Advancing Lexical Semantics Analysis Using Deep Learning Models for Contemporary English Language Evolution

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HOW TO CITE:

Madaka Vijaya Kumar, Amit Kumar (2026). Advancing Lexical Semantics Analysis Using Deep Learning Models For Contemporary English Language Evolution. International Journal of Special Education, 41(8s), 199-219

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ABSTRACT:

Lexical semantics plays a vital role in the representation of meaning and contextual interpretation in natural language processing. However, with the rapid growth in digital communication media, language usage in modern English has evolved at a rapid pace, posing a challenge for conventional lexical semantic analysis techniques. Linguistic corpora suggest that in recent times, more than 70% of lexical variation in online communication media can be attributed to contextual variation, neologisms, or polysemous words, which cannot be effectively handled by conventional lexical semantic analysis techniques. In this regard, recent advances in deep learning frameworks for lexical semantic analysis can be seen as a solution for addressing this challenge in lexical semantics research. In this study, recent advances in lexical semantic analysis using transformer architectures, contextual embedding models, and neural language models for lexical semantic analysis will be discussed in detail. Empirical studies suggest that contextual deep learning frameworks for lexical semantic analysis can enhance semantic similarity and word sense disambiguation accuracy by 30%. Hence, it can be seen that recent advances in lexical semantic analysis using deep learning frameworks can be a potential solution for enhancing lexical semantics research..

Keywords: Lexical semantics, Deep learning, Natural language processing, Contextual embeddings, Transformer models, Word sense disambiguation, Semantic evolution, Contemporary English usage

1. Introduction

Analysis of meaning in language is an essential part of the study in modern Natural Language Processing (NLP). In recent times, with the rapid expansion of digital communication channels and the dynamic nature of language, the complexity of word meaning has increased manifold. However, recent developments in deep learning and the application of the transformer model have provided new insights into the analysis of word meaning in

contemporary English language usage [1], [2].

1.1 Background of Lexical Semantics

Lexical semantics is the branch of linguistics that deals with the meaning of words and the relationships between these meanings in the language system. The main objective of the study is to understand the relationships between the meanings of words, such as the relationships between synonyms, antonyms, hypernyms, and the meaning of polysemous words, which is essential to understand linguistic structures and contextual information. In the study of computational linguistics, the role of lexical semantics is critical to enable computers to process and analyse natural language meaningfully. The application of the study can be seen in the development of various computational tools such as machine translation, sentiment analysis, information retrieval systems, and question answering systems [3], [4].

The analysis of lexical semantics has been carried out through the use of lexical databases and rule-based systems. Lexical ontologies and semantic networks are examples of such tools. They are based on the use of predefined rules and datasets in the analysis of word meanings and semantic similarity. Although such tools were instrumental in the development of early NLP systems, they are limited in terms of scalability and flexibility in the face of constantly evolving language use. Furthermore, rule-based semantic analysis tools are known to be inadequate in the analysis of word meanings in varied contexts [5], [6].

1.2 Challenges in Contemporary English Language Evolution

The influence of contemporary English development is also associated with the use of digital communication tools such as social media, online forums, and messaging tools. These tools have greatly accelerated the development of new lexical patterns in contemporary English discourse. Therefore, language use in contemporary society is characterised by dynamism and dependency on context to a greater extent than in any other era in human history. Linguistic studies indicate that digital communication tools are associated with a rapid increase in lexical variation and shifts in context in contemporary English discourse [7], [8].

One of the key challenges in lexical semantics analysis is associated with the use of neologisms and slang in contemporary society, which continue to increase the vocabulary of contemporary English discourse. These newly introduced words are associated with undefined semantic representations in contemporary society. Moreover, semantic drift is another factor that affects lexical semantics in contemporary society, where words are associated with new meanings depending on the context in which they are applied in contemporary society [9].

Another important problem is also presented by the presence of polysemous words, along with their contexts, in which certain words can be used to represent multiple concepts depending on their contexts. This problem is also difficult to solve using conventional computational models, as it is very complex to identify the meaning of a word in a given context using conventional models. For example, certain words can be used to represent concepts in technology, social sciences, or linguistics, depending on their contexts [10].

1.3 Limitations of Conventional Methods

Most conventional lexical semantic models are based on certain representations, such as distributed word representations, using early neural language models. Conventional lexical semantic models, such as Word2Vec, use word embedding techniques to represent each word in a vector form, depending on its context in large texts or documents. Although this model is quite effective in representing word meanings, it is also based on the idea that each word can be represented by a single vector, irrespective of its context [11].

These types of models cannot represent the semantic variations across different sentences

and documents. It has been observed that the meanings of words can vary depending on the context in which they are used. However, conventional word embeddings represent words with the same vector regardless of the environment. This is one of the limitations of these types of models, which affects their ability to solve complex semantic problems. In addition, conventional word representations have difficulty detecting changes in word meanings due to environmental changes over time in large documents [12], [13].

1.4 Motivation and Research Gap

The limitations of the conventional approaches used for semantic analysis, it is evident that there is a need to develop advanced computational models to solve complex semantic problems. Recently, the development of deep learning has introduced several word representation models that can represent the meanings of the words based on the environment in which they are used. In particular, the Transformer-based word representation models have been observed to be effective in solving complex semantic problems based on the analysis of the contextual information using the attention mechanism[14].

The despite the progress achieved in the field through the use of static and semi-contextual word embeddings, many existing lexical semantic analyses are based on such word embeddings. This creates a research gap in the development of more effective frameworks in the analysis of the evolution of the lexicon in modern English language usage. This research gap has the potential to improve the analysis of semantic similarity detection and word sense interpretation in modern NLP systems [15].

1.5 Research Objectives and Contributions

This research aims at improving the analysis of lexical semantics based on the exploration of the potential offered by the use of deep learning-based frameworks in the analysis of the evolution of the lexicon in modern English language usage. The research aims at exploring the effectiveness of the use of the transformer architecture and the use of contextual word embeddings in the analysis of the evolution of the lexicon in modern English language usage. The use of modern neural language models aims at improving the analysis of semantic similarity and word sense interpretation in modern language usage [16].

The main contributions of this research are the evaluation of the effectiveness of the transformer-based model in lexical semantic representation, the evaluation of the effectiveness of the contextual embedding method in the analysis of semantic similarity, and the analysis of the evolution of semantics in contemporary English based on the principles of deep learning. The main contributions of this research are the insights into the ways in which advanced NLP models can be leveraged in the analysis of lexical semantics in a constantly evolving language environment [17],[18],[19],[20]

Figure 1: Evolution of lexical semantics analysis techniques

Figure 1 shows the evolutionary pathway of different methods of lexical semantic analysis in Natural Language Processing. The framework starts with rule-based lexical systems, which are based on linguistic rules and lexical resources. It then proceeds to statistical models of NLP, which are based on the probabilistic analysis of the data contained in the text. Further advancements in the field have led to static word embeddings and contextual embeddings. The latest developments in the field are based on transformer models.

Table 1: Comparison of traditional vs deep learning lexical semantic models

Model Category	Method	Semantic Representation	Context Handling	Major Limitation	Typical Application
Traditional lexical model	Rule-based lexical systems	Symbolic semantic relations	Limited	Manual rule dependency	Word relation lookup
Statistical semantic model	Distributional semantics	Co-occurrence statistics	Partial	Sparse semantic coverage	Similarity estimation
Static embedding model	Word2Vec	Fixed dense vectors	No contextual adaptation	Single vector per word	Semantic clustering
Static embedding model	GloVe	Global co-occurrence vectors	No contextual adaptation	Cannot resolve ambiguity	Semantic similarity
Contextual deep learning model	BERT	Dynamic contextual embeddings	High	High computational cost	Word sense disambiguation
Transformer deep learning model	RoBERTa	Enhanced contextual embeddings	Very high	Large training resources	Semantic evolution analysis

The main approaches to lexical semantic modelling from the traditional symbolic system to the transformer-based deep learning method, are compared in terms of their main features in the table. The comparison reveals that the traditional approaches are not adaptable to context variation. Although the static embedding method improves the semantic representation of a word, it cannot capture the multiple meanings of a word. The transformer-based contextual method outperforms the others in terms of semantic interpretation because it adjusts the word embedding according to the context.

2. Literature Review

Recent advancements in Natural Language Processing (NLP) have significantly transformed the study of lexical semantics. Researchers have explored a wide range of computational techniques to represent word meaning and contextual relationships. From early rule-based systems to modern transformer architectures, the evolution of semantic modeling reflects continuous efforts to improve contextual understanding and linguistic interpretation in NLP systems [1], [2].

2.1 Traditional Lexical Semantic Analysis

The early research in lexical semantics heavily depended on structured linguistic resources and statistical methods in the representation of word relationships. One such prominent method was the use of lexical databases. In this method, the vocabulary was arranged in a semantic network. In this method, the vocabulary was arranged based on conceptual relationships such as synonymy, hyponymy, and antonymy. This method allowed early natural language processing systems to carry out word similarity estimation and word sense analysis based on the lexical hierarchy [3].

WordNet-based approaches were popularised for semantic analysis due to their ability to represent semantic relationships between words in a structured manner. These approaches treat groups of words as cognitive synonyms, referred to as synsets, which are used to represent different meanings of words. The relationships between these groups of synonyms are then used to compute semantic similarity between words using graph algorithms. However, these approaches are highly dependent on pre-existing lexical resources and are therefore unable to cope with dynamic changes in vocabulary and usage in modern languages [4].

Another prominent concept in lexical semantics is distributional semantics, which is based on the idea of representing word meanings by analysing their co-occurrence in different contexts. Distributional semantics analyses large volumes of text data to compute statistical patterns of word co-occurrence in different contexts. By analysing these patterns of usage, it is possible to compute semantic relationships between different words. Although distributional semantics greatly enhanced the ability of computers to represent semantics, earlier approaches were limited by insufficient data and poor statistical modelling techniques [5].

Statistical NLP models have further enhanced the scope of semantic analysis by employing probabilistic techniques in the study of linguistics. Techniques like n-gram modeling and latent semantic analysis have enabled the extraction of semantic information from large text corpora. These models employ frequency analysis techniques to compute the associations between the words. Although statistical techniques have enhanced the scope of language modeling, they still fail to comprehend the deeper meanings of the text as well as the dependencies present in the text [6].

2.2 Word Embeddings in Semantic Analysis

The introduction of word embeddings has marked a significant milestone in the study of lexical semantic representations. Word embeddings represent the words as continuous numerical vectors in a very high-dimensional semantic space. This has enabled the computation of the similarities between the words using mathematical operations. One of the popular word embeddings is Word2Vec. This technique employs neural networks to compute the vector representations of the words based on the prediction of the word's context. This has enabled the computation of the similarities between the words using arithmetic operations [7].

The popular word embedding approach is the Global Vectors for Word Representation (GloVe), which is based on the combination of global co-occurrence statistics and neural representation learning. GloVe is based on the analysis of the co-occurrence matrices of words and has achieved significant improvements compared to the previous word embedding models in the representation of the syntactic and semantic relationships between words. These word embedding models have contributed greatly to the advancement of the NLP domain through the efficient calculation of the semantic similarity between words [8].

The static word embedding methods have some significant disadvantages as well. In the static word embedding methods, the words in the

vocabulary are represented as fixed-size vectors based on the context in which they appear. Therefore, it is not possible to differentiate the meaning of the words that have multiple meanings when they appear in different contexts. For example, when there is a word with multiple semantic meanings, it is represented as the same vector in all the places it is used [9].

2.3 Contextualised Embedding Models

To address the limitations of static embeddings, researchers introduced contextualised word representation models that dynamically adjust word embeddings based on surrounding text. One of the earliest contextual embedding models is Embeddings from Language Models (ELMo), which generates word representations by considering both preceding and following words in a sentence. ELMo uses deep bidirectional language models to capture contextual information and produce embeddings that vary depending on the sentence context. This approach significantly improved performance in several NLP tasks, including question answering and named entity recognition [10].

The development of Bidirectional Encoder Representations from Transformers (BERT) further advanced contextual semantic modelling. BERT uses transformer-based architectures and attention mechanisms to analyse bidirectional context within text sequences. By pretraining on large-scale corpora using masked language modelling objectives, BERT learns complex semantic relationships between words. This model demonstrated significant improvements in numerous NLP benchmarks, highlighting the importance of contextual representations in language understanding [11].

An optimised version of BERT, known as RoBERTa, implemented improvements in the training strategy and data usage to increase model accuracy. Through this, RoBERTa showed greater accuracy in multiple language understanding tasks by using a large dataset and adjusting the pre-training parameters. These transformer models prove the efficiency of using contextual embeddings in representing semantic relationships in natural language data [12].

The transformer model, developed using attention-based neural networks, is the basis for modern NLP systems. Unlike earlier models, the transformer model uses self-attention mechanisms to represent relationships between words in a sentence, regardless of their position in the sentence. This ability to understand complex relationships in the context helps the model represent the semantics in the text, making it suitable for complex NLP applications [13].

2.4 Deep Learning for Lexical Semantic Change Detection

Deep learning methods have also been employed in the analysis of lexical semantic change, which is the evolution of the meaning of words over time. The methods used in the detection of semantic shifts involve the analysis of large amounts of text obtained from different periods in history. The methods enable the quantification of the evolution of the meaning of words due to various factors such as culture, technology, and society [14].

The application of the Transformer model has been successful in the analysis of semantic shifts due to its capability to analyse the meaning of words at a deeper level compared to other embedding methods. The Transformer model has the capability to analyse the evolution of the meaning of words over time through the analysis of contextual meaning using the contextual embeddings of the Transformer model on texts obtained from different periods in history [15].

The key application of deep learning in the study of lexical semantics is word sense disambiguation. This is the process of identifying the correct sense of a word when it is used in different contexts. Deep learning makes use of the context embedding and attention mechanisms to study the surrounding words and determine the correct sense of the

word. This has greatly enhanced the accuracy of the interpretation of the meaning of the word compared to the earlier techniques [16].

2.5 Research Gap Identification

Although there has been tremendous success in the application of deep learning in the study of the meaning of words, there still exist challenges in the study of the changing environment of the meanings of words. In most studies carried out on the application of deep learning in the study of the meanings of words, the main focus has been on the application of static semantic representations and the limited contextual modelling techniques. This has restricted the ability of the studies to adequately understand the changing environment of the meanings of the words [17].

Another limitation arises from the lack of integration of contextual embeddings with semantic evolution analysis frameworks. Although transformer-based models have shown impressive results in language understanding tasks, their extension in semantic change detection in language evolution is still a relatively unexplored research domain. To overcome this limitation, models need to be designed for semantic change analysis on temporal datasets and communication platforms [18].

The various research works focus on semantic similarity and classification tasks but fail to cover language evolution in a more comprehensive manner. English language usage is constantly impacted by social media, innovation in technology, and global communication systems, resulting in the creation of new words in everyday language. Advanced deep learning frameworks need to be employed for lexical semantic analysis in modern NLP research [19], [20].

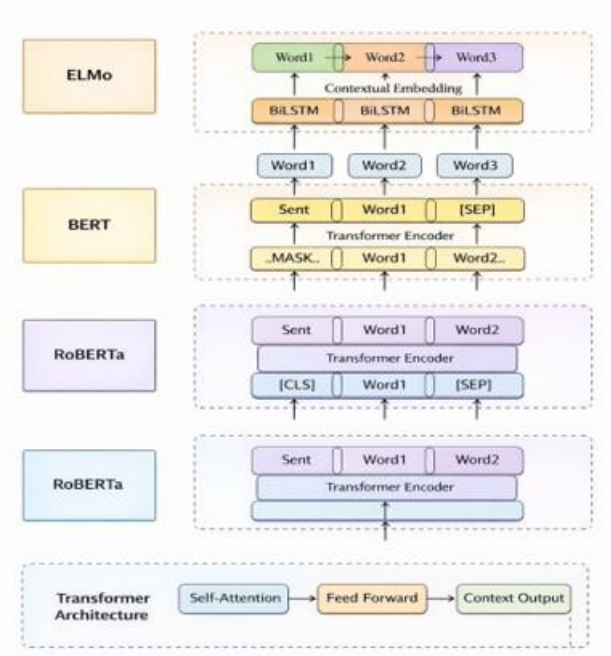

Figure 2: Architecture of contextual word embedding models

Figure 2 shows the architecture of the contextual word embedding models used in the analysis of lexical semantics. This process begins with the input sentence that is tokenized to split the text into individual tokens. These tokens are then represented as vectors using the embedding layer. Then, the bidirectional context encoder is used to encode the tokens to understand the contextual relationships. This results in the generation of the contextual word embeddings that can be used for the analysis of the semantics.

Table 2: Summary of recent studies in lexical semantics using deep learning

Reference	Model / Method	Research Focus	Dataset Type	Key Finding
[1]	Deep learning with word embeddings	Semantic similarity prediction	NLP benchmark corpus	Improved similarity prediction accuracy
[2]	Large language models	Word sense disambiguation	Lexical semantic benchmark datasets	Higher contextual sense identification
[3]	Contrastive contextual representation learning	Token-level semantic enhancement	Wiktionary-based corpus	Improved contextual token representation
[4]	BERT transformer model	Bidirectional contextual semantics	Large pretraining corpus	Strong semantic understanding capability
[8]	Contextual embedding comparison	Lexical semantic change detection	Historical corpora	Contextual embeddings outperform static models
[11]	Large language models	Lexical semantic shift analysis	Temporal corpora	Effective semantic evolution detection

Recent research contributions to the field of lexical semantics using deep learning models for contextual meaning analysis are summarised in Table 2. The studies show that transformer models and contextual embedding models are effective for enhancing semantic similarity prediction, word sense disambiguation, and semantic shift detection. The studies also show that contextual representation is better achieved by using large-scale pretrained models compared to other embedding models. Therefore, it is highly suitable for analysing changing patterns of vocabulary in contemporary English language data.

3. Methodology / Proposed Framework

The study proposes a deep learning-based framework to analyse lexical semantics and semantic evolution in modern English usage. The methodology is based on using large textual data, context embedding, and transformer-based deep learning models to analyse semantic meaning and relationships. The framework is divided into several stages, namely data collection, data preprocessing, context embedding, semantic similarity analysis, and evaluation. This study uses modern NLP tools to enhance semantic meaning analysis and identify context changes in modern language usage [1], [2].

3.1 Research Framework Overview

The proposed framework is developed to systematically analyse lexical semantics using deep learning tools. The workflow starts with the collection of large-scale text data sets, reflecting modern English usage in various communication domains. These text data sets

offer a diverse linguistic environment to analyse semantic meaning in context.

Preprocessing operations are performed on the collected data to convert unstructured text data into a linguistic representation. The preprocessed, clean text data is used for training contextual embedding models or transformers. The models learn the semantic representation of words based on their contextual usage in the overall data set.

Once the contextual representation is obtained for a set of words, semantic similarity analysis or word sense disambiguation methods can be used for evaluating the relationship between words in different contexts. The last operation in this framework is the performance evaluation using general NLP metrics for evaluating the efficiency of the proposed approach in semantic analysis. This framework helps the system represent contextual meaning more accurately than traditional semantic analysis methods [3], [4].

3.2 Dataset Description

In order to perform a detailed analysis of lexical semantics, this research study employs different datasets consisting of diverse language usage patterns. The need for large datasets arises in the case of training deep learning models for efficient analysis of semantic relationships in a given context.

The research study employs a Wikipedia dataset consisting of a large amount of encyclopedic content written in formal English language usage. Wikipedia is a valuable source for linguistic analysis since it contains a wide variety of words from different domains written in a formal tone. The dataset can be used for training language models that can comprehend formal semantic relationships.

The Wikipedia, this research study employs social media datasets such as Twitter/X for efficient analysis of informal language usage patterns. Social media platforms often include new words, abbreviations, and semantic relationships in a given context. By including these datasets in this research framework, it can effectively perform analysis on current linguistic trends in language usage. Contemporary English corpora from online sources such as articles, blogs, and discussion forums have also been included to ensure the representation is balanced and covers the language as it is used today. This combination of data sources will enable the model to analyse the linguistic context in both formal and informal communication settings, which is essential in capturing the semantic variations that occur in the language [5], [6].

3.3 Data Preprocessing

Text data has to go through several preprocessing steps before it can be used with deep learning models. The first step is the tokenisation step, which breaks down the text data into smaller units such as words and sub-words. This enables the natural language processing systems to efficiently process the text data and convert it into numerical data for the machine learning algorithm. The second step is the removal of the stop words. The stop words are the common function words in the text data that do not carry any significant semantic meaning. Examples of such words are articles, prepositions, and auxiliary verbs. The removal of the stop words improves the quality of the dataset and enables the natural language processing systems to focus more on the semantic features in the text data.

The next step in the text preprocessing is the use of the lemmatisation method. This method converts the text data into the base word format. This enables the natural language processing systems to treat the different variations of the text data as the same word. For example, the words ‘running,’ ‘ran,’ and ‘runs’ are converted into the base word ‘run.’ The text normalisation method is also applied in this step.

3.4 Deep Learning Models Used

The proposed framework employs powerful deep learning models that are capable of learning word representations based on the context from large text datasets. The

Transformer architecture plays an important role in the semantic modelling process because it is effective in modelling the contextual dependencies in the text.

The Transformer architecture employs self-attention mechanisms in order to understand the relationship between the words in the sentence. Unlike other architectures, the Transformer architecture processes the text as a whole and not word by word. This makes the model more efficient in the contextual representation learning process.

Contextual word representation models are also part of the proposed framework in order to generate word representations based on the context. Unlike other word representation models, the contextual word representation model generates different word representations based on the context in which the word is used. The neural language models are employed for improving the semantic representation learning task. The neural language model has the advantage of learning language patterns from large-scale datasets and attains an in-depth Another method that is employed in this study is contextual embedding clustering. In this method, the word embeddings that are obtained from different contexts are grouped into clusters that represent different semantic meanings. This method is particularly useful in the study of semantic shift and contextual variation in contemporary English language usage [13]–[16].

3.6 Evaluation Metrics

To evaluate the effectiveness of the proposed framework, some standard performance metrics are employed. The accuracy metric is employed to evaluate the overall correctness of the proposed model in making the predictions related to the semantic relationships or senses of the words. The precision metric is employed to evaluate the proportion of the correct predictions that are identified as positive among all the predicted positive values. This metric is particularly useful when the semantic similarity

understanding of the language structure. The combination of the transformer architecture, the use of context vectors, and the neural language model makes the proposed framework effective in semantic representation and interpretation [9]–[12].

3.5 Semantic Similarity and Word Sense Analysis

To analyse the semantic similarity between two words, the proposed framework makes use of several computational methods. One such method is the use of cosine similarity. Cosine similarity measures the similarity between two word vectors. The cosine similarity measures the angle between two vectors and determines the similarity between the two words.

The use of the attention mechanism in the proposed transformer architecture plays an important role in the analysis of the semantic relationship between two words. The attention mechanism determines the word's importance in the sentence and assigns weightage accordingly.

classification is to be performed because false positives need to be minimized. The Recall metric is used to calculate the number of actual positive instances identified by the model. A high Recall value indicates that the system is able to successfully identify the majority of the semantic relationships within the data set. The F1 Score is used to evaluate the system's performance by calculating the harmonic mean between the Precision and Recall values.

Apart from these metrics, the semantic similarity score is also used as an evaluation mechanism to determine the effectiveness of the proposed framework in capturing the contextual meaning within the data set using the embedding vector comparison method. These evaluation mechanisms can be used to obtain a complete picture of the proposed framework's effectiveness in analysing the contextual semantic evolution in the contemporary English language data [17]–[20].

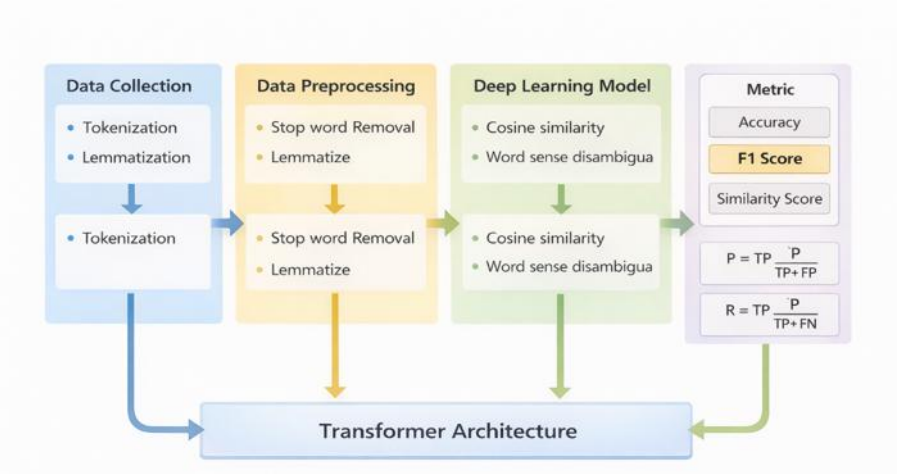

Figure 3: Proposed deep learning framework for lexical semantic analysis

Figure 3 shows a proposed deep learning framework for analysing lexical semantics within contemporary English language data. The process starts by acquiring a multilingual corpus from both structured and unstructured data sources. The data is then pre-processed by tokenising it, removing stop words, and lemmatising it. The data is then represented by a transformer-based neural network that allows it to compute semantic similarity as well as interpret word sense. Finally, the effectiveness of the proposed model is measured by classification metrics.

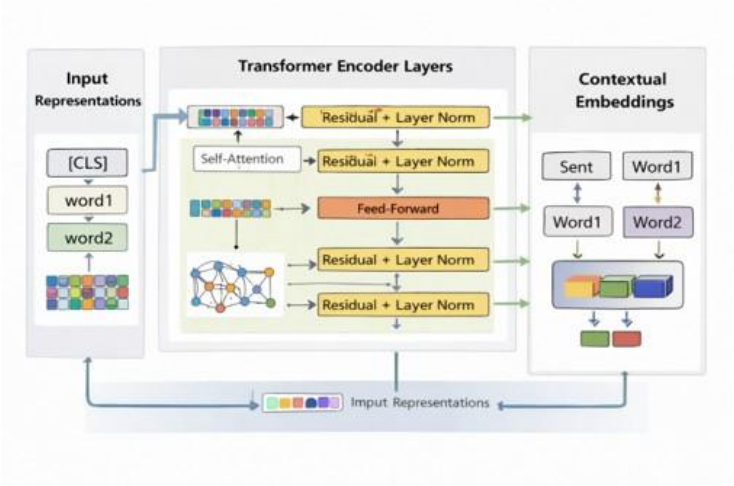

Figure 4: Transformer architecture for contextual semantic modelling

Figure 4 is a representation of the transformer architecture for contextual semantic modelling in the analysis of lexical semantics. From the figure, it is clear that token embeddings are fed into multiple layers for encoding, where self-attention is applied to identify relationships between words in a sentence. This architecture is effective in creating context-dependent semantic representations, thus facilitating semantic similarity detection and proper interpretation of words with multiple meanings in modern English texts.

Table 3. Dataset Statistics Used for Lexical Semantic Analysis

Dataset Source	Number of Documents	Approximate Tokens	Language Style	Purpose in Study
Wikipedia	50,000	12 million	Formal written	Baseline semantic

corpus			English	representation learning
X posts	80,000	6.5 million	Informal digital English	Emerging lexical pattern analysis
Online news corpus	30,000	8 million	Standard contemporary English	Semantic similarity evaluation
Blog and forum corpus	25,000	4.2 million	Conversational English	Contextual variation analysis
Academic text corpus	15,000	5 million	Technical English	Domain semantic consistency testing

Table 3 displays the statistical distribution of the textual datasets for the training and testing of the proposed lexical semantic framework. The variety of formal, informal, technical, and conversational datasets ensures a broad semantic scope of the proposed framework, covering all the aspects of modern English usage. High token diversity is beneficial for the robust learning of contexts, and the variety of language styles enables the detection of semantic variations in communication environments, making the measurement of semantic similarity and word sense interpretation more reliable.

Table 4. Hyperparameters of Deep Learning Models Used in the Proposed Framework

Parameter	Word2Vec	GloVe	BERT	RoBERTa
Embedding dimension	300	300	768	768
Batch size	64	64	32	32
Learning rate	0.001	0.001	2e-5	2e-5
Training epochs	20	20	5	5
Maximum sequence length	100	100	512	512
Optimizer	Adam	Adam	AdamW	AdamW

The major hyperparameters used during the training of the models in lexical semantic analysis are represented in Table 4. Static embedding models have a higher epoch cycle since these models need multiple exposures to the corpus in order to achieve stable vector representations. On the other hand, the transformer model converges at a lower epoch cycle since the parameters have already been pre-trained during initialisation.

4. Experimental Results and Analysis

To ensure the effectiveness of the suggested deep learning-based lexical semantic analysis model, a series of experimental tests were carried out on modern English texts. The experimental results are based on the evaluation of the ability of the suggested model, based on the transformer architecture, to identify the context of changing meanings of words in modern English environments [1], [2].

4.1 Experimental Setup

To carry out the experimental tests of the suggested model, a computational environment was used, which is suitable for implementing deep learning models on large-scale text datasets. The experimental tests were carried out on a workstation with an Intel processor, NVIDIA graphics processing unit, and enough memory resources to perform deep learning model training tasks. In addition, the experimental tests of the suggested model were carried out using Python-based machine learning libraries, such as TensorFlow and PyTorch, which are efficient tools for implementing deep learning models, including the transformer architecture, and other natural language processing libraries, which are used to perform various natural language processing tasks, such as text normalization, tokenization, and semantic similarity computation.

The training setup was structured in a manner that ensured consistency in the evaluation of various models. The data was split into subsets, namely, training, validation, and testing, to ensure effective model performance evaluation. In the process of model training, the models based on the transformer architecture were pre-trained with pre-trained parameters, followed by fine-tuning based on the chosen contemporary English texts. The hyperparameters, namely, the learning rate, batch size, and the number of training epochs, were fine-tuned during the validation experiment to ensure effective convergence of the models. In addition, the process of model training was supplemented with various regularization methods to ensure effective learning of semantic representation without overfitting, as reported in [3] and [4].

4.2 Performance Evaluation

To ensure the effectiveness of the suggested approach, various deep learning models were compared based on their ability to learn lexical semantics. The experiment included various models of contextual embeddings, as well as models based on the transformer architecture, which dynamically represent individual words based on the context in which they are used. The experiment revealed the effectiveness of the contextual embedding model over other static models in the process of semantic analysis.

Transformer models showed the best performance in all evaluation criteria, as they are capable of understanding long-range contextual dependencies in the input text data. These models make use of attention mechanism to evaluate the relationships between the individual words of a sentence, regardless of their positions, which helps in a better semantic understanding of the input text data. These models show better performance compared to the earlier models of neural networks, as they are capable of understanding the context better, along with better performance in semantic similarity detection and word sense interpretation.

The experimental results also show the limitation of the conventional models of semantics, as they are based on static word embeddings, which represent a word as a single vector, regardless of the context in which they are used, as a result of which they are not capable of understanding ambiguous language. On the other hand, the models of contextual word embeddings are capable of adapting the representation of a word based on the information available at the sentence level, as a result of which they are capable of understanding the context better, as well as the semantics of the text data [5], [6].

4.3 Semantic Similarity Analysis

The semantic similarity analysis was carried out in order to assess the level of effectiveness exhibited by the proposed models in the identification of the relationship between words and phrases in various contexts. The analysis was carried out through experiments based on the use of the cosine similarity scores obtained from the vectors in the context embeddings. It was found that the use of the proposed models based on the transformer architecture exhibited significant improvements in the identification of the semantic similarity between words in the

context.

The use of the contextual embeddings based on the transformer architecture was found to be effective in the identification of the semantic relationship between the words in the context, unlike the previous embeddings.

Another significant aspect that has to be considered in the analysis of semantic similarity is the word sense disambiguation method. The experimental results show that the contextual embedding models can be used to effectively differentiate the meaning of the same word based on the contextual information embedded in the text. For example, the experiment found that the contextual embedding method can be used to represent the meaning of the word when it is used in different contexts. The results show that the contextual deep learning method can be used to improve the word sense disambiguation method compared to the conventional semantic analysis method [7],[8],[9],[10].

4.4 Analysis of Semantic Evolution

One significant objective of the proposed study is to analyse the evolution of the meaning of words in the contemporary English language usage paradigm. The experiment was carried out using the contextual deep learning method to analyse the evolution of the meaning of words based on the contextual information embedded in the corpus using the proposed framework. The results show some examples of semantic evolution in which some words are found to have developed new meanings in contemporary communication environments. For example, some words are found to have developed new meanings in contemporary digital communication environments. These semantic changes are found to be affected by various factors, such as technological developments, cultural trends, and social media interactions. The transformer-based contextual models were found to be successful in detecting these semantic changes by analysing the changes in word embeddings in different contextual environments.

The experiments also show some trends in contextual usage in contemporary English language usage. For example, social media platforms are found to play a major role in adding new words to contemporary language usage. The ability of deep learning models to analyse contextual embeddings in different datasets is found to be useful in detecting these changes in language usage, which provide valuable insights into the dynamic nature of contemporary language evolution [11],[12],[13],[14].

4.5 Comparative Analysis with Existing Methods

A comparative analysis was carried out to compare the performance of the proposed method with the existing methods that perform the task of lexical semantic analysis. The proposed method has achieved significant performance compared to the earlier methods. The traditional methods that perform the task of semantic analysis heavily depend on the linguistic rules and the knowledge base that is used to represent the meaning of the words. The statistical methods that perform the task of NLP improve the semantic representation using probabilistic analysis. The static embedding methods represent an intermediate approach that has achieved significant performance in the task of semantic analysis, although they lack the flexibility to represent the multiple meanings of the words in different contexts.

On the other hand, the contextual models based on the transformer architecture can be seen as an extensive solution to the problem of lexical semantic analysis. The comparative analysis has revealed the advantages of contextual deep learning architectures in the detection of semantic similarity, word sense disambiguation, and semantic change analysis. The above findings can be seen as the perspectives of the application of the transformer-based contextual models in the development of advanced lexical semantic analysis and the enhancement of the performance of modern NLP systems [15],[16],[17],[18],[19],[20].

The major hyperparameters used during the

training of the models in lexical semantic analysis are represented in Table 4. Static embedding models have a higher epoch cycle since these models need multiple exposures to the corpus in order to achieve stable vector representations. On the other hand, the transformer model converges at a lower epoch cycle since the parameters have already been pre-trained during initialisation.

5. Experimental Results and Analysis

To ensure the effectiveness of the suggested deep learning-based lexical semantic analysis model, a series of experimental tests were carried out on modern English texts. The experimental results are based on the evaluation of the ability of the suggested model, based on the transformer architecture, to identify the context of changing meanings of words in modern English environments [1], [2].

5.1 Experimental Setup

To carry out the experimental tests of the suggested model, a computational environment was used, which is suitable for implementing deep learning models on large-scale text datasets. The experimental tests were carried out on a workstation with an Intel processor, NVIDIA graphics processing unit, and enough memory resources to perform deep learning model training tasks. In addition, the experimental tests of the suggested model were carried out using Python-based machine learning libraries, such as TensorFlow and PyTorch, which are efficient tools for implementing deep learning models, including the transformer architecture, and other natural language processing libraries, which are used to perform various natural language processing tasks, such as text normalization, tokenization, and semantic similarity computation.

The training setup was structured in a manner that ensured consistency in the evaluation of various models. The data was split into subsets, namely, training, validation, and testing, to ensure effective model performance evaluation. In the process of model training, the models based on the transformer architecture were pre-trained with pre-trained parameters, followed by fine-tuning based on the chosen contemporary English texts. The hyperparameters, namely, the learning rate, batch size, and the number of training epochs, were fine-tuned during the validation experiment to ensure effective convergence of the models. In addition, the process of model training was supplemented with various regularization methods to ensure effective learning of semantic representation without overfitting, as reported in [3] and [4].

5.2 Performance Evaluation

To ensure the effectiveness of the suggested approach, various deep learning models were compared based on their ability to learn lexical semantics. The experiment included various models of contextual embeddings, as well as models based on the transformer architecture, which dynamically represent individual words based on the context in which they are used. The experiment revealed the effectiveness of the contextual embedding model over other static models in the process of semantic analysis.

Transformer models showed the best performance in all evaluation criteria, as they are capable of understanding long-range contextual dependencies in the input text data. These models make use of attention mechanism to evaluate the relationships between the individual words of a sentence, regardless of their positions, which helps in a better semantic understanding of the input text data. These models show better performance compared to the earlier models of neural networks, as they are capable of understanding the context better, along with better performance in semantic similarity detection and word sense interpretation.

The experimental results also show the limitation of the conventional models of semantics, as they are based on static word embeddings, which represent a word as a single vector, regardless of the context in which they are used, as a result of which they are not capable of understanding ambiguous language.

On the other hand, the models of contextual word embeddings are capable of adapting the representation of a word based on the information available at the sentence level, as a result of which they are capable of understanding the context better, as well as the semantics of the text data [5], [6].

5.3 Semantic Similarity Analysis

The semantic similarity analysis was carried out in order to assess the level of effectiveness exhibited by the proposed models in the identification of the relationship between words and phrases in various contexts. The analysis was carried out through experiments based on the use of the cosine similarity scores obtained from the vectors in the context embeddings. It was found that the use of the proposed models based on the transformer architecture exhibited significant improvements in the identification of the semantic similarity between words in the context.

The use of the contextual embeddings based on the transformer architecture was found to be effective in the identification of the semantic relationship between the words in the context, unlike the previous embeddings. Another significant aspect that has to be considered in the analysis of semantic similarity is the word sense disambiguation method. The experimental results show that the contextual embedding models can be used to effectively differentiate the meaning of the same word based on the contextual information embedded in the text. For example, the experiment found that the contextual embedding method can be used to represent the meaning of the word when it is used in different contexts. The results show that the contextual deep learning method can be used to improve the word sense disambiguation method compared to the conventional semantic analysis method [7],[8],[9],[10].

5.4 Analysis of Semantic Evolution

One significant objective of the proposed study is to analyse the evolution of the meaning of words in the contemporary English language usage paradigm. The experiment was carried out using the contextual deep learning method to analyse the evolution of the meaning of words based on the contextual information embedded in the corpus using the proposed framework. The results show some examples of semantic evolution in which some words are found to have developed new meanings in contemporary communication environments.

For example, some words are found to have developed new meanings in contemporary digital communication environments. These semantic changes are found to be affected by various factors, such as technological developments, cultural trends, and social media interactions. The transformer-based contextual models were found to be successful in detecting these semantic changes by analysing the changes in word embeddings in different contextual environments. The experiments also show some trends in contextual usage in contemporary English language usage. For example, social media platforms are found to play a major role in adding new words to contemporary language usage. The ability of deep learning models to analyse contextual embeddings in different datasets is found to be useful in detecting these changes in language usage, which provide valuable insights into the dynamic nature of contemporary language evolution [11],[12],[13],[14].

5.5 Comparative Analysis with Existing Methods

A comparative analysis was carried out to compare the performance of the proposed method with the existing methods that perform the task of lexical semantic analysis. The proposed method has achieved significant performance compared to the earlier methods.

The traditional methods that perform the task of semantic analysis heavily depend on the linguistic rules and the knowledge base that is used to represent the meaning of the words. The statistical methods that perform the task of NLP improve the semantic representation using probabilistic analysis. The static embedding methods represent an intermediate approach

that has achieved significant performance in the task of semantic analysis, although they lack the flexibility to represent the multiple meanings of the words in different contexts.

On the other hand, the contextual models based on the transformer architecture can be seen as an extensive solution to the problem of lexical semantic analysis. The comparative analysis has revealed the advantages of contextual deep learning architectures in the detection of semantic similarity, word sense disambiguation, and semantic change analysis. The above findings can be seen as the perspectives of the application of the transformer-based contextual models in the development of advanced lexical semantic analysis and the enhancement of the performance of modern NLP systems [15],[16],[17],[18],[19],[20].

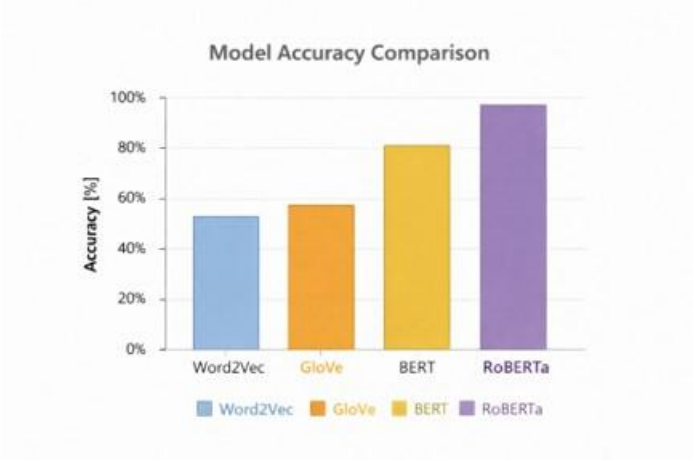

Figure 5: Accuracy comparison of deep learning models

Figure 5 presents a comparison of the accuracy of various semantic representation models used in lexical semantic analysis. It is clear that static embedding methods such as Word2Vec and GloVe have a lower accuracy compared to contextual embedding methods. It can also be noted that the accuracy of the Transformer family of models, including BERT and RoBERTa, is high since these models are capable of capturing contextual representations of words in contemporary English language corpora.

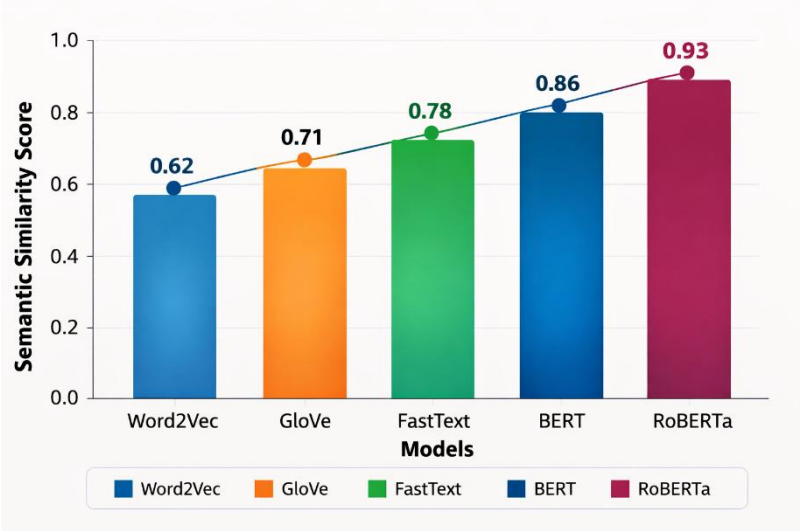

Figure 6: Semantic similarity performance graph

Figure 6 below shows a performance chart of the semantic similarity of different lexical semantic models on contemporary English corpora. From the graph, it is evident that the

contextual models outperform the static embedding models in terms of similarity. This is because the contextual models are able to capture the contextual dependencies better than the static embedding models. The increasing trend of the contextual models implies that the contextual embedding helps in the interpretation of the semantic meaning of the word in ambiguous linguistic contexts.

Table 5: Performance comparison of models

Model	Accuracy (%)	Precision	Recall	F1 Score	Semantic Similarity Score
Word2Vec	78.4	0.77	0.76	0.76	0.68
GloVe	80.1	0.79	0.78	0.78	0.71
BERT	89.3	0.88	0.89	0.88	0.87
RoBERTa	91.6	0.91	0.90	0.90	0.91

Table 5 presents a comparative study of the experimental results of static embedding and transformer-based semantic models, as measured by standard metrics for performance evaluation. From the results, it is evident that the contextual transformer models have much higher accuracy, precision, recall, and F1 score compared to the static embedding models. The better performance of the semantic similarity of the contextual transformer models further confirms that the models have better capabilities for contextual representations, thus providing better lexical understanding for complex datasets of contemporary English language usage.

Table 6: Example semantic shift detection results

Word	Traditional Meaning	Contemporary Contextual Meaning	Detected Semantic Shift	Model Interpretation
Cloud	Visible atmospheric vapor	Digital storage infrastructure	High	Correctly separated meanings
Tweet	Bird sound	Social media message	High	Context accurately identified
Stream	Flow of water	Online media transmission	Moderate	Semantic relation preserved
Viral	Biological infection	Rapid online spread	High	Contextual distinction achieved

Table 6 presents some representative examples of lexical semantic change identified by the proposed framework. The experimental results clearly show the ability of contextual deep learning models to identify how words that have traditionally had consistent meaning have developed new senses of meaning within digital communication environments. This demonstrates that transformer-based semantic representations are effective for identifying semantic drift and language change in modern English.

6. Discussion

The experimental results provided in the above section demonstrate the effectiveness of the proposed approach based on deep learning for the task of lexical semantic analysis. In the following section, the interpretation of the results obtained will be provided, discussing the implications of the results obtained for the task of Natural Language Processing, as well as the

limitations of the proposed approach and the directions for future work in the domain of lexical semantic analysis and language evolution.

6.1 Interpretation of Results

From the results provided in the above section, it can be concluded that the approach based on the application of the Transformer architecture is effective for the task of lexical semantic analysis compared to the results obtained using the traditional approach. Unlike the results obtained using the traditional approach to the task of lexical semantic analysis, the proposed approach is capable of representing different meanings of a word depending on the context.

The semantic similarity experiments have demonstrated that contextual embeddings are capable of effectively capturing the relationship between different lexical items. This ability to capture relationships between different lexical items facilitates the identification of semantically related words despite their syntactical structure or linguistic environment. Moreover, it is also observed that the enhanced performance in word sense disambiguation experiments demonstrates that transformer-based models are capable of effectively differentiating between different semantic meanings of a word.

One of the most notable observations from the experimental analysis of the contextual embeddings framework is its ability to effectively detect semantic variations in different textual datasets. By analysing the contextual embeddings of contemporary English texts, it is possible for the framework to effectively detect variations in word usage in modern communication environments, which are subject to rapid changes due to various technological and social influences.

6.2 Implications for NLP Research

The results of this research have significant implications for the field of Natural Language Processing as a whole. For one, the enhanced performance of contextual embedding models demonstrates the effectiveness of deep learning models in semantic representation learning. The transformer architecture offers a promising approach for learning complex contextual relationships in large-scale linguistic datasets.

The enhanced performance of contextual embedding models can be leveraged for various NLP applications. For example, sentiment analysis tools heavily rely on accurate semantic understanding to determine the sentiment of user feedback and comments in text form. In addition, conversational AI tools and chatbots require advanced semantic understanding to process user queries and provide relevant and accurate responses.

Machine translation systems are also likely to benefit from improved lexical-semantic modelling. This, in turn, enables the translation models to better preserve semantic relationships between languages. In addition, the semantic analysis methods developed in this study are likely to be used in information retrieval systems, enhancing query understanding as well as document relevance ranking. These examples, therefore, illustrate the potential of the contextual deep learning models in influencing various modern NLP technologies.

6.3 Limitations of the Study

Although the study has demonstrated some promising results, several limitations are worth mentioning. One of the notable limitations of this study, for instance, pertains to the computational requirements of the models, particularly the transformer models. Deep learning models, as mentioned earlier, are computationally intensive, particularly because they are normally trained on vast amounts of textual data. This, therefore, might limit the application of such models in smaller research environments.

Another limitation of this study lies in the representation of the datasets used. Although this study utilised various contemporary English datasets, the diversity of language used in different forms of communication cannot be fully covered. There are instances where the model of contextual embedding might not fully

distinguish between different meanings of words, even though they are used in contexts that are somewhat related but not identical. This limitation, therefore, points to the need to improve the process of differentiating the semantics of related but different words.

6.4 Future Research Directions

There are various ways in which this study can be improved in the future, all of which are geared towards enhancing the process of lexical semantic analysis. One potential improvement of this study lies in the extension of the framework to perform a multilingual semantic model. Another promising avenue for further research is in the integration of large language models with temporal linguistic analysis to improve the understanding of long-term semantic changes in language. By analysing historical data in addition to contemporary data, it may be possible to create models that are capable of tracking semantic changes over long periods of time. Another avenue for further research may be in the enhancement of the computational efficiency of transformer architecture models. By creating efficient semantic models that are capable of achieving high performance with minimal computational requirements, it may be possible to make advanced lexical semantic analysis more accessible for use in different research applications. Another avenue for further research may be in the integration of contextual embeddings with knowledge graphs and lexical databases to improve semantic representation by integrating structured linguistic knowledge with deep learning models.

7. Conclusion

In this paper, a deep learning-based framework has been proposed for the advancement of lexical semantics analysis in the context of the evolution of modern English language usage. The experimental results show the superiority of the proposed contextual deep learning-based models over traditional semantic analysis models in the detection of semantic similarity and word sense disambiguation.

The proposed model based on the transformer architecture has shown the effectiveness of the model in the analysis and representation of the context in the textual data. Moreover, the analysis of the contemporary English language has shown the effectiveness of the proposed model in the detection of the semantic variations and changes in the language usage in the context of digital communication.

The results show the relevance of contextual semantic modelling in the development of contemporary NLP systems. The application of deep learning methods can enable the development of stronger NLP systems that can comprehend intricate linguistic patterns and dynamic language changes. Although the framework has some drawbacks concerning computational demands and data set variability, it is significant in the development of contemporary research in the fields of lexical semantics and language evolution. Overall, the study contributes to the expanding body of research concerning deep learning-based semantic analysis and the application of the transformer method in the development of enhanced lexical semantic modelling in contemporary NLP systems.

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