# Bridging Classic and Modern English: An NLP Approach to Translation and Educational Chatbots in English Literature

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***Abstract*—The development of technology, especially of Artificial Intelligence, has impacted numerous fields like education, finance, healthcare and others. In the area of education, variety of tools are used to assist in the process of learning, for example-chatbots. These tools are very useful and beneficial for students as well as teachers as it creates a personalized learning environment for every individual which makes it easier to understand as well as depend on. We are using NLP techniques like NER in this paper for the development of a chatbot using LLMs. The chatbot we are building also focuses on translation of old English text to modern English, such as translating Shakespearean text to modern English text making it easier to understand classical literature. Following with a literature review and methodology, our paper presents how chatbots enhance education and explores the future of these tools.**

***Index Terms*—LLMs, Chatbots, Llama3, NLP, Text Translation, T5, BERT, NER, SpaCy**

## I. Introduction

As the digital world progresses, AI has impacted many fields including education. Educational tools hold great potential for changing the way we study English literature. Traditional methods of teaching are going out of fashion now as it limits creative thinking and understanding. Although technological tools have improved these methods to some degree they can still fall short of providing a personalized and engaging experience that takes into consideration the varied needs of different individuals. By utilizing advanced technology, we can invent a better and tailored learning experience for users that make understanding literature easier than before [1].

In Literature we often come across complex themes, character dynamics and narrative structures that can be handled in an innovative manner. This is where AI comes into picture and can make a difference. Using advanced techniques of NLP, users can interact with literary texts in new ways creating an interactive learning environment [2]. Modern technological tools have some important added benefits, but they often lack the personalized and dynamic experience that literature students need to connect with complex texts. Our approach addresses this gap, aiming to create a tailored learning platform that not only supports comprehension but also enhances a learner's engagement with literary works.

In our research paper, we have put forward an approach that builds on current resources of education by integrating AI chatbots tailored for analysis of literary texts. We have measured the efficiency of a popular model – LlaMA-3. In our approach we design a system where users can upload a range of literary works. Then we train the model on a variety of literary texts like poems, sonnets, stories, plays and novels. Moreover, we have implemented a translator which translates old English text into modern English text for ease of processing. We make use of transfer learning to train the translation model. The chatbot puts NER to use for identifying characters and locations. Users can then engage with these entities through the chatbot gaining new perspectives and thus appreciating the narrative more.

This interactive approach is a significant step forward in literature education, offering a personalized and meaningful way for students to connect with the English language. It bridges the gap between traditional methods and modern AI techniques, making the study of literature more accessible and engaging. Our aim is to not only show the advantages of this approach but also showcase its potential to enhance the students experience.

In this paper, we begin by presenting a thorough literature review of the existing approaches and architectures. Then we move on to the methodology, first the translation module followed by the chatbot module. We then showcase the results of our proposed system, from which we draw a final conclusion.

## II. Literature Review

### A. Impact of Chatbots on Student Engagement

AI-driven chatbots have been gaining significant traction in the education sector because of their ability to make personalized and interactive learning environments. Chatbots use algorithms to simulate human dialogue allowing students to converse in a way that helps to clarify their doubts which facilitates self-paced learning. Chatbots are being integrated into virtual learning environments to address student problems and provide feedback [3]. This change has led to better student engagement and made a shift in the landscape of pedagogy, enabling teachers to focus on more complex nuances.

### B. Chatbots in EdTech

Significant research highlights the impact of chatbots on language learning, and the enhancement in understanding language and literature through its interactive and tailored support. Furthermore, analyzing state of the art AI chatbot models, including ChatGPT, Llama, and others highlight their diverse applications across fields such as education and healthcare. The review identifies both the benefits and limitations of AI-driven chatbots, especially within e-learning environments, where hybrid models aim to improve educational outcomes. Additionally, student feedback on these technologies is analyzed to assess their effectiveness and identify potential areas for enhancement. Broader discussions on AI and large language models cover their design, applications, and challenges, emphasizing the transformative impact of AI on education and the necessity for ongoing assessment and ethical considerations

Advancements in AI, like the development of intricate models like Llama 3 enables chatbots to process complex queries with increased accuracy and better comprehension. The integration of chatbots has shown a visible impact on the learning experience of students as the systems provide personalized and context-aware assistance which is of immense importance for a better understanding. The feedback loop formed by these systems helps students to stay motivated and eager for learning. Research in [4] demonstrated that students who interacted with Llama 2-powered chatbot reported better academic performance and a positive learning experience. These observations emphasize the potential of AI models to create adaptive and effective learning environments.

### C. Translation of Archaic Texts

The use of Artificial Intelligence in translation tasks has evolved from conventional statistical methods, which depended on bilingual datasets, to modern techniques like transfer leaning. Traditional methods, for example, the use of Hansard corpus in English to French language translation, concentrated on translation without intermediate representations. These methods were undoubtedly successful but were restricted by the need for large amounts of data and battled with syntactically diverse languages.

Latest progress in Neural Machine Translation, have exploited the concepts of transfer learning [5] to refine translation accuracy and quality specifically for resource lacking languages and sophisticated texts like Shakespearean English. By using a low-resource language pair for fine-tuning and a high-resource language pair for training, models like BERT and T5 have proven to show substantial advancements, attaining superior BLEU scores [6] and garnering the nuances of outdated languages like the early modern English (Shakespearean texts). This technique indicates a positive change from conventional statistical models to AI-powered techniques, displaying great results in machine translation of literary texts.

Pre-existing works like Shakespearify and OpenAI's ShakespeareGPT, have pioneered AI-driven translation of Shakespearean texts.

- Shakespearify [7] converts modern English text to Shakespearean texts. It is available to use on the HuggingFace website for free.
- ShakespeareGPT is another already existing model, which is OpenAI's own chatbot that generates extremely accurate Shakespearean text.

These pre-existing models exhibit AI's capability to generate texts in obsolete languages, clearing the way for upcoming refinements in this field.

## III. Methodology for the Translation Module

Translation from Archaic Texts into Modern English is an extremely important step, for the chatbot, since text in modern English is efficient to process and understand, as compared to early English texts like Shakespearean texts. In this paper, we use Transfer Learning, for the process of translation.

### A. Transfer Learning

Transfer learning uses knowledge from a learned task to improve the performance on a related task, typically reducing the amount of required training data [8]. Today, NLP projects successfully utilize Transfer Learning for speech recognition, document classification and sentiment analysis. Our study applies transfer learning to neural machine translation [9]. Translation can be regarded as a three-stage process [10]:

1) Partitioning the source text into a set of fixed locations.
2) Using contextual information to select the corresponding set of fixed locations in the target language.
3) Arranging the words of the target locations into a sequence that forms the final target sentence.

### B. Contextual Awareness

Gathering contextual information from any text that is going to be used for processing is one of the most crucial tasks that you must perform. It is extremely important for correctly understanding texts, since it provides the background of the text. Context is what shapes the text, be it for translation, summarization or comprehension; it shapes the meaning of words and phrases. Specifically in translation, context makes the denotation, tone and background of a sentence clear, making sure that it is true to the original text. Combining contextual awareness with NLP techniques gives us a final product that catches the true intention, meaning and depth of the actual text.

To implement contextual awareness, a study suggests three most common methods [11]. These are mentioned below:

1) Concatenation method: This method concatenates all contextual sentences as a longer one, and then inputs it into the pre-trained BERT model to get the contextual features [12].
2) Flat method: Encodes each separate sentence using BERT model and concatenates their outputs as the contextual features [13].
3) Hierarchical method: Sums up the features in a hierarchical manner, where the features generated by the previous method are worked on further [14].

### C. Models

There are two main pre-trained models that come to mind when the task is to translate Archaic text to modern English texts - T5 and BERT. These are two of the most advanced models that can be used to perform translation tasks. Both models leverage deep learning techniques to grasp language in a way that understands the syntax as well as the semantics of the text. By implementing these models, translators can achieve a higher degree of accuracy as well as pronounced preservation of meaning and context across many languages, especially if you are dealing with Archaic material.

### D. Procedure

In our paper, for the implementation of contextual awareness in transfer learning, we have made use of two of the previously mentioned models: T5 and BERT. These models excel in handling sophisticated linguistic structures. They capture both global and local contexts very efficiently, which is of absolute importance for the translator.

We used a dataset that has pairs of Archaic and Modern English texts. The following steps summarize the methodology of the translator:

1) Data Preprocessing: Acquired pairs of Archaic and Modern English texts. Performed a thorough pre-processing before continuing further.
2) Model Selection: T5 was selected for its seq-to-seq skills, BERT was also selected for its contextual information gathering capabilities.
3) Fine Tuning: Fine-tuned the models on our dataset.
4) Contextual Awareness: Used the aforementioned contextual awareness capturing methods to get the contextual information of the texts.
5) Training: Trained the model and monitored their performance.

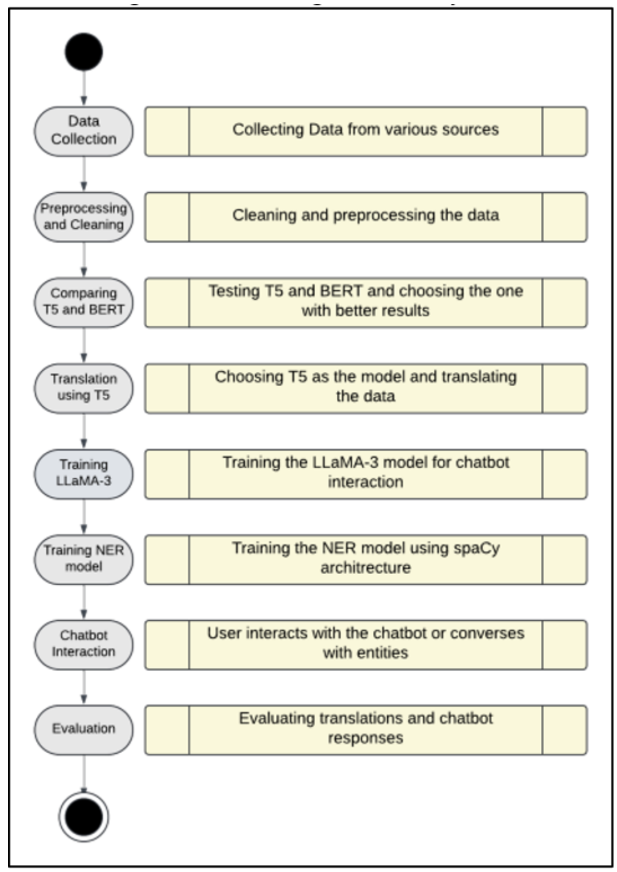


Fig. 1. Block diagram of the system

6) Evaluation: Evaluated both models using evaluation metrics like BLEU score as well as on the model's ability to preserve the meaning of the original.
7) Post Processing: Refined the outputs of the two models ensuring they are comprehensible.

The result of the methodology will be discussed in the results section of the paper.

Finally, this translated text would serve as the ideal input for the chatbot that we have implemented. More about the chatbot is mentioned in the subsequent sections.

## IV. Methodology for the Chatbot

### A. Overview

Our system gives an end-to-end approach that helps in enhancing the learning experience of English literature students by allowing them to interact with a chatbot that has a deep understanding of classical and modern English texts [15], [16]. The block diagram depicting the process of building the model is shown in Fig 1. The system takes user-inputted text and determines whether the input is in classical (archaic or Shakespearean) or modern English. If the text is identified as classical literature, it is routed through a translation module that converts it into modern English. Once the text is in modern English, or if it was originally in modern English, it is sent to our primary model. This model, built on the LLaMA-3 architecture [17]–[19], has been fine-tuned on a comprehensive literature dataset, the ”Classic English Literature Corpus and Meta Data” [20] from Kaggle. The system using NER identifies the key literary elements allowing users to engage in story specific interactions with these entities or converse generally with the chatbot i.e. the narrator [21].

### *B. Model architecture*

The model is based on the LLaMA-3 framework, which is known for its capability to handle large language models with high accuracy. We have trained the model on an extensive dataset that has a variety of literary works with a range of genres, authors, and time periods. This provides a rich corpus for the model to be fine-tuned on, in order to allow for deeper understanding of literary styles, themes, and structures [22].

The first step is analysing if the input text is written in classical or modern English. This step is crucial for ensuring that archaic texts, such as those written by Shakespeare, are accurately translated into modern English before further processing. If the text is classified as classical English, its processed by a translation module. As discussed before, it has been fine-tuned on pairs of classical and modern English texts to accurately translate archaic language into a more contemporary form of English making the text easier for the chatbot to process and understand.

The text is then processed using the NER architecture. Through this we identify important literary entities such as characters, locations, and historical references within the text [23]. Users can choose to interact with these identified entities directly or engage in a general conversation with the chatbot. This feature allows users to dive deeper into specific aspects of the text, such as character analysis or understanding the significance of certain locations in the narrative.

### *C. Procedure*

Our end to end system performs a sequence of well-defined steps to ensure a seamless user experience. Fig. 2 describes this pipeline of data flow and interactions between the modules. The flow of the system is as follows:

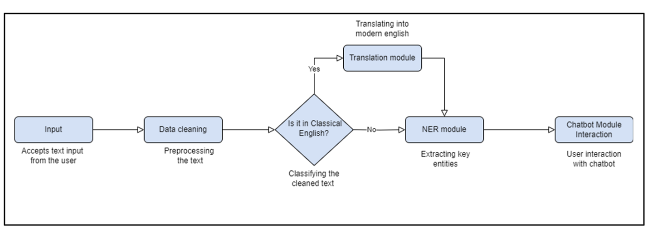


Fig. 2. Data Flow through the model

1) Text Input and Classification:
First, the user enters a literary text into the system. The system classifies the text as either classical or modern English. If the text is identified as classical English, it is forwarded to the translation module.
2) Translation Module:
In case the text is classified as classical English, it is sent translation module to convert the text into modern English. The translated text is then prepared for further processing by our primary model.
3) NER and User Interaction:
The translated text is processed using SpaCy’s NER framework. In this step the system extracts the key entities within the text, such as characters, locations, and historical contexts. The user can interact with these entities, which enables focused learning on specific elements of the text. Alternatively, the user can choose to engage in a general conversation with the chatbot, allowing them to explore it as the narrator.

The system supports diverse literary texts, ensuring that students can study and analyze various forms of literature, including novels, plays, and poems. Hence our model ensures that the system provides a personalized and engaging learning experience, leveraging advanced AI techniques to make the study of English literature more accessible and interactive [24].

## V. Results

The research from our experimentation on both T5 and BERT, concluded that for the task of translating Archaic texts to a more Modern form of English, T5 would give better, satisfactory results. Moreover, T5 consistently produced accurate and more contextually aware translations, retaining the meaning and of the original archaic text. After noting down the BLEU scores (Fig.3) as well as after human assessments of both the models, we observed that T5 was the superior model, and was able to generate natural translations.

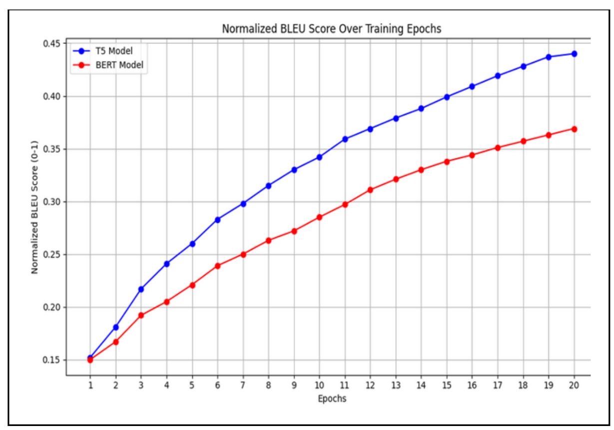


Fig. 3. BLEU Score of T5 v/s BERT

Other than the BLEU Score comparison, we can also perform a qualitative evaluation, which is a Visual Inspection. We tested both T5 and BERT on a line from the renowned playwright Shakespeare’s Romeo and Juliet. The input sentence was: “But, soft! What light through yonder window breaks?” as seen in Fig 4.

Overall, T5 focuses on retaining the narrative flow or the poetic flow of the original text. The text gets translated correctly, moreover the meaning and creativeness of the text is maintained. Whereas, BERT’s translation is more literal,

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T5 Translation:
Wait, what is that light coming through the window?

BERT Translation:
Hold on, what light is shining through that window?
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Fig. 4. Output of translation module

focusing on the accuracy of the translation. The structure of the translated text is more direct and lacks the poetic touch that is present in T5.

Finally, we decided that we needed the translations that were more natural and captured the poetic essence of the original text better than the other one. The model that achieved this, was T5, thus proving that it is an exceptional model for archaic text translation.

We also performed qualitative analysis of the chatbot module with a few general questions from the same play. The answers provided by the chatbot were both precise and accurate as seen in Fig 5.

```
User: What is the main theme of Romeo and Juliet?
Chatbot: The main theme of Romeo and Juliet is the tragedy of young love and the destructive power of feuding families.

User: Who are the main characters in Romeo and Juliet?
Chatbot: The main characters in Romeo and Juliet are Romeo Montague, Juliet Capulet, Mercutio, Tybalt, and Friar Lawrence.
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Fig. 5. Output of queries to the chatbot

We also performed a quantitative analysis, where we tested the chatbot on our own dataset [25] that contains question and answers about various characters of Merchant of Venice. The chatbot was asked 10 questions that were present in the dataset, after which the responses of the chatbot were compared to the answers present in our dataset of the same questions. The metric used to compare the answers, was BLEU score. The result was that we got a good score of approximately 0.6, which is considered as a good score for an application like this (Fig 6).

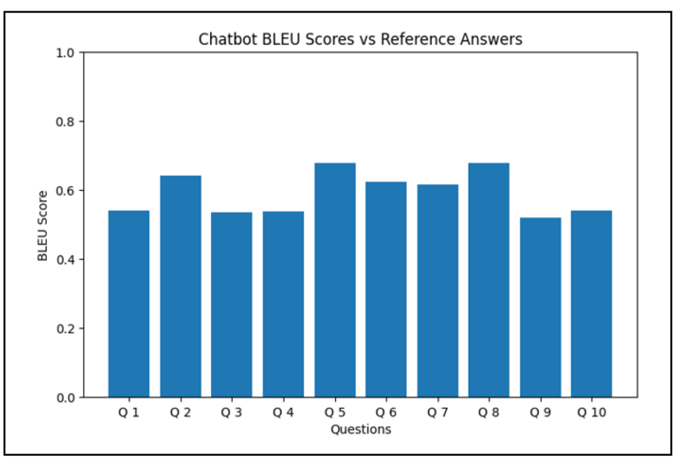


Fig. 6. Quantitative Analysis of Chatbot answers

The chatbot even presented a high level of accuracy in the identification of key identities from the questions and generation of relevant answers. For instance, the chatbot accurately extracted the entity and provided the user with explanations. Moreover, the chatbot's ability to adapt and learn over time enables it to provide personalized assistance to users.

## VI. Conclusion

To conclude, our research emphasizes the importance of incorporating advanced AI applications into the domain of English Literature. By applying present day Natural Language Processing techniques and AI chatbots particularly crafted for literary analysis, we have devised a system that substantially improves on both interaction and personalization in the field of English Literature. The utilization of a model like LLaMA-3, paired with T5 as a translator tool to simplify Archaic Texts into Modern English, shows a major upgrade in making sophisticated literary texts more comprehendible and graspable.

Our research uses NER to pinpoint important literary elements like characters of a story, locations of the story, contexts, plots of the story, etc. provide the students with a more personalized and immersive learning experience. This personalized approach enhances students' understanding of complex themes and narratives. But everything considered, this system does not come without its limitations and challenges, one major challenge being the computational intensity that is needed to fine-tune LLMs like LLaMA-3 and T5 on specialized literary data. This complexity, along with the necessity of high-quality datasets that reflect diverse literary styles, themes, and historical contexts to fully capture the nuances of English literature increases the difficulty in doing so. Additionally, while the translation of archaic texts into modern English enables greater accessibility, it often struggles to retain subtle linguistic intricacies unique to early English texts, leading to potential loss of authenticity. The chatbot's ability to simulate human-like interaction is also inherently limited, as it may not fully address the depth of student queries on complex literary themes.

The purpose of this paper was to fill up the gap between pre-existing methods, and up-and-coming innovative AI aided methods. Our research shows how state-of-the-art NLP techniques can be used to create personalized learning experiences. This method not only showcases the benefits of AI in the education sector, but also gives way for further studies and advancements, highlighting the current possibilities for AI to transform education for all. In the future we intend to further develop this chatbot to allow bringing in more diverse character interactions where the language models are concerned and taking wider varieties of literary genre into consideration. Further potential advancements could include responses that adapt to personality traits or stylistic choices, making the literary chatbots even more vibrant. Even emotional and tone recognition in response depth could make character-based conversations more realistic. This could possibly open up even more possibilities for improving literary analysis, and the opportunities for personalized learning, increasing students motivation towards the reading of classical literature in educational settings as well.

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