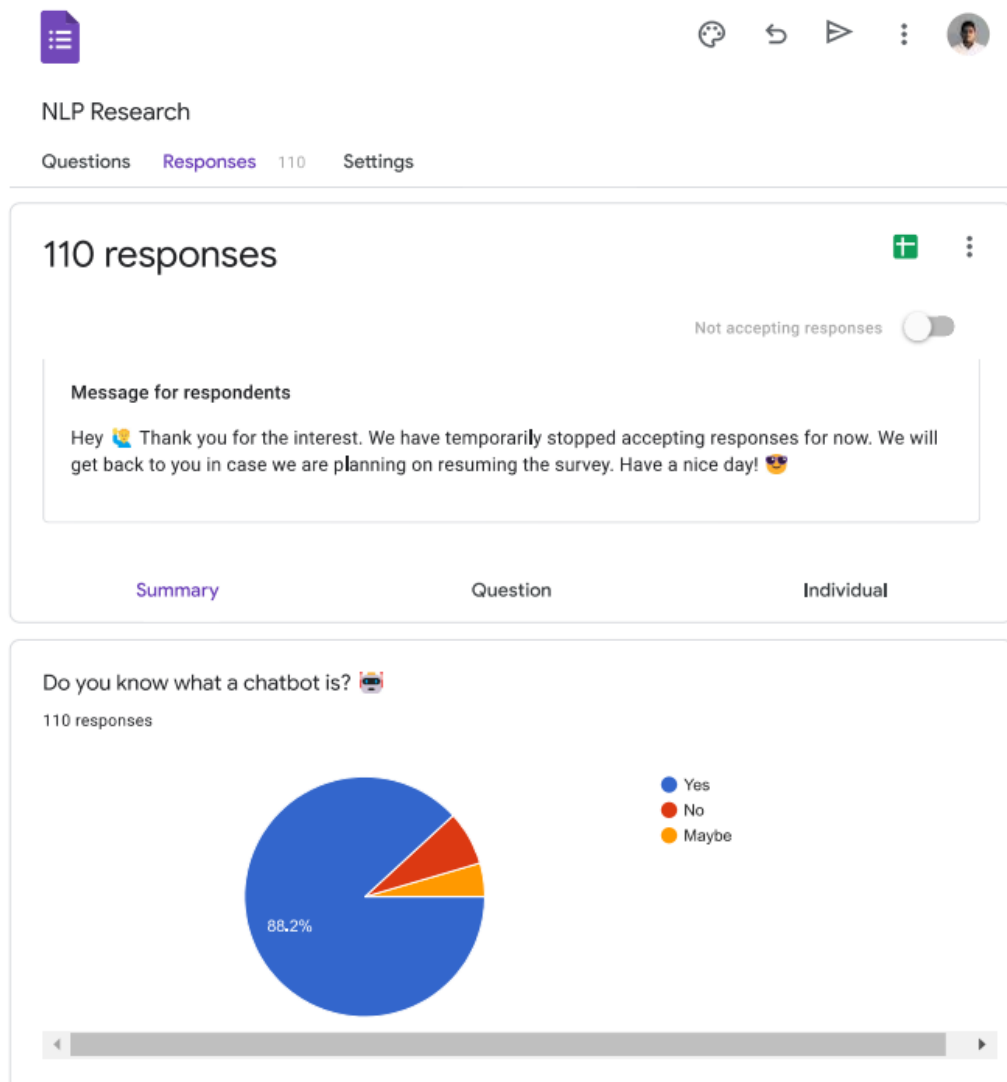


Figure A.1: Complete survey form questions and responses – part 1

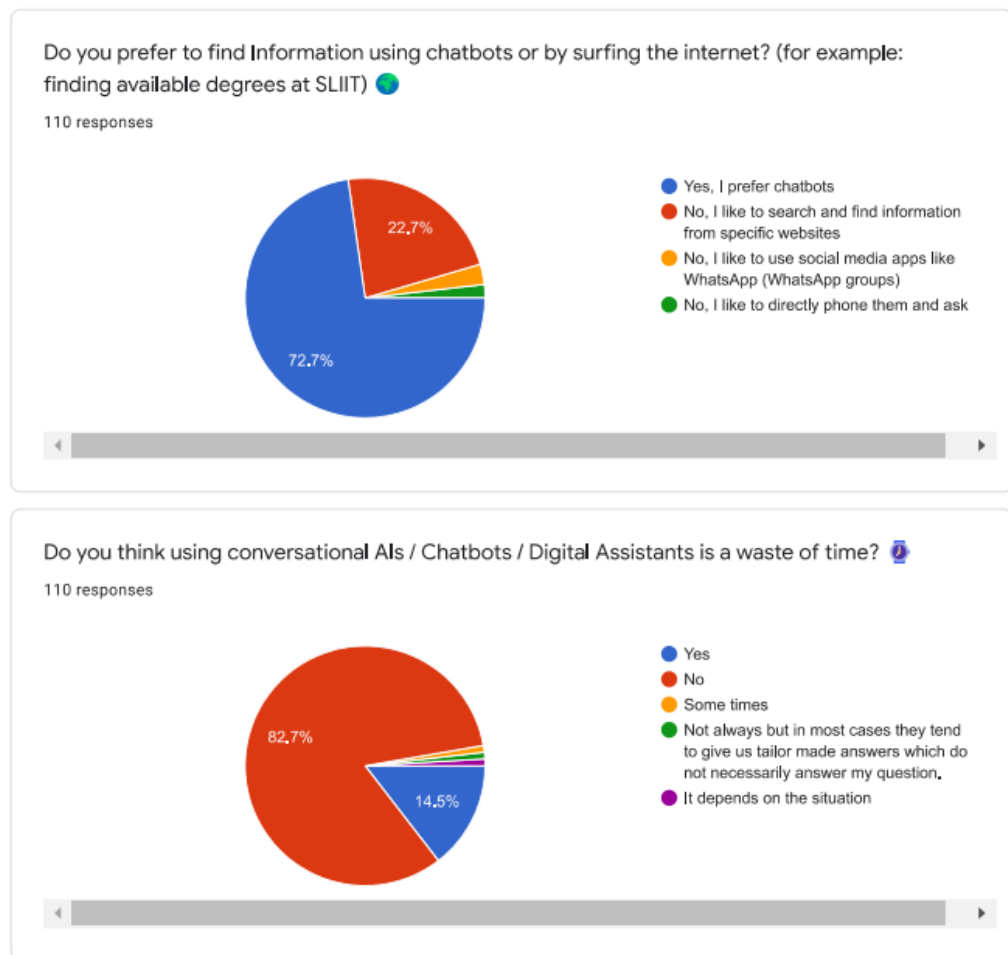


Figure A.2: Complete survey form questions and responses – part 2

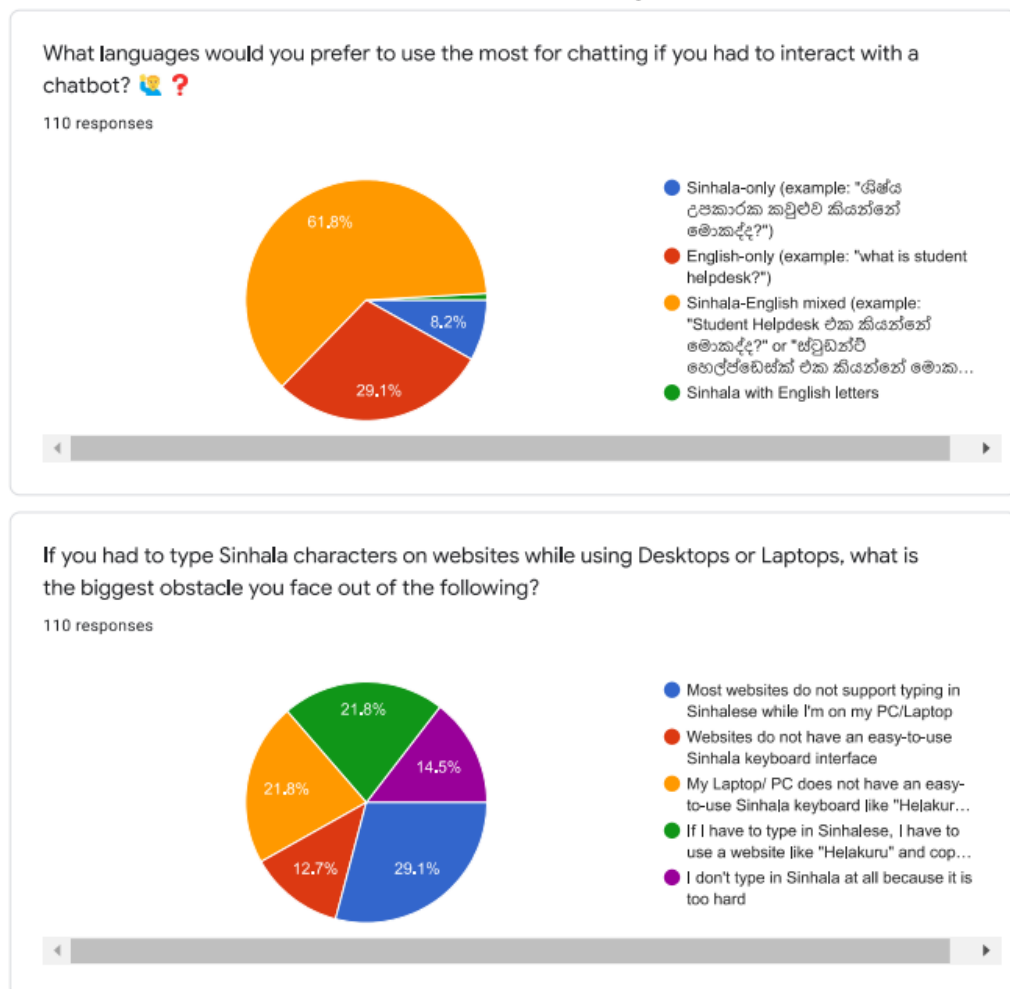


Figure A.3: Complete survey form questions and responses – part 3

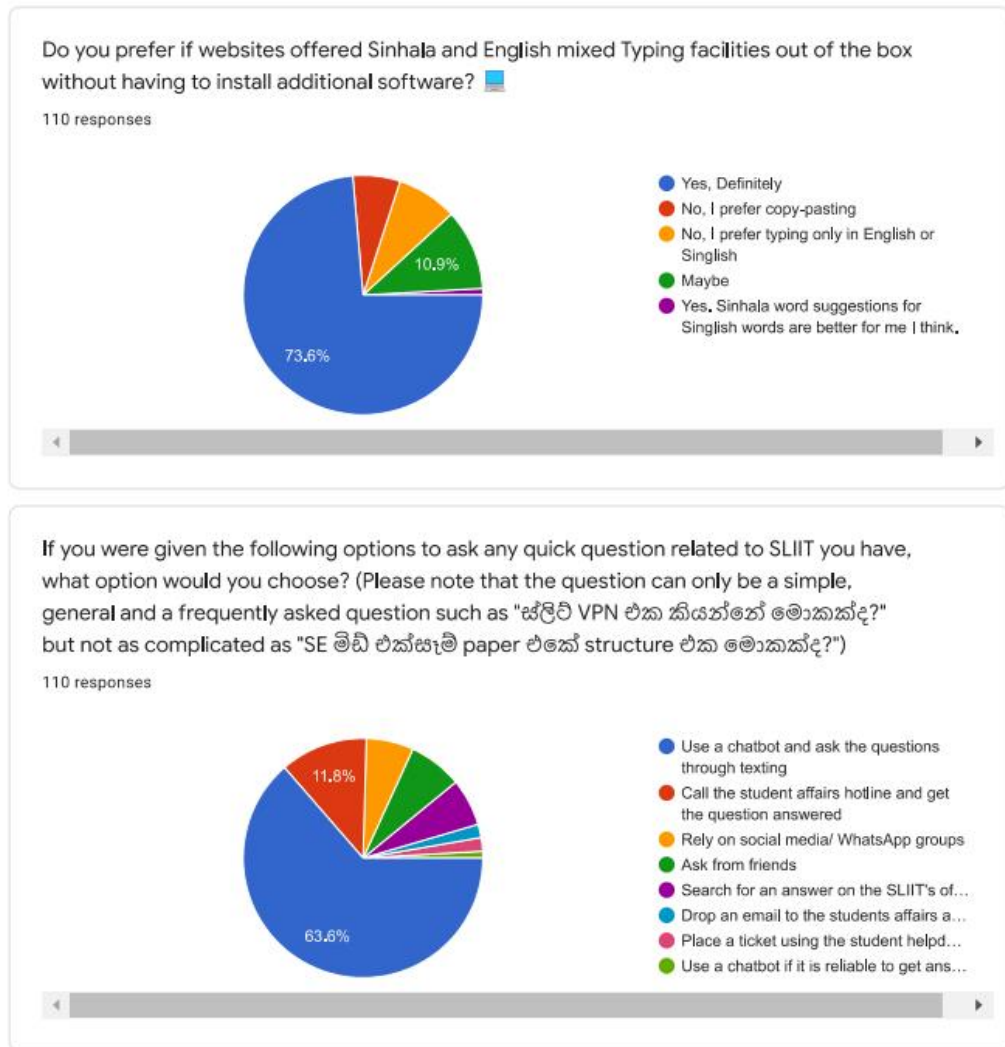


Figure A.4: Complete survey form questions and responses – part 4

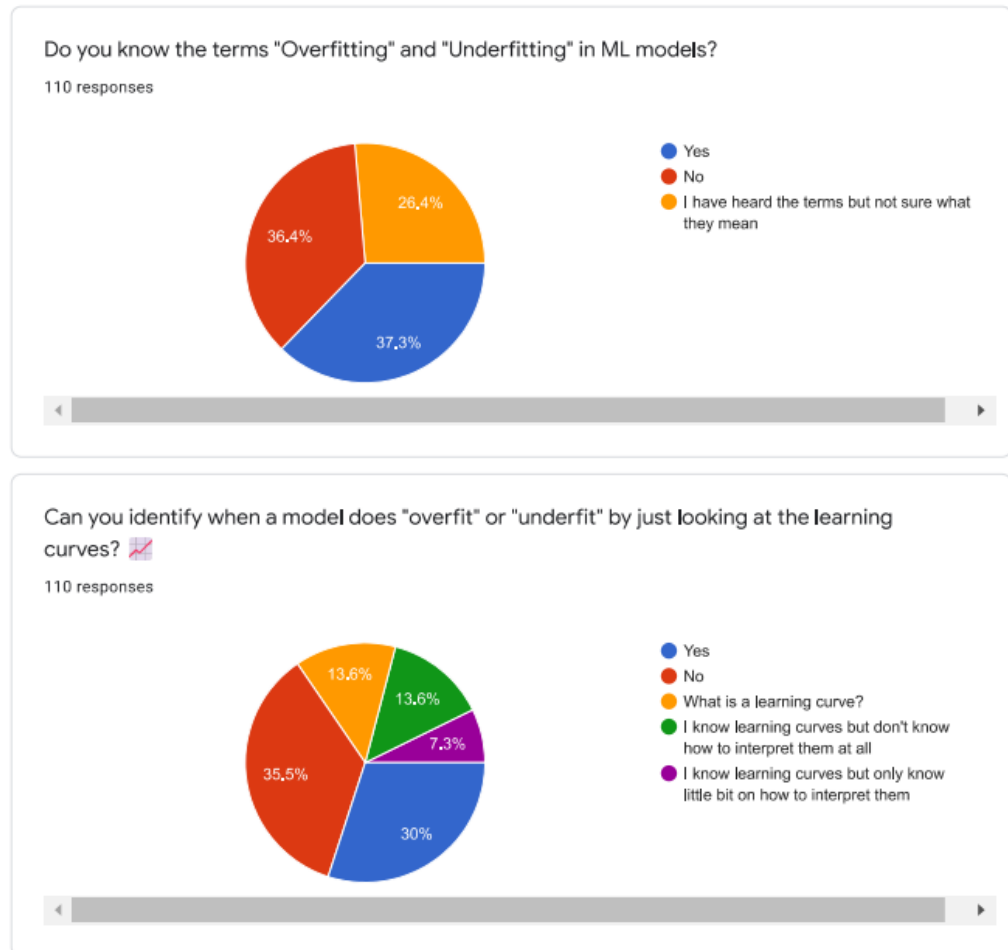


Figure A. 5: Complete survey form questions and responses – part 5

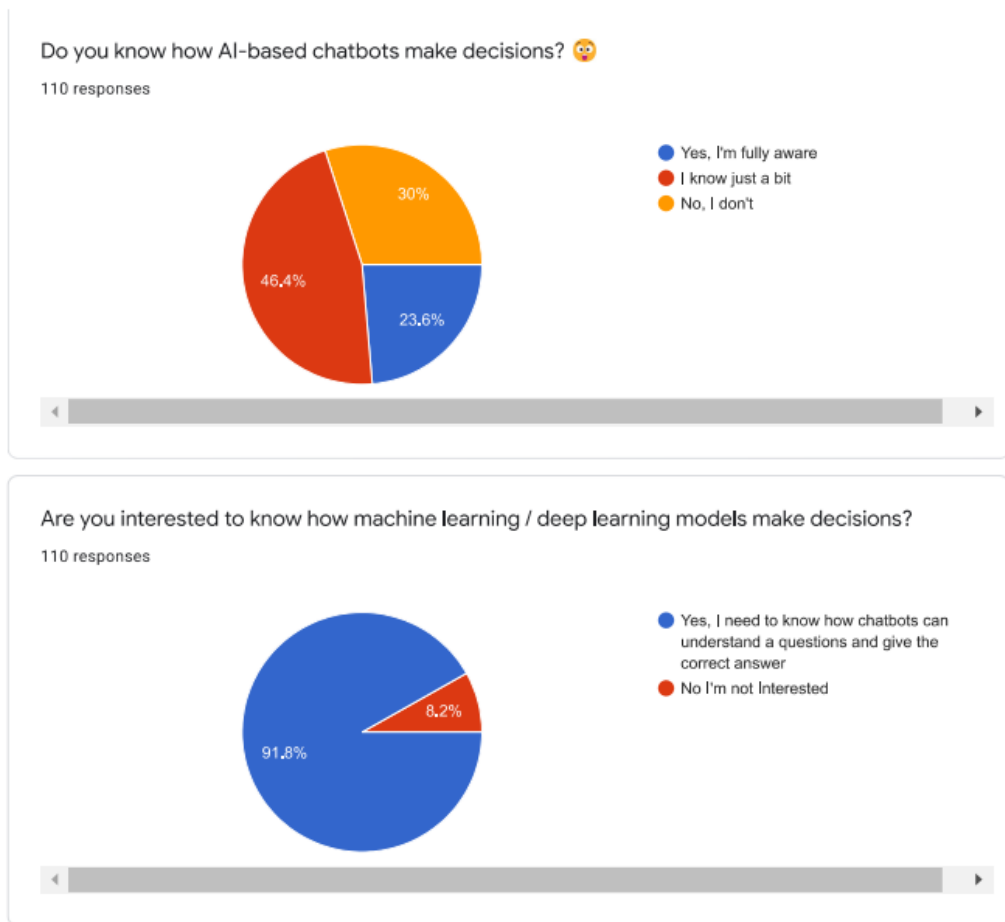


Figure A.6: Complete survey form questions and responses – part 6

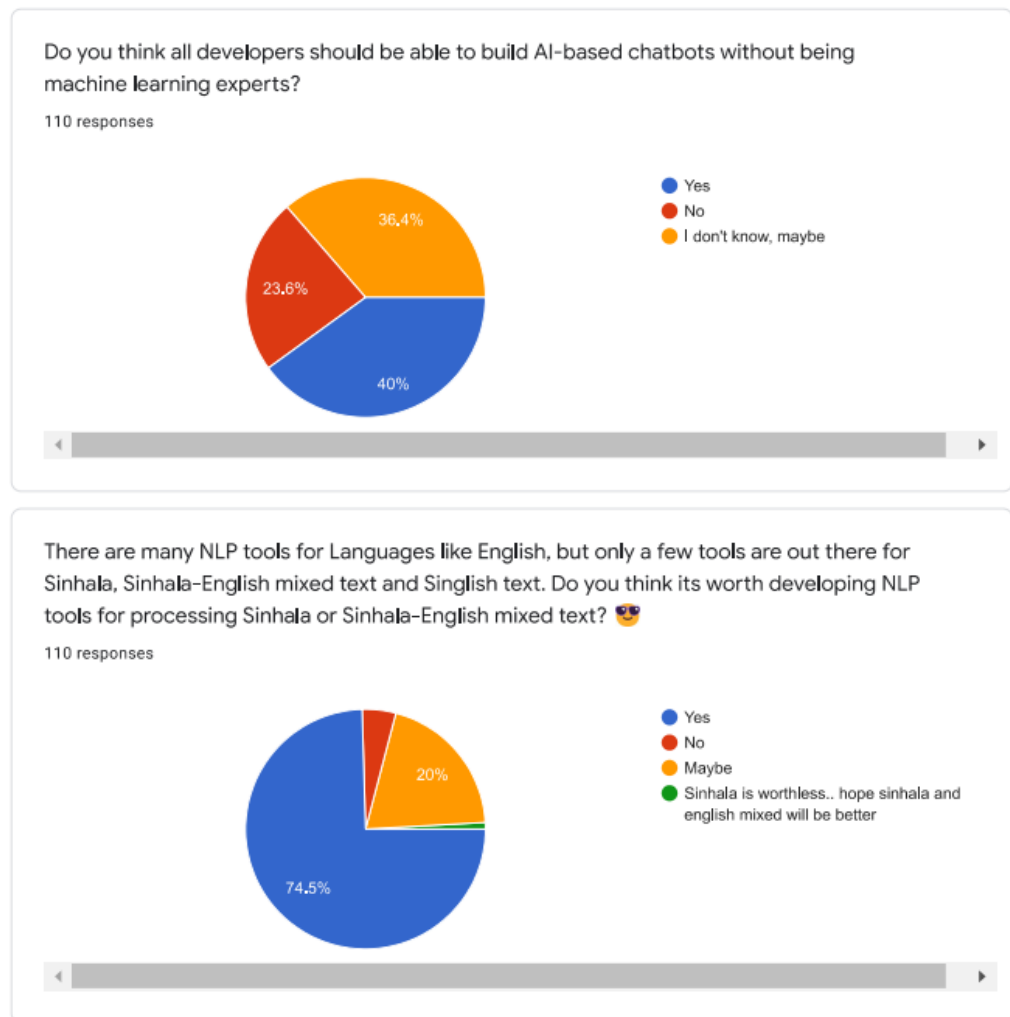


Figure A.7: Complete survey form questions and responses – part 7

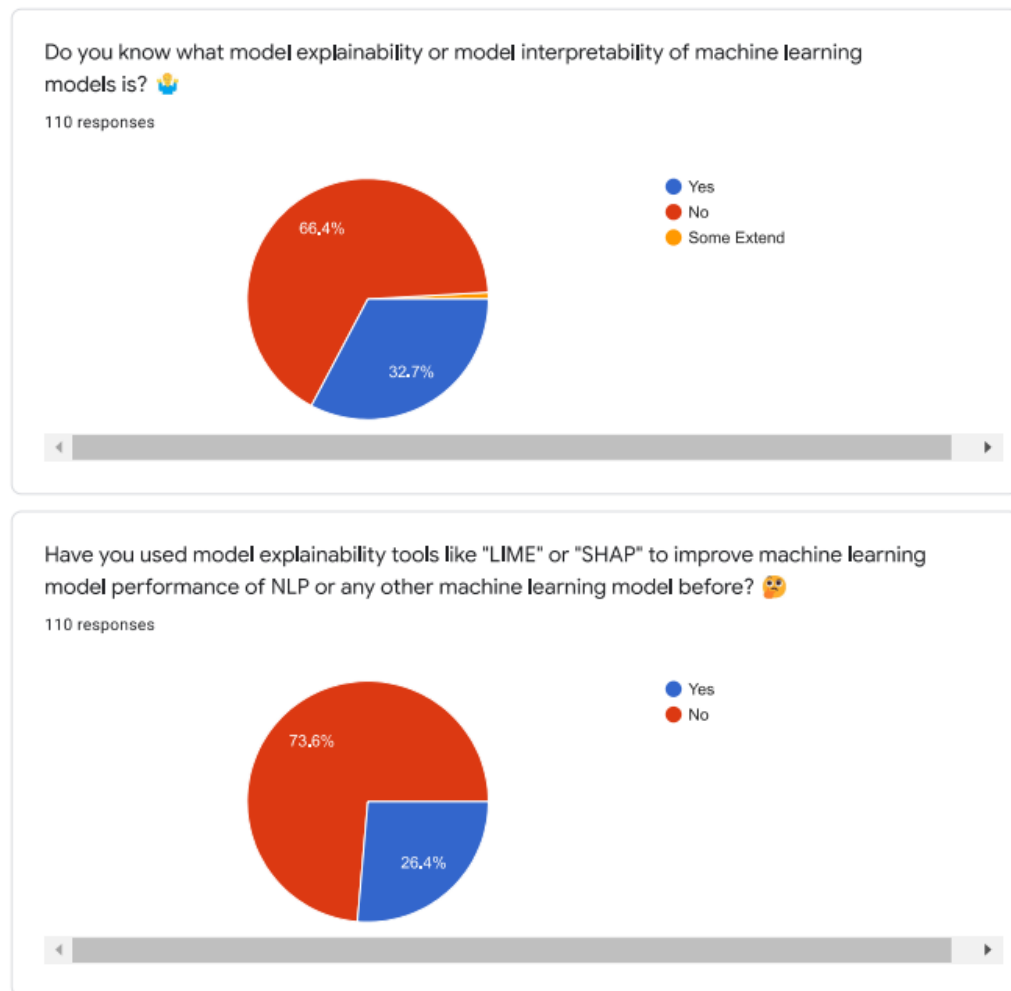


Figure A.8: Complete survey form questions and responses – part 8

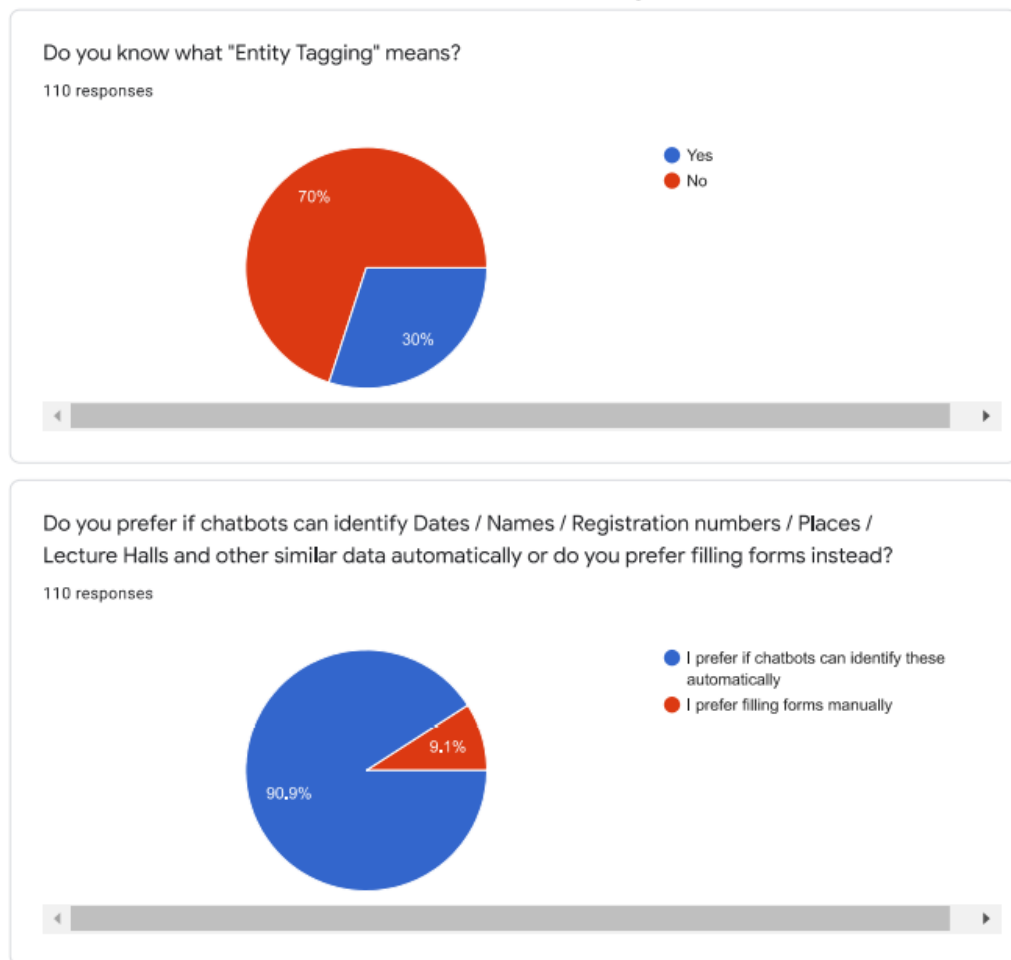


Figure A.9: Complete survey form questions and responses – part 9

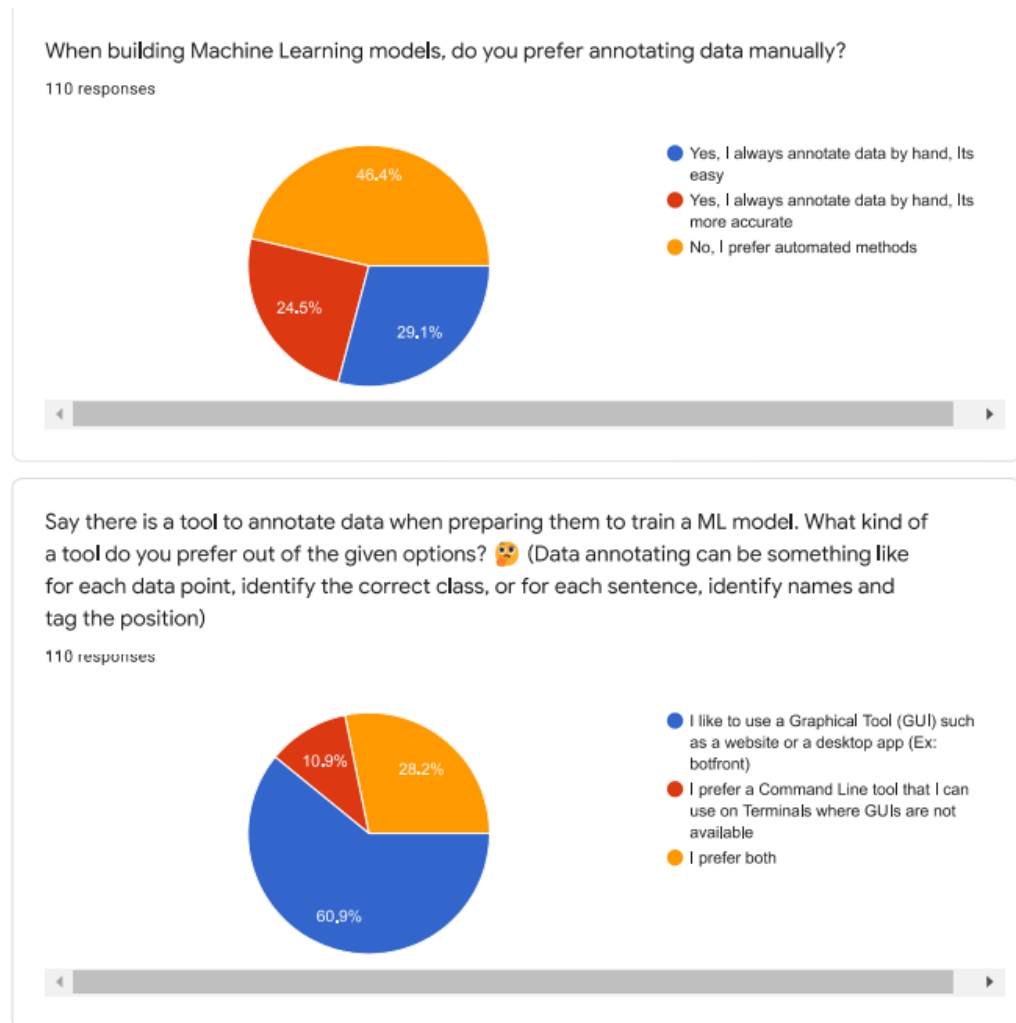
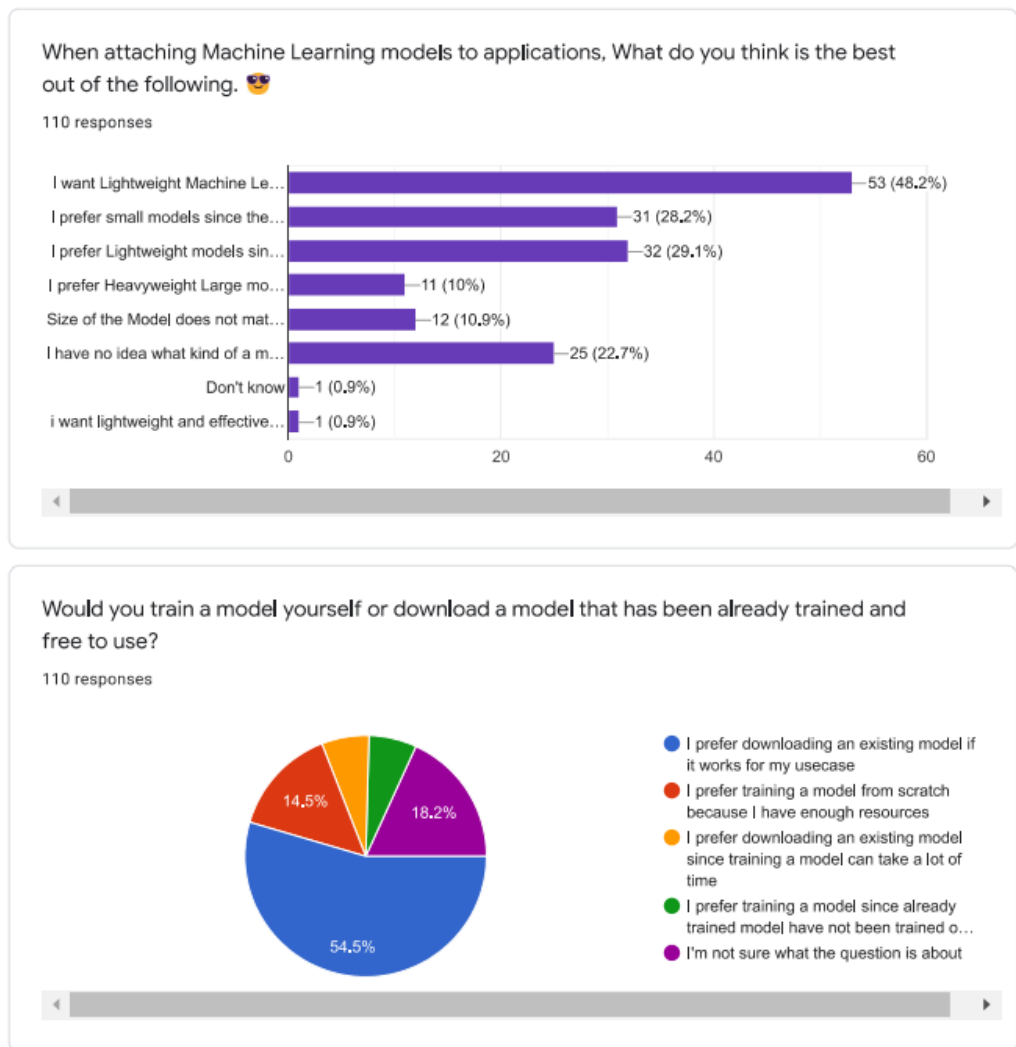


Figure A.10: Complete survey form questions and responses – part 10



Thank you! 🙏

Figure A.11: Complete survey form questions and responses – part 11

Appendix B: Supervision Confirmation Emails

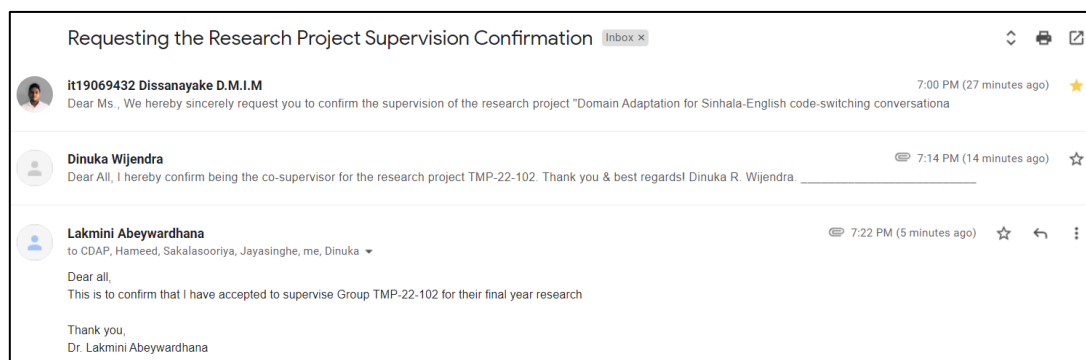


Figure B.1: Research project supervision confirmation email

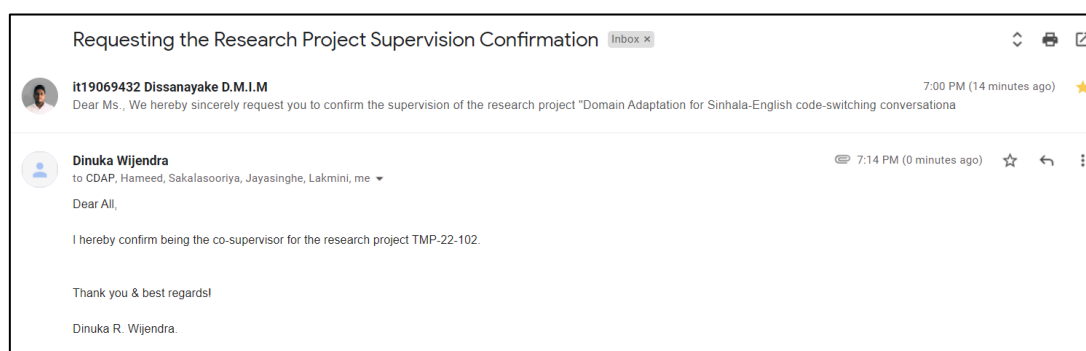


Figure B.2: Research project co-supervision confirmation email

Appendix C: SIENA user interfaces

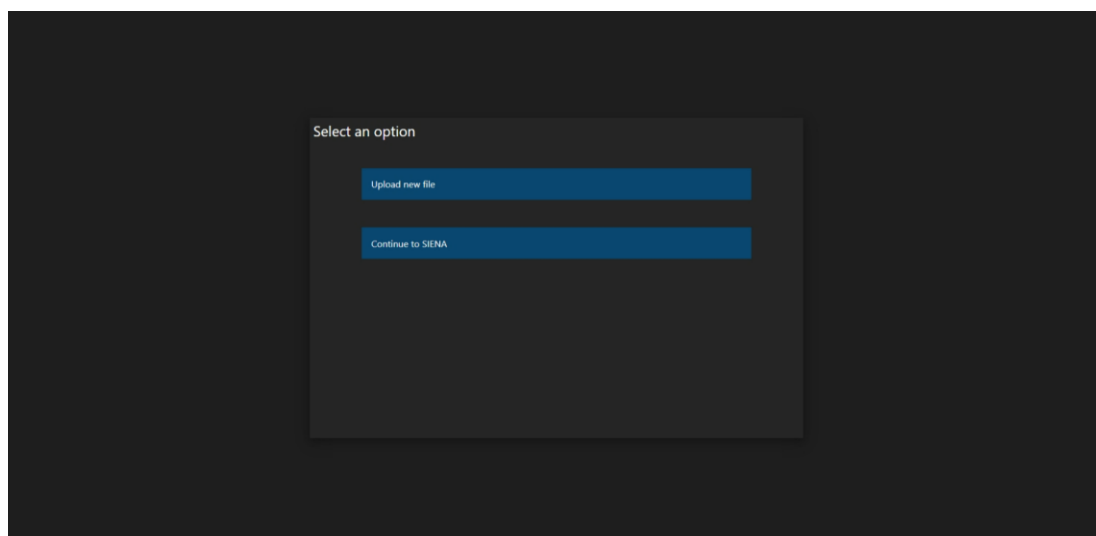


Figure C.1: SIENA initial pathway selection user interface

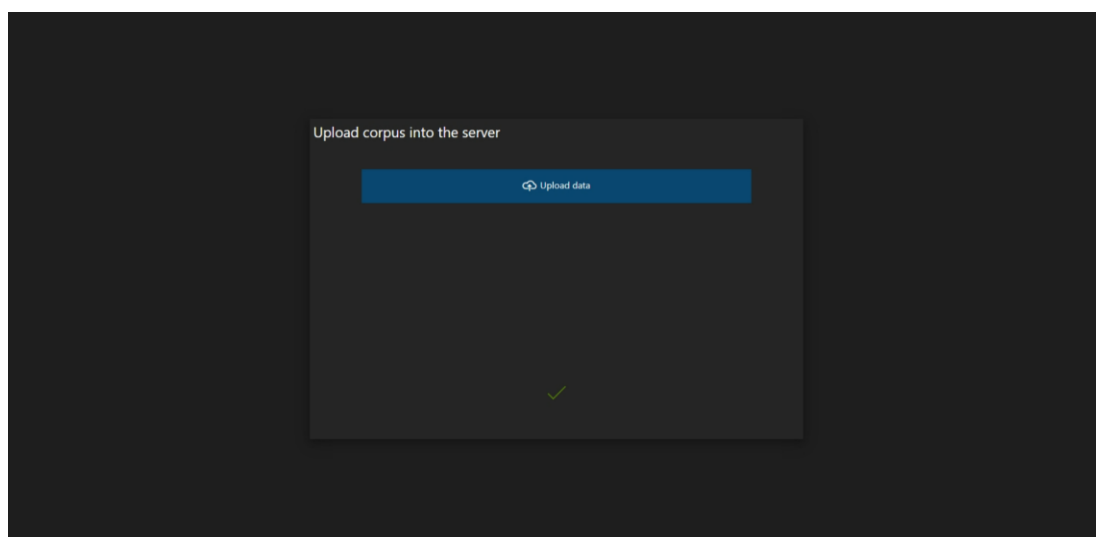


Figure C.2: SIENA file selection user interface

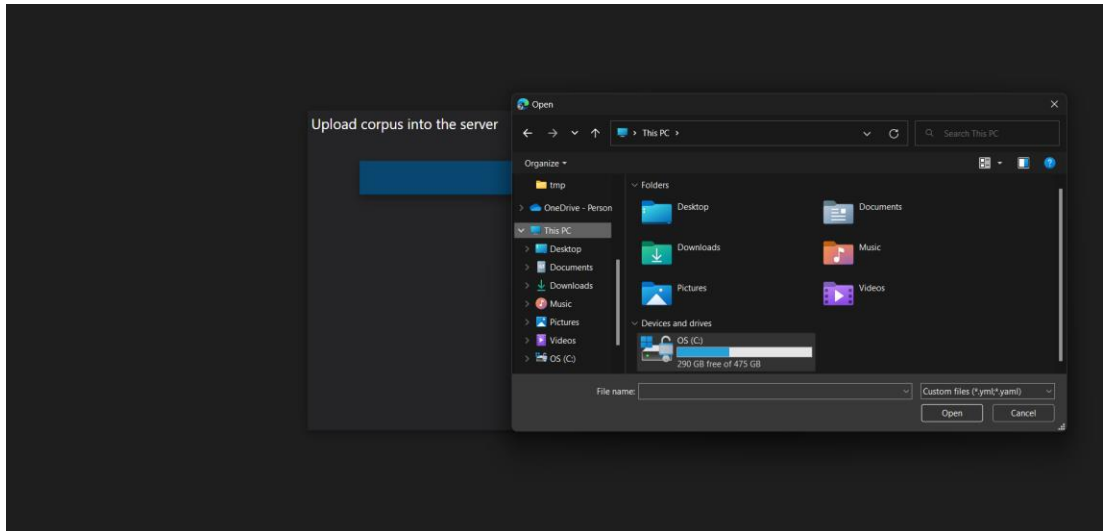


Figure C.3: SIENA file picker

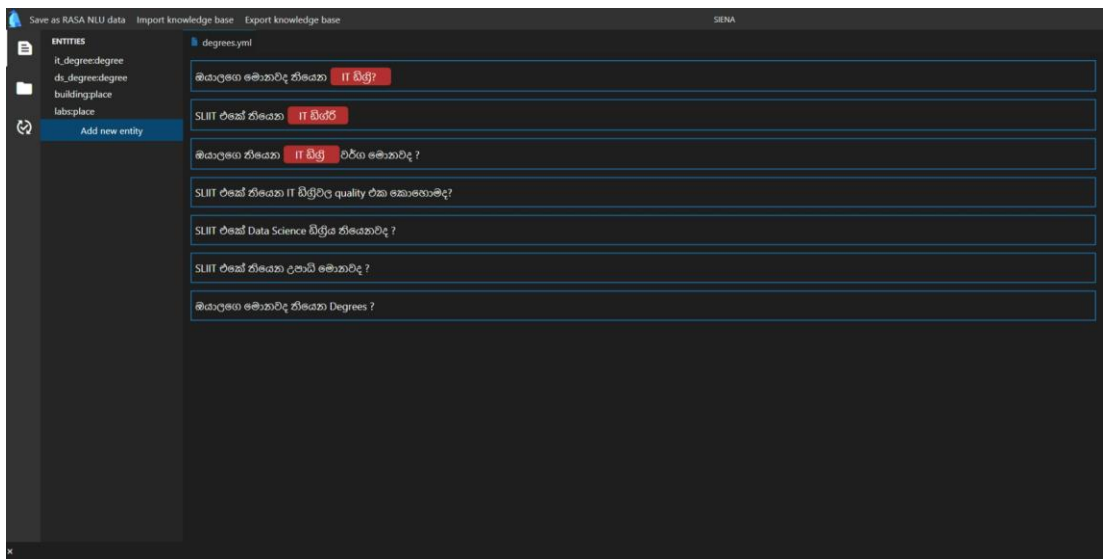


Figure C.4: SIENA entity list side menu

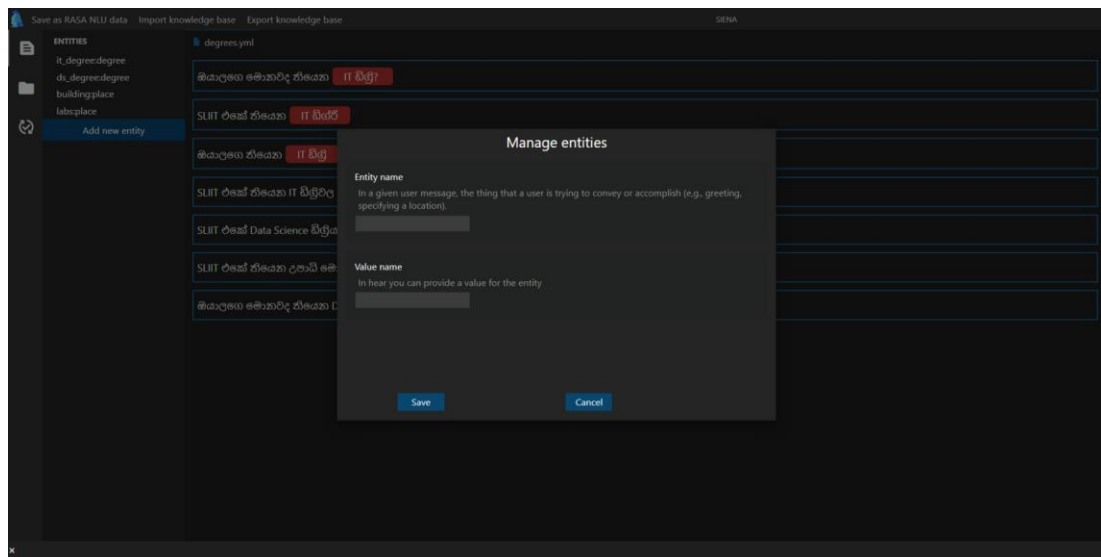


Figure C.5: SIENA add new entity user interface

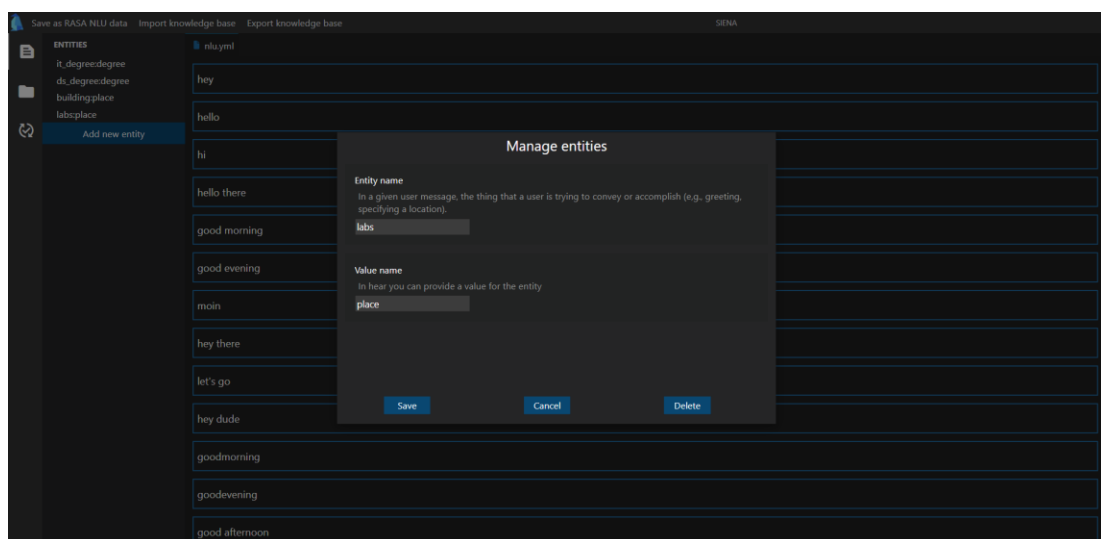


Figure C.6: SIENA edit entity user interface

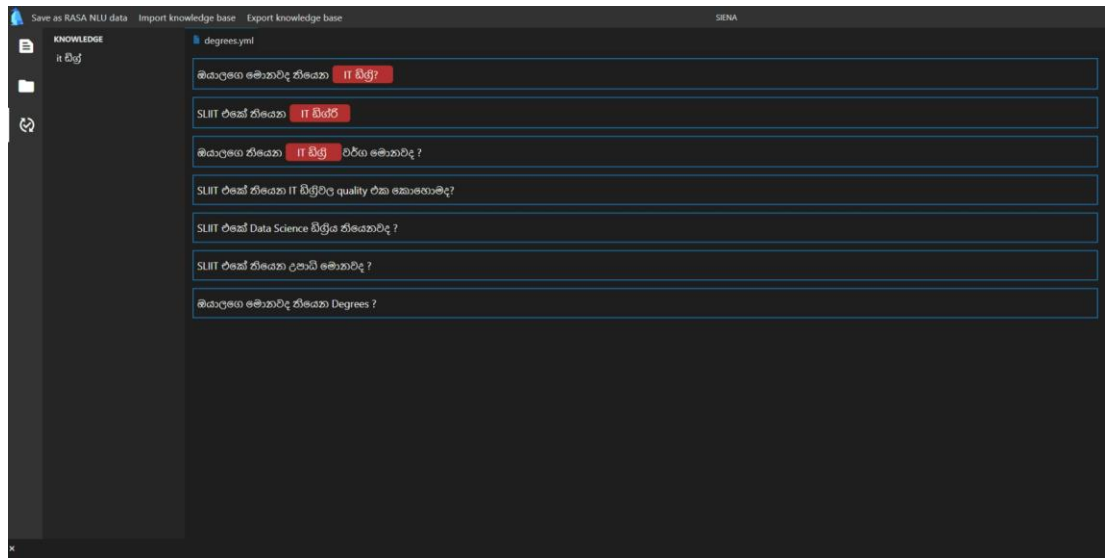


Figure C.7: SIENA base word list side menu

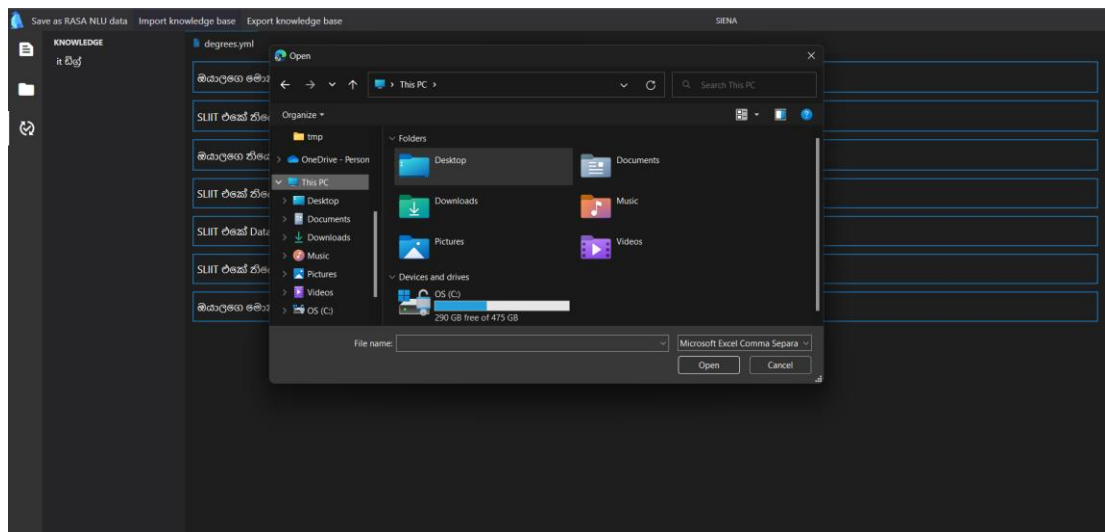


Figure C.8: SIENA knowledge base file picker

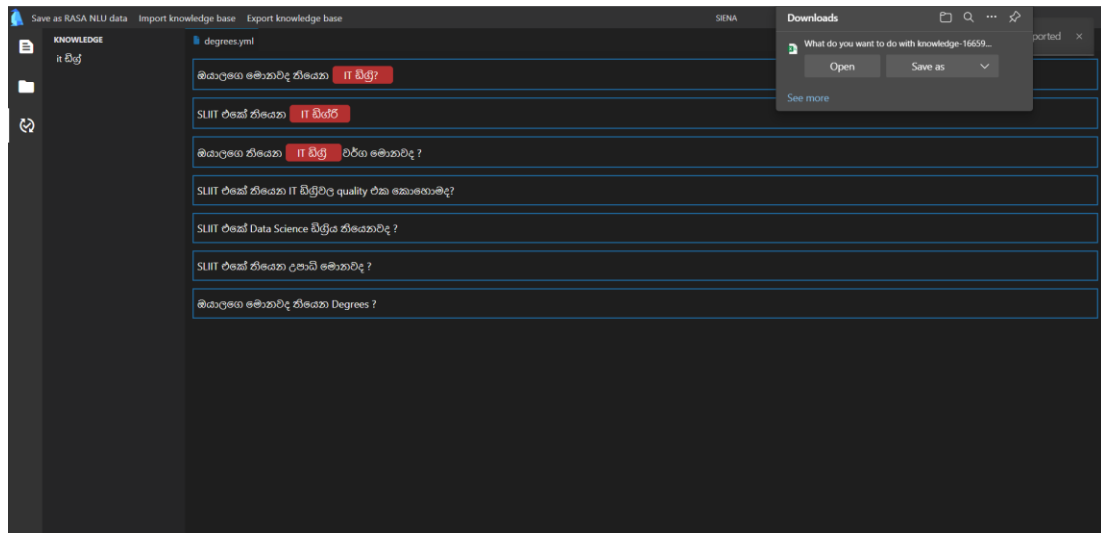


Figure C.9: SIENA knowledge base export

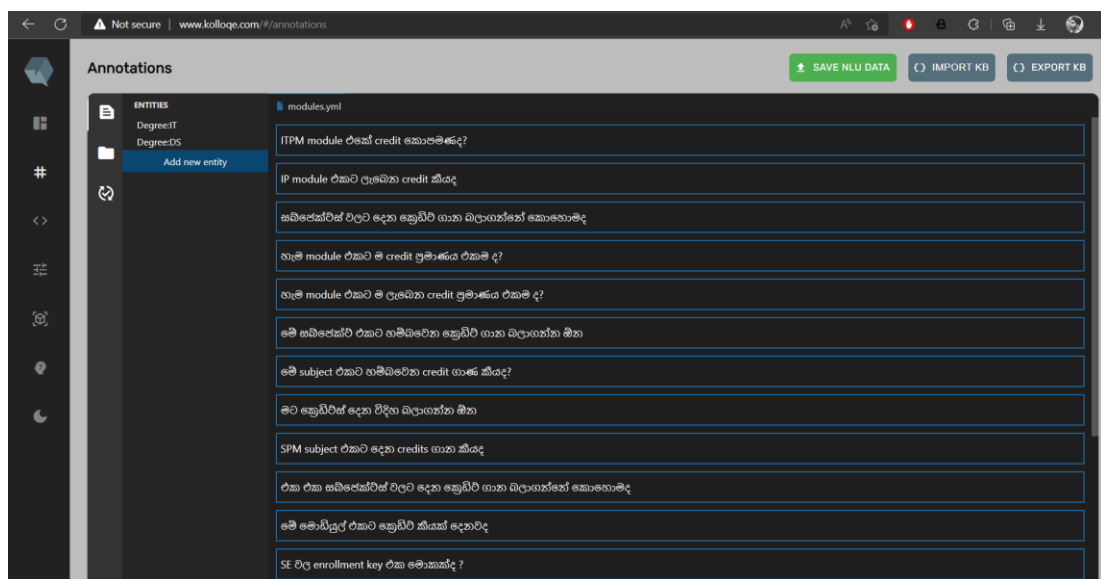


Figure C.10: Integrated SIENA into Kolloqe