Natural Language Processing Challenges and Issues: A Literature Review

Abdul Ahad ABRO[1], * (iD) , Mir Sajjad Hussain TALPUR[2,] (iD) , Awais Khan JUMANI[3] (iD)

[1]*Ege University, Department of Computer Engineering, 35030, Izmir, Türkiye*
[2]*Sindh Agriculture University, Information Technology Centre, TandoJam, Pakistan*
[3]*Ilma University, Department of Computer Science, Karachi, Pakistan*

Highlights
• This paper mainly focuses on a review of natural language processing algorithms respectively.
• Several applications and approaches have been demonstrated correspondingly.
• Maximum cardinals of natural language processing in every sector have been enlighten accordingly.

Abstract

Natural Language Processing (NLP) is the computerized approach to analyzing text using both structured and unstructured data. NLP is a simple, empirically powerful, and reliable approach. It achieves state-of-the-art performance in language processing tasks like Semantic Search (SS), Machine Translation (MT), Text Summarization (TS), Sentiment Analyzer (SA), Named Entity Recognition (NER) and Emotion Detection (ED). NLP is expected to be the technology of the future, based on current technology deployment and adoption. The primary question is: What does NLP have to offer in terms of reality, and what are the prospects? There are several problems to be addressed with this developing method, as it must be compatible with future technology. In this paper, the benefits, challenges and limitations of this innovative paradigm along with the areas open to do research are shown.
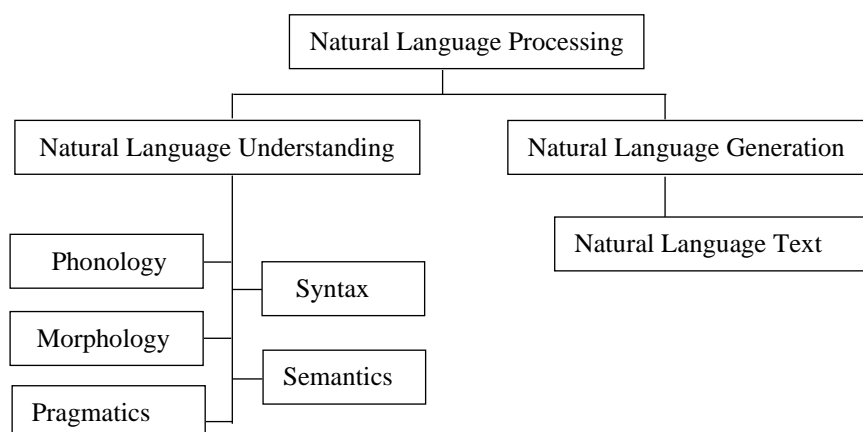
1. INTRODUCTION

In this article, we describe current research and development efforts in the domain of NLP with an emphasis on applications, as well as Deep Learning (DL) technology analysis. It provides the power of patterns, insights from data, and concept-based reasoning by using NLP annotation technologies like SS, MT, TS, SA, NER and ED. The purpose of this article is to give thorough NLP assessments of a variety of techniques in terms of problems and limitations. We have recommended the pre-trained models to produce efficient and effective solutions that may have eluded human observers, all while using a fraction of the computation, effort, and resources.

Recent advances in deep neural network training methodologies and technology have resulted in impressive accuracy gains across a wide range of core NLP tasks. [1,2]. The goal is to accommodate one or more algorithm or system specialties. Language model pre-training has been proven to improve several natural language processing tasks that seek to anticipate the links between sentences by analysing them [3].

2. OVERVIEW OF NLP

NLP is a crucial research domain in the sciences of artificial intelligence (AI) and computer science. Methods and theories for natural language communication between people and computers are studied in NLP. It is classified into two parts i.e. Natural Language Understanding (NLU), (human to machine) and Natural Language Generation (NLG) (machine to human) [4], which progresses the assignment to recognize and generate the text in Figure 1.

*Corresponding author, e-mail: abdulahadabro1@gmail.com

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                        ┌──────────────────────────────┐
                        │ Natural Language Processing   │
                        └──────────────────────────────┘
              ┌──────────────────────────┐      ┌──────────────────────────────┐
              │ Natural Language         │      │ Natural Language Generation  │
              │ Understanding            │      └──────────────────────────────┘
              └──────────────────────────┘                  │
                                                  ┌──────────────────────────┐
   ┌──────────────────┐                           │ Natural Language Text    │
   │ Phonology        │     ┌──────────────┐      └──────────────────────────┘
   └──────────────────┘     │ Syntax       │
   ┌──────────────────┐     └──────────────┘
   │ Morphology       │     ┌──────────────┐
   └──────────────────┘     │ Semantics    │
   ┌──────────────────┐     └──────────────┘
   │ Pragmatics       │
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Figure 1. *Broad Classification of NLP*

NLP has gone through several stages of development, but four major phases are discussed: The germination phase occurred earlier in 1956, the prompt development phase occurred from 1957 to 1970, the low-speed progress phase occurred from 1971 to 1993, and the recovery phase occurred from 1994 to the present. The germination stage covers the early stages of the NLP study. In 1936, Alan Turing introduced the notion of the Turing Machine. During this time, basic research in NLP was conducted to meet the demands of machine translation. Shannon automated the descriptive language automation in 1948 using Discrete Markov processes that have a probabilistic model. NLP saw its first major development between 1957 and 1970 when it was quickly absorbed into the field of AI. During this time, both probabilistic and rule-based techniques research advanced significantly [5]. The second phase of NLP development began in 1971 and ended in 1993. By that time, it was clear that NLP-based applications could not be addressed in a reasonable period, and new difficulties relating to the use of statistical techniques and the creation of corpora were frequently evolving. Two developments in the mid-1990s were pivotal in reviving and expanding NLP research. The first was the fast rise in computer speed and storage, which strengthened NLP's material base and enabled commercial speech and language processing research. The commercialization of the Internet, which occurred in 1994, was the second major event [5].

Network technology advancements have increased requests for natural language-based information repossession and abstraction throughout this time phase. Yoshua Bengio suggested the feed-forward neural network, the first neural language prototype, in 2001. Ronan Collobert was the first to use multitasking to a neural network for natural language processing in 2008 [5]. In 2013, Google's Tomas Mikolov created Word2Vec, a statistical approach for learning independent word embedding from a text corpus using neural networks. In 2014, Ilya Sutskever presented the sequence-to-sequence learning paradigm, which is a generic framework for mapping one sequence to another using a neural network. People are using statistical models to help robots comprehend and generate human language. Scholars in various areas have recently initiated to recognise the usefulness of NLP and relate it to study, in accumulation to research focusing directly on refining current algorithms or suggesting new techniques for NLU and NLG in the field of computer science. Many management academics, for example, have developed new approaches and better algorithms based on various management circumstances.

As a result, our study examines how NLP has been utilised in a variety of restraints in order to figure out how it has been employed and suggest research prospects established on the interdisciplinary assessment.

3. NLP METHODS

NLP is a field that combines computer science, linguistics, and AI. Many researchers contributed to it, developing applications, tools, and systems to address current and future concerns and challenges. This section addresses this requirement by examining the most often utilised NLP techniques in research, such as SS, MT, TS, SA, NER, and ED. This section's goal is to present available approaches, commonly used packages, and each method's benefits and disadvantages.

3.1. Semantic Search

Semantic search produces the most accurate results by understanding the intent, query context, and word relationships. It's centered on the user's intention as well as the context of search terms. It searches for literal matches of query words or variations without comprehending the question's overall meaning, in contrast to lexical search, which looks for literal matches of query words or variants without understanding the query's overall meaning [6]. It enhances and analyze the accuracy by accepting the purpose and contextual significance of phrases as they exist in the searchable data area.

3.2. Machine Translation

Machine translation is the conventional test of language understanding. It is made up of two parts: language analysis and language creation. A collection of texts is translated into one or more languages other than the original in a typical machine translation system. Machine translation is the process of automatically translating one natural language into another. Machine translators examine the structure of the original text and then break it down into individual words that can be readily translated. It can translate enormous amounts of text in a short amount of time. Naturally, the goal of machine translation is to convert a source language word sequence into a semantically equivalent objective language word grouping. Statistical Machine Translation (SMT) is a type of machine translation that relies on the analysis of large amounts of multilingual information. Second, Rule-based Machine Translation, or RBMT, interprets grammatical rules at their most fundamental level. Furthermore, HMT (Hybrid Machine Translation) is a hybrid of RBMT and SMT. It makes use of translation memory, which makes it undeniably more successful in terms of quality. Finally, Neural Machine Translation (NMT) is a form of machine translation that builds statistical models using neural network models (based on the human brain) with the final aim of translation [7,8].

3.3. Text Summarization

Text summary is most employed in news stories and academic papers. Text summary techniques include extraction and abstraction. To create a summary, extraction techniques extract sections of the text. Methods of abstraction create new language that communicates the core of the original content, yielding a summary. In summarization, different methods such as LexRank, TextRank, and Latent Semantic Analysis can be employed. Because of the massive volume of textual material that develops exponentially on the Internet, it is becoming increasingly more significant [9]. The challenge of generating a brief and fluent summary while retaining important statistics content and complete connotation is known as text summarization. For text summarising, a variety of techniques have been developed and widely used in a variety of fields. Search engines, for example, create snippets as document previews. Other examples are news websites that provide simplified summaries of news subjects, generally in the form of headlines, to make surfing easier, or knowledge extraction techniques [10].

3.4. Keywords Extraction

Keyword extraction is a text analysis approach that uses NLP. The chief objective of this approach is to automatically extract the most prevalent words and phrases from the body of a document. It's commonly employed as a first step in summarising a text's main ideas and conveying the text's main topics [11]. The potential of machine learning and artificial intelligence is hidden in the backend of keyword extraction techniques. They are used to extract and simplify text so that a machine can understand it. The algorithm may be tweaked and used in a range of settings, from academic papers to social media postings using colloquial text. In today's environment, keyword extraction has a variety of uses, including social media monitoring, customer service/feedback, product research, and search engine optimization [12].

3.5. Sentiment Analysis

Sentiment analysis is the most extensively used NLP approach. In situations where individuals express their thoughts, such as customer surveys, reviews, and social media comments, sentiment analysis is very beneficial. The most basic result of sentiment analysis is a three-point scale: positive, negative, and neutral.

Both supervised and unsupervised approaches can be utilized for sentiment analysis. The naive bayes approach is the most often used supervised model for sentiment analysis. It requires a sentiment-labelled training corpus, which is used to train a model, which is utilized to identify the sentiment. Numerous machine learning approaches such as gradient boosting or random forest can also be used instead of Naive Bayes. In [13], extracts sentiments on a specific topic. For a particular topic, sentiment analysis entails feature term extraction, sentiment extraction, and association by relationship analysis. It uses two linguistic resources to analyse sentiment: the sentiment lexicon and the sentiment pattern database. It searches papers for positive and negative words, attempting to score them on a range of -5 to +5.

3.6. Named Entity Recognition

In NER several major discoveries have been made in this field, which includes both contemporary feature-inferring neural network models and traditional feature-engineered machine learning models. NER extracts information from the text to identify entities such as persons, places, organisations, dates, and currencies. Neural network models outperform feature-engineered models, and character+word hybrid neural networks outperform alternative representational options, as demonstrated by the state-of-the-art performance of our proposed affix-based extension of character+word hybrid models. Further the state-of-the-art performance of our proposed affix-based extension of character+word hybrid models, more improvements are conceivable by applying past discoveries to present neural network models. In [14], developed approaches based on unlabelled in-domain and out-domain data by annotating phrases or tweets and creating techniques based on unlabelled in-domain and out-domain data. Its performance is superior to that of standard natural language processing methods.

3.7. Emotion Detection

Emotions have a significant role in our lives. Emotions may be used to examine a person's basic behaviour. This information can include facial expressions, speech, and text, among other things. It identifies subjective emotions like sarcasm from text with excellent accuracy in the actual world. The computation and results are completed in a very short amount of time, fulfilling the needs of a variety of sectors. Pleasurable or unpleasant, stimulating or subduing, and tension or relaxation are the three aspects of these feelings. Pleasant vs. unpleasant, attention vs. rejection and level of activity are examples of the three dimensions. Both theories of emotion representation have been used in certain studies. In [15], is like sentiment examination, but it may also be used on social media sites to combine two languages. It divides statements into six types depending on their emotional content. By identifying the speaker's base language, they were able to determine the language of ambiguous terms that were common and tag lexical categories or portions of speech in mixed script [16].

3.8. Text Embedding

Word embedding is a kind of word representation in which words with related meanings are represented similarly. They are a distributed representation for the text that may be one of the major breakthroughs for deep learning approaches' outstanding performance on difficult natural language processing tasks. Methods of word embedding from a corpus of text, learn a real-valued vector representation for a pre-defined fixed-sized vocabulary. The learning process can be supervised, in which case document statistics are used, or unsupervised in which case a neural network model is used for a specific task, such as document classification. In word embedding, a class of techniques, individual words are represented as real-valued vectors in each vector space. The technique is usually associated with deep learning since each word is mapped to a single vector and the vector values are learned in a way that mirrors that of a neural network [17]. The significant global impact of NLP shown in Figure 2.
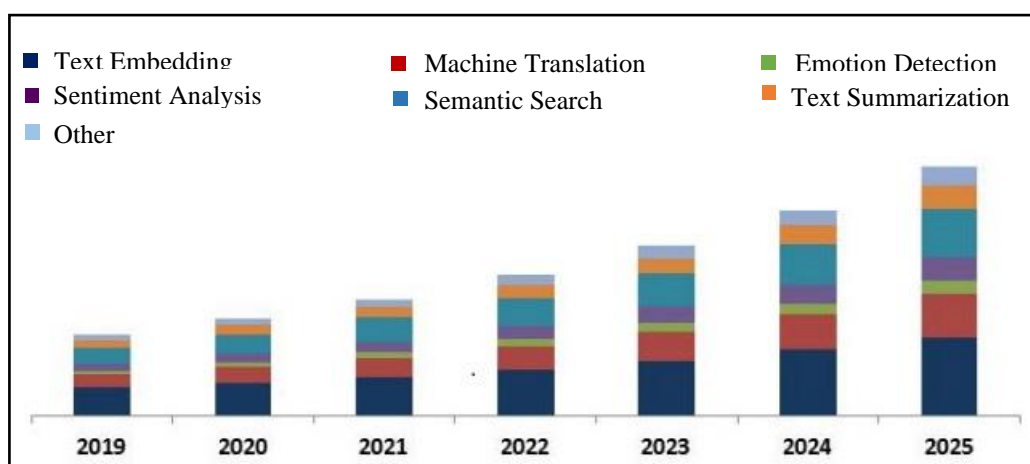
Figure 2. *Analytics of NLP Global Impact*

4. LITERATURE REVIEW OF NLP APPLICATIONS

Most of these NLP systems are based on Deep Learning (DL), a branch of Machine Learning (ML). As shown in Figure 3, DL provides a very flexible, ubiquitous, and learnable framework for characterising the environment for both visual and verbal information.
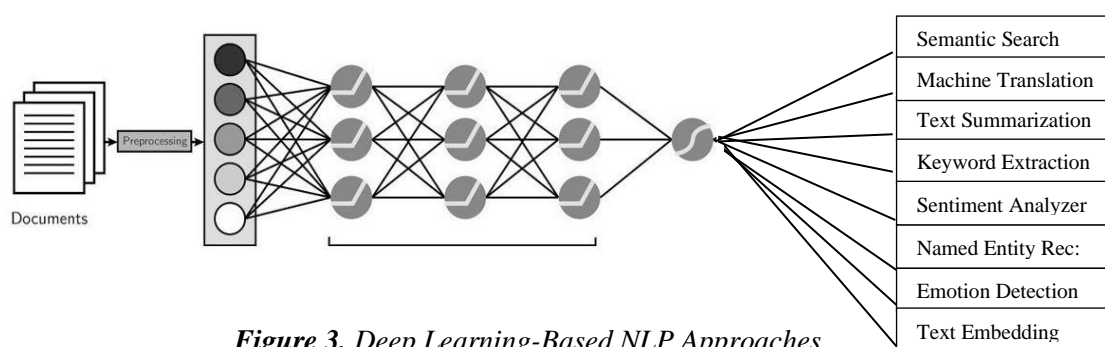

Figure 3. *Deep Learning-Based NLP Approaches*

4.1. NLP in Accounting

Application

Accounting researchers are primarily interested in the many elements that influence business performance, such as firm value. Customers utilise online forums to voice their thoughts on firms or brands, thanks to the fast development of the Internet and social media. This information, as well as the feelings associated with it, might influence the purchasing decisions of other consumers and stockholder's asset behaviour [18], which can have an impact on a company's worth Investor kinds, senders, and commenters all have distinct influencing mechanisms in this process.

Approach

The most widely utilised approaches in accounting research include classification algorithms, modelling, and sentiment analysis. In text classification, supervised learning approaches (e.g. SVR) allow researchers to examine how certain words and phrases in Management Discussion and Analysis (MD&A) explain accrual levels, allowing them to explore the latent link between files. Accounting researchers estimated the subject number using NLP standards such as perplexity score, which entailed hiring many people with accounting or financial experience and manually categorising LDA subjects into broad categories. LDA outcomes have been used to check subject fluctuations over time, with several of them assisting in the broadening and updating of specific concepts [19].

In conclusion, scholars have mostly intensive on the importance of themes, tone, and sentiment in understanding the role of textual characteristics in annual reports, announcements, and customer opinions expressed on social media. Among the most often utilised algorithms by these academics are LDA and sentiment analysis methods.

4.2. NLP in Finance

Application

The impact of linguistic features such as tone, mood, frequency, and corporate sales or reverse causation on the predictive value of news and announcements has been studied extensively in finance [20]. They also looked at the transformations in forecast impact between established and growing markets at the national level.

Approach

Some databases, like Thomson Reuters, provide published summaries and systematic tools to aid researchers in their research. It provides an algorithm to determine tone, which determines the degree of positivity, negativity and neutrality of words used in company media [21]. Even though new technologies are emerging to aid in sentiment analysis, many funded researchers believe that one of the most important obstacles in the study is existing word list for sociology and psychology is insufficient for the circumstance.

In conclusion, financial study subjects are more concentrated than accounting research topics, and researchers have benefited from the use of existing databases and platforms to apply NLP to the calculation of associated variables.

4.3. NLP in Information Systems

Application

Organizational research and consumer behaviour are the most researched areas in the field of information systems when it comes to NLP application Topics covered in organisational studies include R&D asset, novelty, and more. In the fast-changing information technology sector, new entry risks have been proven to have a substantial influence on business decision-making, such as in the case of R&D expenditure and industry attributes that distinguish the mechanism. Additionally, studies have shown that data analytics skills have assisted incorporate innovation, a finding that has been classified as process improvement, new technology improvement, as well as centralised and decentralised innovation [22].

Approach

Text pre-processing, text representation, deep learning, categorization, and topic modelling are the five primary categories of NLP used by information systems researchers. Parts of speech are utilised to identify nouns, verbs, and adjectives in the pre-processing technique, and the resultant word frequency is utilized for additional analysis. Depending on their study settings, researchers use various components of speech, such as assessment phrases (adjectives and adverbs), to measure service qualities. This approach is frequently used with clustering or classification algorithms, as well as human coding, to extract information and improve accuracy. Unsupervised learning and supervised learning are the two most used approaches for categorising texts. In [23], utilised a supervised learning approach to assess two text features: readability (e.g., linguistic complexity, syllables and spelling mistakes) and subjectivity, both of which were thought to influence consumers' intellectual efforts in internalising review material.

Finally, topics in information systems research that uses NLP as an approach of analysis include mutually individual and organizational levels of analysis. In information systems research, the most often used techniques are LDA and TF-IDF, which are utilised in data extraction to generate metrics such as business data analytics skills, customer character and innovation.

4.4. NLP in Marketing

Application

Marketing research based on natural language processing intentions to improve sales performance, customer experience and brand reputation. Businesses closely monitor their customers' online behaviour in terms of browsing and searching engaging with users and stating their opinions on social media. Smartphones have made it possible for consumers to send short text messages and convey emotion at any moment. These tools lower barriers between people, even strangers, and permit for the instant interchange of concepts, potentially promoting originality and allowing distinct customers to influence product/service conceptions [24].

Approach

One of the most challenging difficulties for marketing researchers is the variety of research methodologies. As a result, all six major NLP approaches are used in marketing studies: text pre-processing, text representation, classification, topic modelling, deep learning and sentiment analysis. Finally, researchers have used a range of algorithms, including part-of-speech, classification approaches, and deep learning algorithms, in their research.

4.5. NLP in Strategy Management

Application

Most of the strategic management research has concentrated on start-ups and established businesses. In [25], suggested the most distinctive entrance point had a great degree of exemplar resemblance (the utmost important category member) and an insufficient amount of procedure correspondence. To this end, researchers have looked at two essential aspects of innovation: how far entrepreneurial firms should explore for accomplishment and how should organisations blend the restricted or diverse information they gather uniquely.

Approach

The calculation index in NLP is commonly used by strategy researchers to measure concepts. NLP was utilised to analyse clean app explanations and assess two impressions: Procedure and example have a lot in common. In [25], compared the text descriptions of a developer's first and second applications on the Google Play store using simple cosine resemblance in NLP. To capture the advising approach, it looked at the percentage of management terms to words labelling the technology, product or customer after being allocated to managers with recognized styles.

In short, one of the most pressing concerns among strategic management experts is how to develop an acceptable strategy for gaining a competitive advantage. Topic modelling and sentiment analysis are used to capture the strategy.

4.6. NLP in Defence

Application

Technology has grown at an amazing rate during the last two decades. However, the technology accessible to intelligence analysts has not advanced in the same way. This is due to a combination of time-consuming acquisition methods and a reluctance to modify intelligence training and practises on a systemic level [26].

Approach

The NLP activities that can go beyond the manual, rules-based method to enhanced grasp the assistances that NLP and ML can provide military analysts; like word embedding analysts do not have to merely be

governed on the procedures they have written to capture all applicable reporting on the topic. This is an actual way AI can augment the method of intelligence analysis. NER technique for automatically identifying and extracting entities from documents or communications, such as persons, locations, organisations, and currencies [27]. Moreover, in sentiment analysis, the military's operational environment has evolved from a battlefield to one that involves complicated civil-military ties and efforts to develop nations. Sentiment models may extract positive, negative, and neutral sentiment from local populations to provide insight into their views on continuing military presence and actions in a specific area.

Essentially, the sensitive nature of intelligence, the fast-paced nature of operations, and the ever-changing nature of intelligence objectives, finding a tailored solution to suit the defence organization. AI demands are tough. It is necessary to invest in NLP and ML techniques to extract critical information for military operations.

4.7. NLP in E-Governance

Application

NLP can help E-Government, which is entirely built on an information and communication technology structure. Using an e-government framework may make contact between citizens and the government easier. Voice-enabled mobile applications, for example, may interpret text and deliver messages to individuals. Similarly, the government can utilise natural language processing to monitor numerous channels through which individuals communicate to discover their problems. Moreover, it may also be used in this context to increase security by preventing any breaches of this agreement [28].

Approach

Massive amounts of data are exchanged between citizens and the government during interactions. Formatting and filtering such vast volumes of data is a difficult process, but it may be accomplished with the help of NLP combined with AI and ML approaches. E.g., to establish what the broad consensus is on a policy, sentiment analysis may be utilized to extract thoughts from massive datasets such as comments, reviews and complaints. This would aid relevant government entities in determining the best methods to solve the concerns indicated. In conclusion, adopting these techniques may significantly enhance communication between government and individuals; in particular, the former could utilise them to detect and resolve the problems in a timely way. Furthermore, it encourages both sides to participate in E-Participation, therefore substantially assisting in the proper execution of government programmes [29].

4.8. NLP in Healthcare

Application

One of the fastest-growing industries is healthcare. It has been combining technology applications with healthcare activities such as diagnosis and treatment to develop effective and efficient services that are accessible to the majority of people, eradicating any regional barriers to access in rural areas via E-Health services. NLP can help companies offer better, more efficient care to patients by reducing subjectivity in decision-making [30].

Approach

NLP is not a one-size-fits-all solution, NLP systems in the healthcare business must be able to comprehend the sublanguage used by medical professionals and patients. The NLP-driven technology platform was created with the healthcare industry in mind, and it can help the company make the most of both real-time and historical feedback data [31,32].

4.9. NLP in Education

Application

NLP has the potential to improve education technology in several ways, including its capacity to analyse data, language and create appropriate outcomes. It can improve language-related education by emphasising speaking, writing, and reading. It may be able to satisfy the requirements of students, instructors, and researchers in general. Language assessment specifically, formative and summative, which is being used to assess student proficiency in speaking, writing and reading using NLP approaches, is one of the next significant areas of NLP use. Other applications include proofreading, detecting machine translation errors, analysing the content and substance of student works such as short/long answers, essays and assessing speaking and reading. Grammarly, an NLP-based programme that make writing clear and error-free, is a superb example of a technological application. The programme analyses text using technology and makes suggestions for changes. One of its current applications is in the education sector, where Chabot/virtual assistant apps are utilised for a range of reasons including assessment, tutoring, training, and teaching [33].
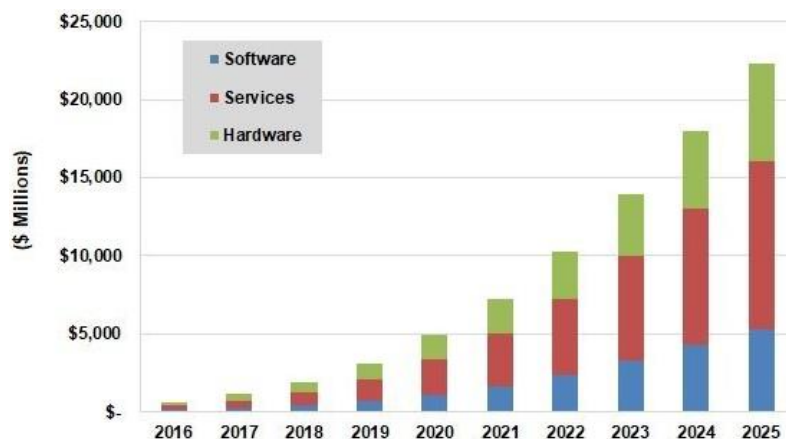
Approach

NLP can also assist in the monitoring of emotional variables through learning tools that can be utilised to highlight the need for transitions and spaced practise. The underlying notion is that the language pupils generate may be good markers of cognitive and knowledge-based skills, which are all dynamic aspects of learning that can influence success [34]. As a result, NLP can assist instructors enhance both the quality of instruction within particular assignments and the learning environment as a whole. Although the research is still in its early stages, the evidence thus far shows that NLP can have a significantly favourable influence on learning.

4.10. NLP in Other Sectors

The use of NLP can help industries such as travel, hospitality, logistics, manufacturing, entertainment, and media so on. NLP may be used in any field where AI is relevant, either by shortening statement processes or by analysing and refining data. Likewise, it is used in the travel industries and hospitality to provide outstanding customer service by using virtual assistants and chatbots to select hotels, book flights, and provide info about places to visit and experience, among other things, all of which is tailored to the traveller's preferences [35]. Similar NLP applications may be found in all areas where services are offered to consumers, such as optimising shows on TVs based on customer watching history or talking with portable chatbots nearly trip routes while driving, such as Google Maps [36]. As a result, NLP may be used in a variety of industries, including not just service but also production.

In addition, according to the Tractica analysis on the natural language processing (NLP) marketplace, the entire market opportunity for NLP services, software and hardware would be approximately $22.3 billion by 2025. According to the analysis, the market for AI-enabled NLP software solutions would rise from $136 million in 2016 to $5.4 billion by 2025 as shown in Figure 4.

***Figure 4**. Tractica Total Revenue World Source:*
https://www.tractica.com/newsroom/pressreleases/natural-language-processing-market-to-reach-22-3-billionby-2025/

5. MODEL EVALUATION

Before being applied, the trained model must be assessed to verify that it is sufficiently generalizable to the corpus. These evaluation indices assist researchers in picking the most appropriate model for their research circumstance. The most often utilized indicators are broken below in Table 1.

***Table 1.** Summary of Natural Language Processing Algorithms*

Sectors	Algorithm Category	Algorithm	Paper	Opportunities
Accounting	Sentiment Analysis	Lexicon	[18]	Deep learning methods to understand" terms in accounting filings
Finance	Classification	Louvain community detection algorithm	[20]	Analytical Method
Information System	Pre-Processing Text Representation	Part of speech Bag-of-Words	[22] [23]	NLP with management theories
Marketing	Pre-processing Classification	Part-of-speech Classifier	[37]	NLP with management theories
Strategy Management	Topic Modeling Sentiment Analysis		[25]	Explore appropriate corpus
Defence	Text Classification, Named Entity Recog: Classification	Neural Network	[26] [27]	Dirichlet Neighborhood Ensemble NLP with active defence system against social engineering attacks
E-Governance	Text Classification, Sentiment Analysis, Topic Modelling	N/A	[28] [29]	NLP with Open Source Social Media Intelligence (OSSMInt)
Healthcare	Semantic analysis, knowledge processing	N/A	[30] [31]	NLP in healthcare association
Education	Text Embedding, Concept Mining	Deep Neural Network (PCNN and PRNN)	[33]	NLP Application

For classification systems, the error rate, accuracy, precision, recall, F1 score, ROC, and AUC are all important performance measures. The error rate is the proportion of misclassified samples to the total number of samples. The proportion of correctly categorised samples to the total number of samples is known as accuracy.

Precision, recall, and F1 scores may be computed for binary classification tasks using the confusion matrix provided in Table 2.

Table 2. *Confusion Matrix*

		Positive	Negative
Predicted Class	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Positive (FN)	True Negative (TN)

Accuracy (Acc) represents how near a measurement is to an identified or accepted [38-40]. It is further defined in Equation (1)

$$Acc = \left(\frac{TP+TN}{TP + FP+FN+TN}\right). \tag{1}$$

In Equation (2), The accuracy metric reflects how many of the predicted positive samples are actually true positive [39-41]

$$Precision = \left(\frac{TP}{TP+FP}\right). \tag{2}$$

In Equation (3), The number of positive instances in the sample that were predicted to be correct is known as recall [40-42]

$$Recall = \left(\frac{TP}{TP+FN}\right). \tag{3}$$

In Equation (4), the F-measure score assesses distinct precision/recall preferences [39-41]

$$F = 2 \, x \, \frac{Precision * Recall}{Precision + Recall}. \tag{4}$$

For the test sample, several algorithms provide a real-valued or probabilistic prediction, which is then compared to a classification threshold. This prediction is classed as a positive class if it exceeds the threshold; otherwise, it is labelled as a negative class. The samples are ranked based on the algorithm's prediction results. In this order, they are anticipated as positive instances one by one. To create the ROC curve, two key variables are calculated each time and plotted with the horizontal and vertical coordinates, respectively. The vertical axis is the True Positive Rate $\left(\frac{TP}{TP+FN}\right)$ and the horizontal axis is the False Positive Rate $\left(\frac{FP}{TN+FP}\right)$ AUC is the area under the ROC curve. If one algorithm's ROC curve fully covers the other, the former may be said to be superior to some others; however, if the two ROC curves overlap, the AUC can be used to make a decision.

6. CHALLENGES & FUTURE DIRECTIONS

NLU's main problem in NLP is that it is required for multiple roles, such as NLG rules. The present NLU algorithm does not yet interpret natural language completely. Though certain fundamental principles for NLU exist, it is challenging to grasp the natural language and for ML to recognise its intrinsic features solely built on these directions because the same meaning may be represented in a variety of ways. It's crucial to acknowledge that human language does not always follow the norms. It removed words and poor grammar may not have an effect on communication because humans can infer the significance of phrases. Through experience and contact, humans acquire language by adapting their environment to the object. In

this case, the computation is huge. Tuning new models and replicating previous outcomes may be surprisingly challenging. On current GPUs, state-of-the-art deep learning models can take up to a week to train and are highly dependent on initialization and hyper- parameter values. The reference executions frequently re-implement NLP components from the ground up, making it problematic to replicate outcomes and posing a hurdle to access for research on several complications.

Conventional algorithms are insufficiently precise to satisfy the needs of unique circumstances. Furthermore, accuracy is not the only method to assess algorithms; researchers must also understand the algorithm's output. However, some clustering methods, on the other hand, may fail to properly define the precise meaning of each class. Some researchers will recode these data manually, significantly increasing expenses. It's also important to select a model that's suited for the study situation, which is a process that requires time and work. Finally, because neuroscience and cognitive science examine the fundamental mechanisms that govern how the human brain interprets language, this information may be used in the development of models.

7. CONCLUSION

NLP is a field of AI that uses traditional ML techniques, proprietary NLP approaches, and DL to create models created on a range of examination circumstances to extract document data and comprehend documents. NLP makes people's lives easier and increases job productivity and accuracy. In recent years, it has exploded in popularity among researchers. Algorithms and unusual datasets are always improving and breaking new ground. As a result, measuring concepts and putting together techniques for interpretation in the business sector has gotten a lot of attention. ML, DL, and AI, as well as NLP are all important technologies for developing value-added applications prior to their emergence, due to the enormous amount of data and processing power required. Sectors and organizations have developed new platforms such as data analysis platforms, business intelligence platforms, and analytical apps to assist them to modify processes, boost productivity, and increase agility.

Moreover, NLP adds to human language competence, which is one of the most ironical elements of technology. It is a field that works with a variety of concepts and techniques for dealing with the problem of communicating with computers using natural language. NLP models are being developed to help decision-makers extract relevant statistics about users, get ahead of upcoming trends, and detect fraud. The most significant disadvantage of traditional language models is unidirectional, limiting the pre-training architectures that may be utilised. In the future, NLP will certainly aid scholars in developing theoretical and practical applications. We believe that this study provides a road map for how NLP may be used as a research tool to create theoretical and practical insights.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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