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Text Classification and its Effect on EFL University Students' Performance in Literary Analysis

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Abstract

The current study aims at finding out the effect of text classification of EFL university students' performance in literary analysis. The sample of the present study consists of 60 students from Department of English Language at College of Arts / University of Tikrit. Students are divided randomly into two groups: the experimental(EG) which represented in (Section B) and the control (CE) which represented in (Section A), each class consists of 30 students. Both groups are matched in terms of parental academic attainment, age, previous year scores in poetry and the+ pretest. The study has lasted fourteen weeks during the first semester of the academic year 2024/2025. To achieve the aims and verify its' hypotheses, Non-randomized Control Group Pretest and Post-test Design has been

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adoptedin this study. The collected data have been statistically analyzed by using different statistical means. The results indicate that the text classification has beensignificantly enhanced the performance of EFL university students' literary analysis.

Key words: Text ClassificationEFL Students**,** Literary Analysis**,** Experimental study

تصنيف النصوص واثره على اداء الطلبة العراقيين دارسي اللغة الانكليزية لغة اجنبية في التحليل الادبي

زينة اسماعيل جاسم

كلية التربية للعلوم الانسانية /جامعة تكريت

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كلية التربية للعلوم الانسانية /جامعة تكريت

المستخلص

تهدف الدراسة الحالية إلى معرفة أثر تصنيف النصوص على أداء طلاب الجامعات الدارسين للغة الإنجليزية كلغة أجنبية في التحليل الأدبي. تتكون عينة الدراسة من 60 طالبًا من قسم اللغة الإنجليزية بكلية الآداب / جامعة تكريت. قُسّم الطلاب عشوائيًا إلى مجموعتين: المجموعة التجريبية (EG) ممثلة في (القسم ب) والمجموعة الضابطة (CE) ممثلة في (القسم أ)، بواقع 30 طالبًا في كل فصل. تتطابق المجموعتان من حيث التحصيل الدراسي للوالدين، والعمر، ودرجات السنوات السابقة في الشعر، والاختبار القبلي. استمرت الدراسة عشرة أسابيع خلال الفصل الدراسي الأول من العام الدراسي 2025/2024. ولتحقيق أهداف الدراسة والتحقق من فرضياتها، تم اعتماد تصميم المجموعة الضابطة غير العشوائية (الاختبار القبلي والبعدي). وقد حُللت البيانات المُجمعة إحصائيًا باستخدام وسائل إحصائية مختلفة. وتشير النتائج إلى أن تصنيف النصوص قد حسّن بشكل ملحوظ أداء طلاب الجامعات الدارسين للغة الإنجليزية كلغة أجنبية في التحليل الأدبي.

الكلمات المفتاحية: تصنيف النصوص، طلاب اللغة الانكليزية كلغة اجنبية، التحليل الادبي، دراسة تجريبية

1.1 Problem of the Study

The use of English persists in active growth as it continues to evolve across broad regions. The essential value of English in present-day communication together with education and cultural interchange enables worldwide individuals to learn and work and communicate effectively. The ability to master both English skills and knowledge proves crucial for worldwide professionals while maintaining its fundamental influence on future international communication practices(Fairclough, 2010).

The discipline of literary analysis requires learners to master multiple complicated abilities including interpretation of themes together with motif recognition and expertise in narrative patterns and cultural evaluation of texts. The traditional methods of literary analysis are based on structuralism, post-structuralism and feminist or post-colonial reading techniques that demand complete knowledge of textual language elements combined with historical and political contexts.

Aims of the Study1.2

The study aims at :

1. Finding out the effect of using Text Classification on EFL university students' performance in Literary Analysis in the post- test.

1.3 Hypothesis of the Study

The current study hypothesized that:

1- There is no statistically significant difference between the experimental group students'performance who have been taught by using text classification and control group who have been taught by using the conventional method in literary analyses in the post test .

1.4 Limits of the study

This study is limited to:

1- University of Tikrit, College of Arts /Department of English.

2- This study is conducted in the first semester of the academic year 2024/2025.

3- English Poetry Textbook for second stage in College of Arts / Department of English.

4- The participants of the study are the students from second grade at Department of English .

5- The instructional model adopted in the study is the Text Classification Approach, which aims to enhance students' performance in literary analysis and cultural awareness.

1.5 Value of the Study

This study bridges the gap between literary teaching and contemporary technology by providing a new method for evaluating and fostering the literary growth of EFL students.

It offers factual support for the usefulness of text categorization in educational evaluation.

The findings support the larger goal of strengthening language skills, such as critical thinking, cultural competency, and digital literacy, among EFL learners. Itmay also influence curriculum design and instructional strategies in literature-based courses within EFL programs.

2. Historical Background of Text Classification

Text classification has seen significant advancements over the last few decades, evolving from basic methods to sophisticated computational systems. The origins of text classification can be traced back to the mid-20th century, a time when there was a growing need to automate the organization and retrieval of information. These early efforts were motivated by the necessity to manage large libraries and information systems filled with extensive amounts of text data. As researchers began to explore ways to systematize the handling of text, they laid the foundation for what would later become automated text classification systems(Lewis, 1992).

In the 1960s, Gerard Salton introduced the Vector Space Model (VSM), marking a pivotal development in text classification. The VSM was groundbreaking because it allowed textual documents to be represented as vectors within a high-dimensional space.

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Each term in the document became a separate dimension, and this allowed the calculation of similarity scores between documents. This innovation made it possible to categorize documents based on their content by measuring the similarity between them, setting the stage for automated document classification systems. The VSM played a crucial role in the advancement of text classification, providing a structured way to represent and organize text data(Joachims, 1998).

The 1980s and 1990s brought about a significant transformation in text classification with the introduction of machine learning algorithms. These algorithms, including decision trees, Naive Bayes, and support vector machines (SVMs), enabled systems to automatically learn classification patterns from labeled training data. This marked a shift toward the automation of text categorization, allowing systems to improve over time by learning from the data. A key development during this period was the use of statistical methods, such as Term Frequency-Inverse Document Frequency (TF-IDF), which allowed systems to assign importance weights to terms based on their frequency within a document in relation to the entire corpus. These advancements significantly improved the accuracy and effectiveness of text classification systems, making them more reliable and efficient in categorizing textual data(Manning, Raghavan, & Schütze, 2008).

In the 21st century, deep learning techniques brought about further revolutionary advancements in text classification. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have proven to be exceptionally powerful tools for tasks such as sentiment analysis, topic classification, and genre identification. These models, with their ability to process large datasets and learn complex patterns, significantly enhanced the performance of text classification systems. CNNs excel in identifying local features in text, while RNNs, especially Long Short-Term Memory (LSTM) networks, are particularly adept at capturing sequential dependencies in textual data, making them ideal for text classification tasks(Devlin , 2019).

One of the most notable developments in recent years has been the advent of transformer-based models, such as BERT (Bidirectional Encoder Representations from

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Transformers). BERT revolutionized text classification by introducing a bidirectional approach to understanding word context, enabling the model to process words in relation to their surrounding words. This development has led to a new standard in text classification performance, setting benchmarks for tasks such as sentiment analysis, topic categorization, and language understanding. Transformer-based models like BERT have raised the bar for text classification systems, pushing the boundaries of what is possible in terms of accuracy and efficiency(Kim, 2014).

The advancements in text classification methods have had a profound impact across various domains. In education, for instance, text classification systems are increasingly being used to analyze and evaluate student essays, offering automated feedback and grading systems. In the field of literary analysis, text classification models have been applied to categorize texts by genre, author, or thematic content, enabling large-scale literary analysis. These developments underscore the growing importance of text classification as a tool that can be applied across numerous fields, from education and healthcare to marketing and content management(Lewis, 1992).

Overall, the history of text classification highlights its transformation from manual methods to the sophisticated machine learning and deep learning techniques that dominate the field today. As technology continues to advance, the potential applications of text classification systems are expanding, offering new opportunities for automating the organization and analysis of textual data(Kim, 2014).

2.1 Types of Text Classification

Text classification is a critical process in the field of natural language processing (NLP), and it plays an essential role in various applications, from document categorization to sentiment analysis. This process can be approached in several ways, depending on the nature of the classification task and the specific operational requirements. The categorization of text can be broadly divided into several types, each suited to different types of tasks and data structures. The following discusses the key types of text classification in more detail, highlighting the distinctive characteristics and applications of each(Sebastiani, 2002).

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Binary classification is one of the most common forms of text classification, where the goal is to assign a document to one of two distinct categories. This type of classification is used in scenarios where the content of the text can be clearly divided into two opposing groups. A well-known example of binary classification is spam detection in email systems. In this case, emails are categorized as either "spam" or "non-spam" based on their content, and the model is trained to recognize specific patterns in the text that are characteristic of each class. The simplicity of binary classification makes it a useful tool for tasks that require a straightforward decision between two mutually exclusive categories. For instance, in the context of sentiment analysis, binary classification can be used to determine whether a piece of text expresses a positive or negative sentiment(Zhang & Zhou, 2014).

Multi-class classification, on the other hand, deals with situations where there are more than two categories into which a document can be classified. This type of classification is suitable when the task requires assigning a document to one of several possible categories. For example, in the case of classifying news articles, each article might belong to one of several topics such as politics, sports, technology, or health. The challenge in multi-class classification lies in training a model to differentiate between a larger set of possible categories, ensuring that each document is assigned to the most appropriate class.

Joachims (1998) discusses multi-class classification in the context of support vector machines (SVMs), where the system is trained to recognize the features of text that are indicative of a specific category, allowing the model to categorize new, unseen documents accordingly.

This method has been particularly successful in tasks such as topic identification and document categorization, where there is a clear and non-overlapping set of categories(Tsoumakas&Katakis, 2007).

In contrast to both binary and multi-class classification, multi-label classification allows a document to be assigned to multiple categories simultaneously. This approach is particularly useful when a piece of text exhibits characteristics that align with more than one category. For instance, a blog post that discusses both “health and fitness” and “nutrition” could be labeled with both of these tags. Multi-label classification systems are designed to handle such scenarios, learning to identify multiple labels for each document based on its content.

Tsoumakas and Katakis (2007) emphasize the importance of **multi-label classification in contexts** where documents can be multidimensional in nature, with different aspects of the content corresponding to different categories. This classification type is often used in more complex systems where content is inherently overlapping or where documents have multiple relevant themes(Tsoumakas&Katakis, 2007).

Multi-label classification is particularly beneficial in applications such as content recommendation systems, social media content categorization, and academic research, where topics are often interrelated and cannot be confined to a single category.Each of these classification types-binary, multi-class, and multi-label-serves a different purpose and is used for specific tasks based on the structure and complexity of the data being processed. Binary classification is ideal for tasks that require a simple, clear distinction between two categories, while multi-class classification is suitable for more complex problems with multiple distinct categories. Multi-label classification, on the other hand, is essential for handling tasks where documents need to be categorized into several relevant categories simultaneously. The choice between these types depends on the nature of the task and the type of data involved, as well as the specific needs of the application(Tsoumakas&Katakis, 2007).

The growing range of text classification methods has enabled more sophisticated and accurate categorization of textual data across various domains. In addition to traditional applications such as email filtering and topic categorization, modern systems now use these techniques for a wide variety of purposes, including automated content tagging, sentiment analysis, and even the classification of complex literary works. As the field of NLP(explain this acronym) continues to evolve, it is likely that new types of classification methods will emerge, offering even greater flexibility and precision in handling textual data(Silla & Freitas, 2011).

The following sections explore the different types of texts that contribute atenhancing literacy skills, critical thinking, and intercultural competence:

a. Written Texts

Written texts are perhaps the most traditional form of textual analysis and include both literary and non-literary texts. Literary texts, such as novels, poems, and plays, are often analyzed in terms of their genre-specific narrative and rhetorical structures. In these texts, the writer's choices regarding language, structure, and style shape the meaning and effect of the work. Written texts allow students to explore themes, character development, and stylistic features that define the genre. Through the analysis of literary works, students gain a deeper understanding of both literary conventions and the cultural contexts in which the texts were produced (Halliday & Hasan, 1976).

Non-literary written texts, such as essays, research papers, and reports, require a different approach. These texts typically focus on informing, persuading, or documenting information. In the context of EFL learning, students analyze non-literary texts to understand their argumentative structures, evidence, and persuasion techniques. This process is essential for academic writing and research, providing students with the tools to critically engage with non-fiction texts while developing their writing skills in a second language.

b. Spoken Texts

Spoken texts refer to verbal communication, including conversations, speeches, interviews, and dialogues. These texts are often classified as dialogical, as they are marked by interaction and exchange between participants. Spoken texts, particularly in genres like drama, highlight the performative aspect of language use, where the tone, pace, and delivery contribute significantly to the meaning of the conversation .For EFL students, analyzing spoken texts helps them develop important listening and speaking skills. It also allows them to gain insights into cultural norms related to communication styles, turn-taking, and speech acts, which are vital for effective cross-cultural communication(Sacks et al., 1974).

c. Visual Texts

The analysis of visual texts involves interpreting images, videos, and other visual forms of communication. Visual texts include photographs, paintings, advertisements, and films, which all rely on symbolism, composition, and visual rhetoric. Visual texts are integral to multimodal literacy, which encompasses the ability to interpret and produce meaning through multiple modes, such as text, images, and sounds. In the context of EFL learning, students are exposed to films and television shows as a means of enhancing their visual literacy. These texts provide an avenue for students to explore symbolism and visual rhetoric, enabling them to better understand how non-verbal elements can contribute to the meaning and message of a text (Kress & van Leeuwen, 2001; Bolter & Grusin, 1999).

Films, for instance, combine spoken dialogue, visual imagery, and sound to convey complex messages and emotions. Analyzing films as a type of visual text enhances students' interpretive skills and their ability to decode symbolism and hypertextual connections. Furthermore, the juxtaposition of novel-to-film adaptations provides an excellent exercise for students to compare how different mediums handle narrative, tone, and characterization.

d. Digital Texts

With the advent of the internet, digital texts have become an essential form of communication. These texts include websites, blogs, social media posts, online reviews, and interactive content such as hyperlinks and multimedia elements. Digital texts are dynamic and interactive, offering readers a more multimodal experience than traditional texts. For example, a blog post or social media update often combines text with images, videos, and hyperlinks to create a richer form of communication .In the context of EFL learning, students engage with digital texts to develop their digital literacy and online communication skills(Herring, 2004).

Social media posts, in particular, offer students insight into how language is used for interaction, self-expression, and identity formation. The informal, interactive nature of social media encourages students to explore how language evolves in different digital environments and how linguistic norms vary across cultural contexts. Analyzing digital texts in this way fosters cross-cultural pragmatics, helping students understand the communication styles of different cultures and interact appropriately in global digital spaces (Bolter & Grusin, 1999).

e. Symbolic Texts

Symbolic texts extend the understanding of ideological consciousness by incorporating meaning beyond the literal interpretation of words. Symbolic texts often involve intertextuality and the use of allegories, metaphors, and symbolism to communicate deeper, abstract meanings. These texts may include religious texts, political manifestos, and cultural artifacts that carry significant symbolic weight within a particular culture .For EFL students, interpreting symbolic texts requires a sophisticated understanding of cultural references and ideological frameworks, which may not be immediately apparent to non-native speakers(Barthes, 1967).

Exposure to symbolic texts challenges students to think critically about how symbols function within different cultures and historical contexts. For example, literary symbols in novels may reference political struggles, religious beliefs, or social movements that are particular to the author's culture. By analyzing these symbolic texts, students gain insight into how ideologies are conveyed and reinforced through language and cultural symbols(Barthes, 1967).

2.1.1 Approaches to Text Classification:

Text classification remains one of the most important operational tasks in the field of natural language processing (NLP), and its methodologies have evolved significantly over time. The process of text classification has transitioned from simple, rule-based systems to sophisticated, state-of-the-art transformer models. These shifts in approach reflect both advances in computational power and improvements in algorithmic techniques, making text classification more accurate, efficient, and adaptable to diverse applications(Hearst, 1999).

In the earliest stages of text classification research, systems were largely rule-based, relying on manually crafted linguistic rules to identify and categorize text. For example, early spam detection systems would flag emails containing specific words, such as "free," as potential spam (Manning, Raghavan, & Schütze, 2008). These early systems were limited by their reliance on predefined keywords and deterministic matching methods, making them inflexible to variations in language. While such systems required minimal training data and were relatively easy to implement, they struggled with scalability and adaptation, especially when faced with linguistic diversity or evolving patterns in the data. The simplicity of these early methods, while effective in controlled environments, soon proved to be insufficient for more complex tasks(Joachims, 1998).

The next significant advancement came with the integration of machine learning (ML) algorithms, such as Naïve Bayes and Support Vector Machines (SVMs), which allowed systems to learn patterns from labeled data (Joachims, 1998). These models represented a shift away from rule-based methods, as they were capable of identifying statistical patterns in data rather than relying solely on predefined rules. SVMs, in particular, emerged as a powerful tool for text categorization, using decision boundary optimization techniques to classify documents based on feature spaces derived from methods like Bag-of-Words or Term Frequency-Inverse Document Frequency (TF-IDF) representations. The ability to learn from labeled data enabled these systems to handle more nuanced tasks and adapt to new, unseen text, making them a significant improvement over earlier approaches(Joachims, 1998).

However, ML-based models still required substantial feature engineering and large volumes of labeled data for training. This limitation led to the next major breakthrough in text classification: deep learning (DL). Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), introduced automatic feature learning. These models were capable of extracting hierarchical text representations, reducing the need for manual feature engineering. Kim

(2014) demonstrated that CNNs, when combined with word embeddings, could effectively capture local semantic structures within sentences. RNNs, particularly Long Short-Term Memory (LSTM) networks, were adept at modeling long-range dependencies, making them suitable for tasks such as document classification, where understanding the context over extended spans of text is essential(Kim ,2014) .

While deep learning models significantly improved the accuracy and scalability of text classification systems, they also introduced new challenges. One of the major criticisms of deep learning approaches was their high computational cost. Training deep learning models requires vast amounts of computational power, which can be prohibitive, especially for smaller organizations or research projects. Additionally, deep learning models are often seen as “black boxes,” meaning that their decision-making processes are not easily interpretable. This lack of transparency can be problematic in applications where understanding the reasoning behind a classification is crucial, such as in legal or medical contexts(Devlin et al., 2019; Minaee et al., 2021).

The introduction of transformer models, such as BERT (Bidirectional Encoder Representations from Transformers), represented a paradigm shift in NLP. BERT and similar models leverage self-attention mechanisms to process text in a bidirectional context, meaning that they consider both the preceding and succeeding words in a sentence when determining the meaning of a word. This capability allows transformers to capture more nuanced linguistic features and improve the model’s performance on a wide range of NLP tasks (Devlin, 2019). Transformers are typically pretrained on large corpora of text and can be fine-tuned on specific tasks with relatively smaller amounts of labeled data, making them highly efficient in certain scenarios. However, these models remain computationally expensive, and their complexity adds to the challenges of interpretability(Devlin, 2019; Minaee, 2021).

Hybrid approaches have emerged as a way to balance the advantages of rule-based systems, machine learning, and deep learning. By combining rule-based preprocessing with machine learning classifiers, these approaches aim to improve both efficiency and accuracy. For example, rule-based systems can be used to perform initial filtering or preprocessing tasks, which can then be followed by machine learning or deep learning models that perform more complex categorization. Such hybrid systems have shown promise in applications like spam filtering, intent classification in chatbots, and content moderation. However, these systems are not without their own challenges, such as handling ambiguous words and addressing the issue of language resource limitations. For instance, polysemous words, such as "apple," can introduce ambiguity into the classification process, requiring more sophisticated methods to resolve(Rennie, 2003).

The integration of text classification in the context of English as a Foreign Language (EFL) instruction has proven to be highly beneficial for enhancing students' literary analysis and cultural awareness. Well-designed text classification tools can provide targeted feedback and facilitate engagement with textual material, enabling students to deepen their understanding of literary works and cultural contexts. By automating tasks such as grammar checking and thematic analysis, text classification systems help scaffold the process of literary analysis, allowing students to focus on the content rather than the mechanics of language. As these tools continue to evolve, future versions must prioritize interpretability, especially for low-resource languages, and offer culturally adaptive systems that can maximize educational equity and effectiveness(Vaswani et al., 2017; Devlin et al., 2019).

As text classification techniques continue to advance, it is expected that future developments will focus on low-shot learning techniques and the optimization of model architectures. These advancements aim to make text classification more accessible and efficient, reducing the computational burden while improving performance on tasks involving small or imbalanced datasets. The evolving landscape of text classification holds great potential for transforming a wide range of applications, from educational tools to content moderation and beyond(Yang et al., 2019).

Literary Analysis

Literary analysis is one of the most important skills that are taught in schools where the language of instructions is English. It is the process through which the students learn to interpret, judge and explore the reading more deeply. It includes numerous cognitive and metacognitive strategies that assist learners in getting in touch with literature for the purpose of not only understanding but also interpretation, critique, and appreciation. In the EFL realm, literary analysis is the ground where one can promote cultural awareness, analytical thinking, and language proficiency(Lazar, 2005).

By analyzing themes, characters, setting, tone, and style, students are motivated to make personal responses and generate their own interpretations of texts. This process of literary analysis in language learning is consistent with Bloom's Taxonomy, and it moves from the simple skills of understanding and remembering to the more sophisticated ones of abstracting and creating .The use of structured frameworks for analysis such as the use of narrative structure or literary devices becomes a great tool for learners as they gained critical insights into how language makes meaning(Anderson & Krathwohl, 2001).

EFL students, in particular, acquire the capacity to engage authentic language and the complex linguistic constructs of literary texts (McRae, 1991). This is what the students, especially the EFL ones, do, the capacity to benefit from accessing scholarly research and to analyze academic language.

The process of language learning through scientific argument is in tandem with Bloom's taxonomy, the learners must craft new ways of scientific thinking starting from the lowest rank of remembering, understanding until they are able to overtake the upper three ranks of applying, analyzing, and evaluating.

The inclusion of literary analysis in the language learning process does not only establish the context of Bloom's taxonomy but also provides a valuable resource for students to work on the upper levels of the hierarchy, e.g., application, analysis, and creation . When the students are given guided support for the analysis of structural elements, such as the use of literary devices or narrative structure, they are able to gain essential insights into the process of how language expresses meaning(Anderson & Krathwohl, 2001).

This kind of exposure is especially important in the context of EFL students, who are in the most need of both authentic language and complex linguistic structures that the literary genre could offer (McRae, 1991).

2.1.2 An Overview and Concept of Literary Analysis

Literary analysis, as a field of study, has its roots deeply embedded in early philosophical inquiries into narrative, rhetoric, and the human experience. The beginnings of literary criticism can be traced back to ancient Greek thinkers, most notably Aristotle, whose work in Poetics (c. 335 BCE) laid the foundation for understanding narrative structure, character development, genre, and most famously, the concept of catharsis in tragedy. Aristotle's framework, along with contributions from other philosophers such as Longinus, became instrumental in shaping the early models of literary interpretation (Aristotle, 1996). These early works primarily focused on the formal aspects of storytelling, emphasizing structure and the emotional response elicited from the audience. Over time, these ancient frameworks influenced subsequent periods of literary analysis, guiding thinkers through the centuries as they sought to understand the complex relationship between narrative and human emotion.

During the Middle Ages, literary criticism was largely defined by religious exegesis, where texts were interpreted primarily through a spiritual or allegorical lens. An example of this can be found in Dante Alighieri's Divine Comedy, a work that was subject to theological interpretation, focusing on moral lessons and spiritual enlightenment rather than the secular or artistic qualities of the text (Dante, 1320?).

This approach to reading emphasized the moral and spiritual purposes of literature, framing texts as vehicles for teaching religious values.The Renaissance brought about a renewed interest in the classical works of ancient Greece and Rome, with scholars like Erasmus emphasizing the importance of authorial intent and the historical context of texts. This period marked a shift away from purely religious interpretations toward a more humanistic approach, where the intentions of the author and the social conditions in which a work was created were considered vital for understanding its deeper meanings (Erasmus, 1516?). The Renaissance period was pivotal in the development of literary analysis because it encouraged a more comprehensive engagement with texts that considered historical, philosophical, and cultural contexts.

By the 20th century, literary analysis had evolved to include more structured and formal methods, such as New Criticism, which emphasized the textual autonomy of a literary work. Leading figures like Cleanth Brooks and W.K. Wimsatt championed “close reading,” a method that focused solely on the text itself, disregarding biographical, historical, or authorial context. Their work, particularly Wimsatt and Beardsley’s seminal essay “The Intentional Fallacy” (1946), argued that the meaning of a text should be determined by its structure, language, and the patterns within the text, rather than the intentions or personal history of the author. This approach was revolutionary because it placed the text at the center of analysis, focusing on its intrinsic qualities and how they functioned within the literary tradition (Brooks, 1947).

Following New Criticism, the late 20th century saw the rise of poststructuralism and cultural studies, which introduced more diverse and interdisciplinary approaches to literary criticism. Feminist theory, as articulated by Gilbert and Gubar (1979), and postcolonial theory, as developed by Edward Said (1978), expanded the scope of literary analysis to include issues of gender, power dynamics, and marginalized voices. These perspectives broadened the focus of literary studies, encouraging scholars to examine how texts reflect or challenge societal structures, power relations, and cultural identities. Poststructuralism further emphasized that texts are not fixed entities but are open to multiple interpretations, influenced by the reader’s cultural context and historical moment.

Currently, literary analysis has evolved into a highly interdisciplinary affair that incorporates a variety of theoretical frameworks, such as psychoanalytic theory, ecocriticism, and digital humanities. This shift reflects the evolving paradigms of culture, intellectual thought, and technology, which have all influenced how literature is studied today. Literary studies are increasingly informed by approaches that examine literature not only as an aesthetic object but also as a cultural product shaped by and influencing the social, psychological, and environmental contexts in which it is produced(Devlin et al., 2019).

At its core, literary analysis involves the study and interpretation of literary texts to uncover their deeper meanings, themes, and stylistic features. Analysts examine aspects of structure, language, characterization, narrative style, and cultural context to better understand how a text communicates its message. In educational settings, literary analysis helps students engage with literature on a deeper level, promoting critical thinking and enhancing their understanding of both the text and the world around them. This approach is particularly crucial in English as a Foreign Language (EFL) education, where students are not only learning language skills but are also developing the tools to analyze and interpret culturally significant texts.

The role of literary analysis in EFL pedagogy is significant because it equips students with the skills needed for deep engagement with both literature and language. EFL students benefit from literary analysis because it requires them to engage actively with the text, fostering critical thinking and cultural sensitivity. As students analyze literary works, theydevelop an understanding of the cultural and historical contexts in which the works were written, allowing them to appreciate the text's themes, symbols, and cultural allusions more fully. Literary analysis thus not only enhances language proficiency but also deepens cultural awareness, which is essential for intercultural communication in a globalized world.

2.1.2.3 Literary Analysis in EFL Education

In the context of EFL education, literary analysis is more than just an academic exercise. It serves as a bridge between language learning and cultural exploration, allowing students to immerse themselves in the realia of the language they are studying. By analyzing texts, students gain insights into cultural practices, social issues, and historical events, which can improve their understanding of the language as well as the society that speaks it. Furthermore, literary analysis helps students develop a more critical perspective on the texts they encounter, encouraging them to question assumptions and explore alternative interpretations (Paran, 2012).

Moreover, literary analysis in EFL can play a crucial role in improving language proficiency. By focusing on the structure and style of literary works, students learn to identify patterns in language usage, such as syntax, vocabulary, and discourse strategies. This enhances their overall language skills, allowing them to use the language more effectively in both written and spoken forms. In essence, literary analysis provides students with the tools to not only understand literature more deeply but also to use the language more competently in a variety of contexts (Mourao & Ghosn-Davis, 2019).

3. Methodology

3.1 Experimental Design

Experimental design is one of the most popular quantitative research criteria for assessing cause-and-effect relationships between variables(Easterling, 2015:12).

Experiments are carried out with a high degree of control and manipulation over the test environment and variables, allowing any change in the outcome measure to be attributed to the procedure or independent variable variance (Easterling, 2015).

It is the procedure outline that helps the researcher to test hypotheses by drawing significant conclusions about the relationship between independent and dependent variables (Best and Khan, 2006).

In an experimental study, data from the experimental and control groups are obtained using pre-test and post-tests. The findings are then compared to determine the treatment's effect on the dependent variable. The experimental group receives the change, whereas the control group is taught using the conventional practice . The comparison of the two groups is typically done through pre-test vs. post-tests using statistical tests of significance like the t-test (Riazi, 2015).

The researcher has followed a quasi-experimental design“non- randomized control group pretest/ posttest design” for achieving the aims of the study and verify its hypotheses. The researcher therefore hasused two groups:one group represents a control group and the other group as an experimental one, as shown in table below:

table (1)

Group	Instrument	Treatment	Instruments
EG	Pretest	Text Classification ,Literary Analysis and Culture Awareness	Posttest and questionnaire
CG	Pretest	Conventional method of teaching (academic lecturing)	

3.2 Population and Sample of the Study

A population in a research study includes all the members of any well-defined group of people, objects, or events. Since large populations are often inaccessible and cannot be studied directly, researchers choose a representative sample from the identified population to study (Riazi, 2015).

In the other hand, the word sample refers to a group of individuals who are selected to be tested and analyzed in order for the findings to be summed up for the whole population (Hayes and Stratton, 2013).

The whole population of the present study includes 150 students from the Collage of Art /University of Tikrit. The total sample of the selected college is 72 second stage students at Tikrit university college of Arts in the academic year 2024/2025.

The students are arranged into two groups (A and B) and they have been randomly selected to be the experimental and control group whose total number is (72). Group (A) consists of 36 students and group (B) consists of 36 students as well. Sixmembers are excluded from each group (A) and (B). Those 12 students serve to be the members in the pilot study groups. Thus, 30students have been selected from section (A) as experimental group and 30 students from section (B) as a control group. The total number the involved sample is sixtystudents as shown in table (2).

Table (2)

The Population and Sample of The Study in Second-Year Students

Population	Sample Size
College of Arts	72
College of Education for Women	65
College of Education for Humanities	210
Total	347

3.2.1 The Sample of the Study

Based on Arikunte (2006) the sample is a group of the population which indeed embodies the main characteristics of the population.

Fraenkel and Wallen (2009) affirm that a sample is a population of participants who select from a population in a manner that they reflect the whole group.

For fulfilling the aims of the study,the sample of the current study is randomly chosen (60) students from second stage, Department of English Language at College of Arts / University of Tikrit at the academic year 2024/2025.

Students are divided into two classes (AandB). Class (B) consisting of (30) students are randomly picked to constitute experimental class, and class (A) consisting of (30) students is the control class. As evident in Table 3.

Table (3)

The Sample of The Study

Groups	Class	No. of Sample	Pilot

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EXG	**B**	**30**	**12**
CG	**A**	**30**	
Total	**72**		

3.3 Students' Scores in the Pre-Test

The pre-test has been conducted for equalization. Both of the experimental and control groups are submitted to the same pre-test. The mean pre-test scores for the experimental group is (30.666), while the mean pre-test scores for the control group is (27.133), with standard deviations of (20.071) and (17.172), respectively, for the two groups. At the degree of freedom (58) and the level of significance (0.05), the calculated t-value is determined to be (0.733), which is lower than the tabulated value (2.00). As indicated in the table, this result implies that there is no statistically significant difference between the two groups in the pre-test as shown in Table (4) below :

Table (4)

The T-Test Value of the Two Groups in the Pre-test

Group	No.	Mean	S.D.	T-Value		DF	Level of Significance
EG	30	30.666	20.071	Calculated	Tabulated	58	0.05
CG.	30	27.133	17.172	0.733	2.00		

3.4 Achievement Post-Test

The instrument involves creating a post-test to measure the experiment's degree of success. According to McNamara, each question on achievement exams only covers a subset of the curriculum. Assigning aspects that students' need to improve their performance in the future might be beneficial. Determining whether or not course

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objectives have to meet at the conclusion of the instructional time is the main function of an accomplishment exam (McNamara, 2000).

Davies asserts that the tool utilized to get the necessary data is one of the key factors in any educational research project's success. The accomplishment exam is a type of assessment that is used to evaluate the effectiveness of education as well as the pupils' ability to make progress toward meeting study objectives. An accomplishment test is a device designed to assess a pupil's progress over a certain amount of time (Davies, 2000).when creating an accomplishment test , the educational materials' behavioral goals and content take in to account . the following are the five question:

Q.1. Read the following sentences and choose the right answer, Five only 1- The following extract "Noli me tangere, for Caesar's I am,", belongs to.............

A- Sir Philip Sidney's "Leave me, O Love",

B- William Shakespeare's "Sonnet 18: Shall I compare thee to a summer's

day"?

C- Sir Thomas Wyatt's "Whoso List to Hunt"

D- Christopher Marlowe's "The Passionate Shepherd to His Love"

-2**This quote "Come live with me and be my love,", belongs to**.............

A- Sir Thomas Wyatt's "Whoso List to Hunt"

B- Christopher Marlowe's "The Passionate Shepherd to His Love"

C- Sir Philip Sidney's "Leave me, O Love",

D- William Shakespeare's "Sonnet 18: Shall I compare thee to a summer's

day"?

-3**This quote "And thou, my mind, aspire to higher things;,", belongs to**..........

A- Sir Philip Sidney's "Leave me, O Love",

B- EdmundSpenser "Sonnet 34: "Lyke as a ship that through the Ocean

wyde"

C- Sir Thomas Wyatt's "Whoso List to Hunt"

D- Christopher Marlowe's "The Passionate Shepherd to His Love"

-4**Sir Thomas Wyatt's "Whoso List to Hunt" is written as .... Poem**.

A- a war B- an elegy C- a lyric D- a pastoral

.... -5**is a sonnet that the poet wrote on the divine love in comparison to courtly love**

A- Sir Thomas Wyatt's "Whoso List to Hunt"

B- Christopher Marlowe's "The Passionate Shepherd to His Love"

C- William Shakespeare's "Sonnet 18: Shall I compare thee to a summer's

day"?

D- Sir Philip Sidney"s" Leave me, O Love",

Q.2/ Identify and Comment on the following

Who list her hunt, I put him out of doubt, As well as I may spend his time in vain. And graven with diamonds in letters plain

There is written, her fair neck round about:

Noli me tangere, for Caesar's I am,

And wild for to hold, though I seem tame.

Q.3\Do you think that the poet in Soote Season is optimistic or pessimistic

Q4/Analyze the following extract.

A- Sir Thomas Wyatt's "Whoso List to Hunt

B- William Shakespeare's "Sonnet 18: Shall I compare thee to a summer's day"?

C- Sir Philip Sidney's "Leave me, O Love",

D- Christopher Marlowe's "The Passionate Shepherd to His Love"

Q5/what is the saying for each one?

A- Sir Philip Sidney

B- William Shakespeare

C- Christopher Marlowe

3.5 Application of the Experiment

The researcher has followed different procedures in teaching RTI strategy:

1- Begin the lesson by warmly greeting the pupils, accompanied by a smile and direct eye contact with each individual.
2- Briefly ask an engaging question: "Who read something interesting this week?"
3- Encourage a few responses to establish a positive and interactive tone.
4- Introduce the (RTI) strategy with a simple explanation: "RTI is a way to ensure everyone understands what we are learning. It has three levels: support for everyone, extra help for those who need it, and special support for specific students."
5- Write the three RTI tiers on the board: Tier 1: Whole class teaching. Tier 2: Small group support for students needing extra help. Tier3: Individualized help for those who need it the most.
6- Emphasize that the strategy is there to support all pupils.

4.1 Results

Comparison between the Mean Scores of the Experimental Group and that of Control Group in The* Literary Analysis at The*Posttest

To analyze the datarelated tothe first hypothesis specifically: *There is no statistically significant difference between the experimental group students' performance who have been taught by using text classification and control group who have been taught by using the conventional method in literary analyses in the post test*, the independent sample test has been used. Therefore, the first aim of the study namely: *Finding out the effect of using Text Classification on EFL university students' performance in Literary Analysis in the post- test*, will be achieved.

According to the following results in table 18, the mean scores of the experimental group is 65.14 and standard deviation is 14.433. While the mean scores of the control group is54.86 and the standard deviationis 19.230.The calculated t-value 2.342is higher than thetabulated t-value 2.00 with a degree of freedom 58 at a level of significance (0.05).

Observing the values of T-calculated above, it is found that the calculated T-value 2.342 is higher than the tabulated T-value of the field 2.00, and from this it can be concluded that *there is statistically differences between the mean scores of the experimental group which is taught by using text classification and that of the control group which is taught according to the conventional method in the posttest*, for the benefit of experimental group. So, the first hypothesis is rejected.

Table (5)

Means, Standard Deviation, and t-Values of the Two Groups in Literary Analyses at the Achievement Posttest

Group	**N.**	**Mean**	**S.D.**	**T-Value**		**DF**	**Level of Sig.**
				Calculated	Tabulated		
Experimental	30	65.14	14.433	2.342	2.00	58	0.05
Control	30	54.86	19.230				

4.2 Discussion of Obtained Results

The findings from the analysis of the first hypothesis indicate a significant difference in the literary analysis performance between the experimental and control groups. The experimental group, which is taught by using text classification, achieved a mean score of 65.14. In contrast, the control group, which received conventional instruction, had a mean score of 54.86, as show in figure 1. The independent sample t-test revealed a calculated t-value of 2.342, which surpasses the tabulated t-value of 2.00. This statistical evidence supports the rejection of the null hypothesis, confirming that the teaching method significantly influenced the students' performance in literary analysis. The results suggest that text classification as a teaching method enhances students' understanding and analysis of literary texts more effectively than traditional approaches. This could be attributed to several factors:

1. Structured Learning: Text classification likely provides a structured framework that helps students categorize and analyze literary elements systematically.

2. Active Engagement: The method may foster greater engagement and interaction with the material, leading to deeper comprehension and retention.

3. Critical Thinking: Students might develop stronger critical thinking skills as they learn to classify and interpret literature, which is essential for literary analysis

Conclusions

According to the findings of the study, the following conclusions have been drawn:

1. Text classification enhances students’ ability to identify, categorize, and respond to different literary genres and styles, thereby improving their literary analysis performance.
2. The integration of text classification models provides EFL students with structured ways to explore narrative structures, themes, and authorial styles.
3. Students trained with text classification strategies showed stronger abilities in distinguishing between cultural references, symbols, and ideologies embedded in literary texts.
4. Text classification helps learners improve their understanding of implicit meanings and contextual inferences, which are crucial in both literary appreciation and cultural understanding.

5. The classification process encouraged critical reading by requiring students to evaluate textual elements in light of genre, tone, purpose, and audience.
6. Literary texts classified under thematic categories enabled students to make intertextual connections and synthesize literary knowledge across different works.
7. Text classification fostered students' metacognitive strategies by training them to reflect on reading purpose, structure, and meaning-making processes.
8. The implementation of text classification as an instructional approach elevated students' analytical confidence and overall motivation to engage with complex texts.
9. Through guided classification, students acquired tools to deconstruct literary texts in a methodical and meaningful way, enhancing their interpretative skills.
10. Text classification empowered students to recognize and label stylistic devices, tones, and rhetorical structures within literary discourse.
11. Despite overall improvement, students found it more challenging to produce original analysis or critique without structured guidance, suggesting the need for more creative expression training.
12. The study confirmed that exposure to varied classified texts results in a more well-rounded and culturally sensitive literary mindset.
13. Text classification provides a foundation for bridging the gap between reading comprehension and critical interpretation, especially in EFL contexts.

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