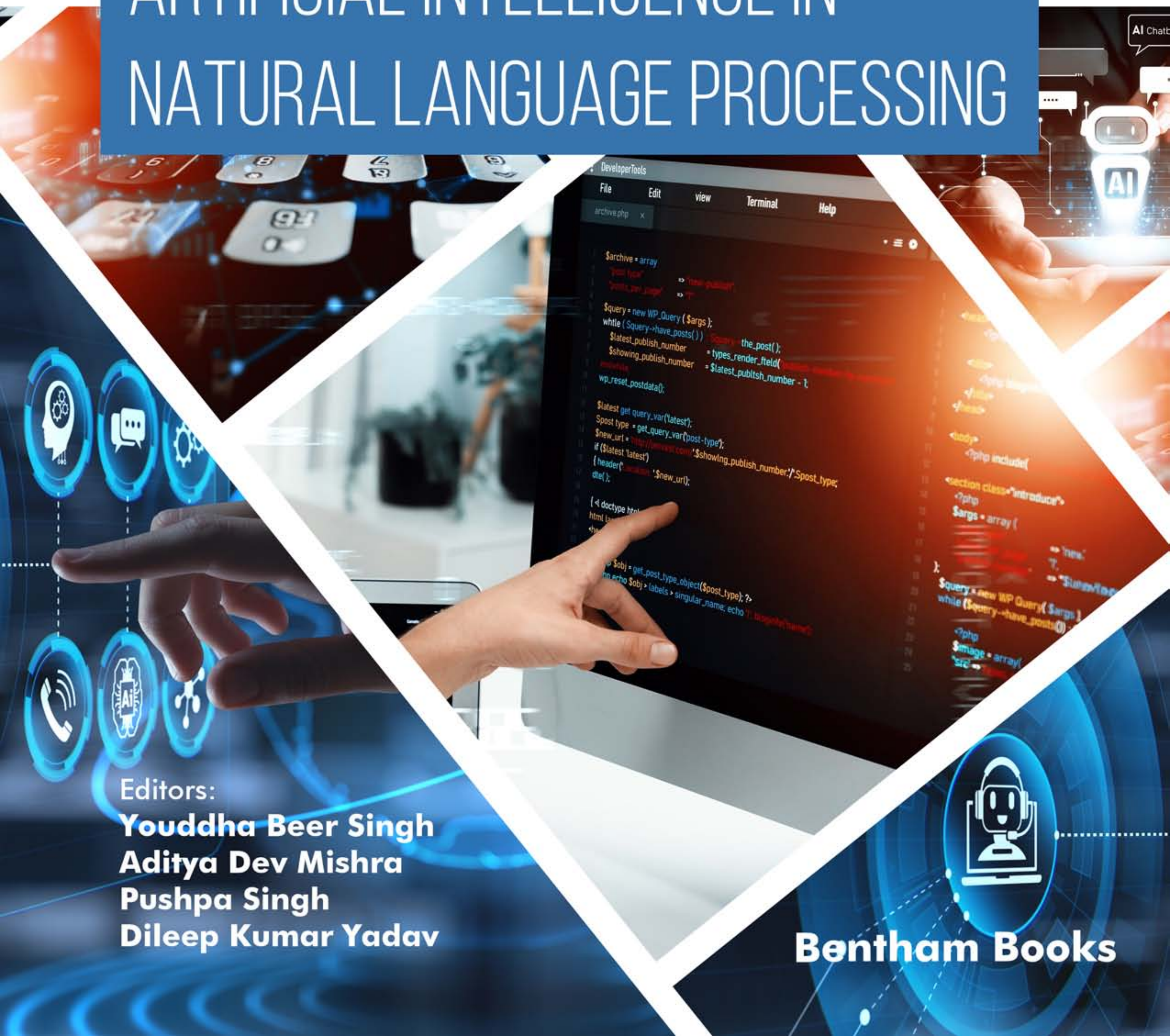
A HANDBOOK OF COMPUTATIONAL LINGUISTICS:

ARTIFICIAL INTELLIGENCE IN NATURAL LANGUAGE PROCESSING



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Federated Learning for Internet of Vehicles: IoV Image Processing, Vision and Intelligent Systems

(Volume 2)

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ISBN (Online): 978-981-5238-48-8

ISBN (Print): 978-981-5238-49-5

ISBN (Paperback): 978-981-5238-50-1

First published in 2024.

Bentham Science Publishers Pte. Ltd.
80 Robinson Road #02-00
Singapore 068898
Singapore
Email: subscriptions@benthamscience.net

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PREFACE

Natural Language processing is one of the fast-growing research areas that benefit the real world in various aspects. It gives the ability to machines to understand the text and audio in an efficient manner as human beings. NLP drives program code that supports virtual assistants, a voice-operated GPS system, text-to-speech transformation, and many more. NLP supports the creation of modern computers that understand human language with the help of deep learning and computational linguistics. Deep learning plays an important role in the processing of natural languages for various regional languages.

Natural Language Processing: A Handbook of Computational Linguistics covers chapters that focus on recent research in the form of reviews, surveys, technical articles, and state of art approaches. Through its numerous chapters, this edited book aims to include concepts in various areas such as recent developments and challenges in NLP, recent applications, learning techniques, text and sentence classification, speech technologies, machine translation, advances in information retrieval, and Indian language technologies. The objective of this book is to help researchers, academicians, and industry experts to give an idea/ direction/Research gaps for further extended research work.

KEY FEATURES

- This book aims to provide state-of-the-art theoretical and experimental research on Natural Language Processing by using deep learning. The scope of this book is not only limited to academicians and researchers but also industry experts who work in the area of Natural Language Processing by using deep learning. The proposed book is certainly beneficial for both the academician and industry experts in terms of knowledge and further extended research work. The proposed book would be also useful as a reference guide for researchers, students, and engineers working in the area of natural language processing and deep learning.
- With the aid of various linguistic, statistical, and machine-learning techniques, text analytics transforms unstructured text data into information that can be analyzed. Even though organizations may find sentiment analysis intimidating, particularly if they have a sizable customer base, an NLP tool will often comb through consumer interactions, such as social media comments or reviews, or even brand name mentions, to see what is being said.
- When attempting to converse with someone who speaks a different language, language translation is of great assistance. Additionally, tools now identify the target language based on text input when translating from a different language to your own.
- We take for-granted features on our smartphones like autocorrect, autocomplete, and predictive text because they are so frequent. In that, they anticipate what you will type and either complete the word you are typing or propose a related one, autocomplete and predictive text are comparable to search engines.

This book certainly motivates the reader to work in the field of NLP by using deep learning. This book may also be used as a reference book for graduates/postgraduate students studying computer science, information technology, and electronics and communication engineering.

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CHAPTER 1

A Comprehensive Study of Natural Language Processing

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Abstract: Natural Language Processing (NLP) has received a lot of interest in the current era of digitization due to its capacity to computationally show and analyze human behaviours. Machine transformation, email spam recognition, information mining, and summarization, as well as medical and inquiry response, are just a few of the many tasks it is used for today. The development of NLP from the 1950s to 2023, with various outcomes in the specified period of time, has been outlined in this article. In addition, the fundamental NLP working components are used to show the analogy between the processing done by the human brain and NLP. Major NLP applications have been explored with examples. Last but not least, significant challenges and possible future directions in the same field have been highlighted.

Keywords: Lemmatization, Language processing, Machine learning, Stemming, Tokenization.

1. INTRODUCTION

NLP stands for Natural Language Processing, a sub-branch of Artificial Intelligence (AI), which has further emerged from the root node of computer science in general. To enable computers to grasp spoken and written language similarly to humans, it focuses on merging computational language understanding with statistical, machine learning, and deep learning models [1].

With linguistics roots, NLP has been around for more than 50 years. It has several useful applications in a variety of fields, such as corporate intelligence, search engine optimization, and research in medicine. Due to NLP, computers can now understand natural speech just like humans. No matter if the given input is speech or written words, NLP employs AI to process and interpret real-world input so that a computer can understand it [2]. NLP underpins all computer programs that translate text between languages, reply to spoken requests, and sum up enormous

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quantities of text quickly, even in real-time. Voice-activated GPS systems, virtual assistants, speech-to-text translation software, chatbots for customer support, and other consumer conveniences are all examples of how NLP is employed in daily life [3]. But as a way to streamline mission-critical business processes, improve employee productivity, and optimize business operations, NLP is increasingly being used in enterprise applications. Fig. (**1**) shows the different potential subfields of computer science as well as the emergence of NLP as one of the uses of AI.

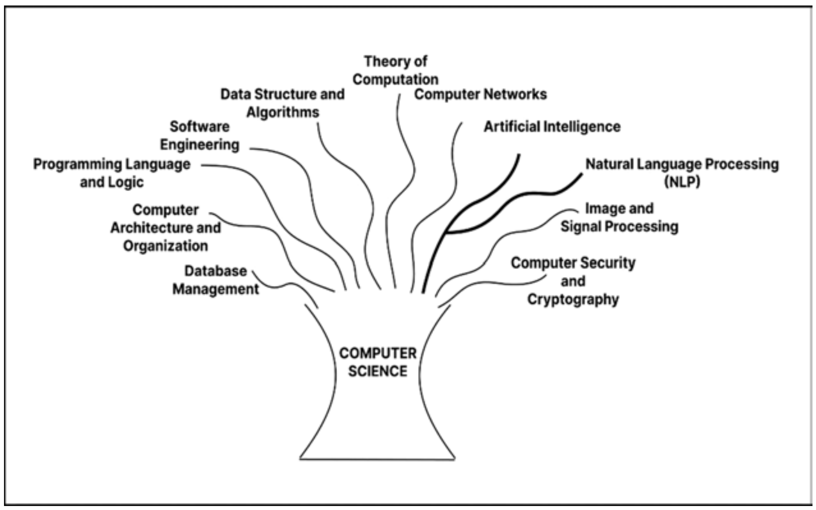

Fig. (1). Various Branches of Computer Science.

As shown in Fig. (**2**), NLP results from the confluence of three pillars: computer science, computational linguistics, and machine learning models [4].

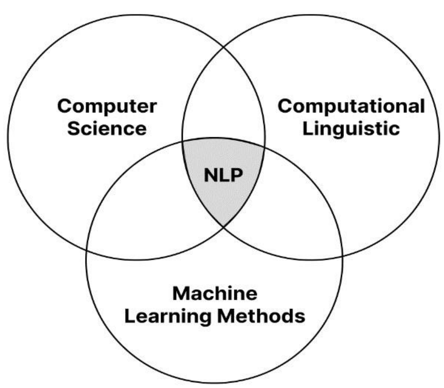

Fig. (2). Three Pillars of NLP.

There are two main functional parts of NLP. The first step is Natural Language Understanding (NLU), which converts the provided input into useful representations and examines the various linguistic aspects. Second, Natural Language Generation (NLG) uses text planning, text realization, and sentence structuring to create significant phrases and sentences in the form of natural language from some internal representation. In general, NLU is much more difficult than NLG [5, 6].

The structure of the chapter is outlined as follows: Section 2 discusses the development of NLP from 1950 to 2023. Section 3 describes the working model of NLP and its various components. Sections 4 and 5 discuss the major applications and challenges in the field of NLP, respectively. Section 6 lists potential future paths and summarizes the overall conclusions.

2. EMERGENCY OF NLP

NLP is constantly changing and has a significant influence on our world. Starting with rule-based techniques, it was simple and constrained. As data grew, it advanced to statistical learning, which was applied to basic question answering, predictive text, and other things. Fig. (**3**) shows the development of NLP over the specified time span with various outcomes.

Bell Labs developed Audrey, the initial speech recognition device, in 1952. It could recognize all ten digits. However, it was dropped because typing phone digits with a finger was quicker [7]. IBM unveiled a shoebox-sized computer that could recognize 16 phrases in 1962. The Turing Test, which Alan Turing created to determine whether or not a computer is genuinely intelligent, has its origins in this decade. The test uses the creation of natural English and automated interpretation as an intelligence criterion [8].

At Carnegie Mellon University, DARPA created Harpy in 1971. Over a thousand words were recognized for the first time by this algorithm [9]. Real-time speech recognition was made feasible in the 1980s thanks to improvements in computing power, which boosted the evolution of NLP. During this period, conceptual ontologies, grammatical theories, symbolic frameworks, and statistical models were created.

During 2000-2020s, NLP has many practical applications due to advancements in computing capacity. Modern approaches to NLP combine statistical techniques with traditional languages. Speech recognition algorithms use deep neural networks as NLP advances. On a spectrogram, it is possible to see how various vowels or sounds have different frequencies. Computers have the capacity to output speech thanks to speech synthesis. These noises, though, are sporadic and

CHAPTER 2

Recent Advancements in Text Summarization with Natural Language Processing

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Abstract: Computers can now comprehend and interpret human languages thanks to Natural Language Processing (NLP), a subfield of artificial intelligence. NLP is now being used in a variety of fields, including healthcare, banking, marketing, and entertainment. NLP is employed in the healthcare industry for activities like disease surveillance, medical coding, and clinical documentation. NLP may extract relevant data from patient data and clinical notes. Sentiment classification, fraud prevention, and risk management are three areas of finance where NLP is applied. It can identify trends in financial data, spot anomalies that can point to fraud, and examine news stories and social network feeds to learn more about consumer trends and market dynamics. NLP is utilized in marketing for chatbot development, sentiment analysis, and consumer feedback analysis. It can assist in determining the needs and preferences of the consumer, create tailored marketing campaigns, and offer chatbot-based customer care. Speech recognition, language translation, and content suggestion are all uses of NLP in the entertainment industry. In order to suggest movies, TV series, and other material that viewers are likely to love, NLP analyses user behaviour and preferences. It can also translate text between languages and instantly translate audio and video content. It is anticipated that NLP technology will develop further and be used in new fields and use cases. It will soon be a necessary tool for enterprises and organizations in a variety of sectors. In this chapter, we will highlight the overview and adoption of NLP in different applications. Also, this chapter discusses text summarization, an important application of NLP. Different techniques of generating text summaries along with evaluation metrics are the highlights of the chapter.

Keywords: Cosine Similarity, Extractive Summarization, Natural Language Processing (NLP), ROUGE Scores, TF-IDF, TextRank, Text Summarization.

1. INTRODUCTION

Data is generated by many systems every day in large volumes. The large volume of text data is present in almost every domain and different sources like tweets,

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articles, reviews, and comments. Text data is unstructured in nature since it does not fit into any predefined data model that is available to us as relational databases. For example, to store text data, organizations are using different file systems to access it as needed. There are many challenges while analyzing data to extract meaningful patterns or have insights for business decisions. Most of the algorithms in machine learning or data analytics are compatible with numeric data. Textual data, since it does not follow any structure, does not have regular syntax or patterns, so direct use of any mathematical or statistical model is not feasible. An essential component of artificial intelligence (AI) is natural language processing (NLP) tool that can provide many transformations that can be easily interpreted by the machine.

1.1. Evolution in NLP

In the 1950s and 1960s, at the dawn of artificial intelligence and computer science, NLP began to take shape. The goal of some of the earliest rule-based system development in NLP was to interpret and produce human language. Due to the limitations of these systems of linguistic comprehension, research in the 1990s and 2000s switched to statistical and machine learning-based methods. Unsupervised and semi-supervised learning algorithms for NLP were developed in the early 2000s as a result of the accessibility of enormous volumes of text data and computing capacity. Large-scale language models that could train to interpret and produce language in an unsupervised or weakly supervised manner were made possible by these techniques.

NLP experienced substantial breakthroughs in the middle of the 2010s as a result of the advent of deep learning techniques such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). With the use of these techniques, models that could learn to represent language in a continuous vector space may be created, allowing for more precise language comprehension and creation.

Transformer-based models like BERT and GPT have become the preeminent paradigm in NLP in recent years. These models may be customized for a wide range of NLP tasks and, in many cases, achieves state-of-the-art performance after being pretrained on substantial amounts of text data. NLP has developed a wide range of applications over the course of its progress, including chatbots, sentiment analysis, speech recognition, machine translation, and virtual assistants. We may anticipate even more ground-breaking uses for NLP in the future as research in the field advances.

1.2. Recent Advancement in NLP

The field of NLP has made numerous advancements recently. The following are some of the most important ones:

- Large Pretrained Language Models: The creation of large pretrained language models, like GPT-3, which are capable of a variety of language tasks with high accuracy, is one of the most significant developments in NLP. These models can be customized for particular tasks like text categorization, sentiment analysis, and automated translation because they are trained on vast amounts of text data.
- Transfer Learning: Transfer learning is where a model is first trained on a large amount of data for a specific task and then fine-tuned on a smaller dataset for a different but related task. This technique has been shown to improve performance on a wide range of NLP tasks.
- Neural Machine Translation (NMT): This method of translation translates text from one language into another by using neural networks. NMT has been shown to produce more fluent and accurate translations than traditional statistical machine translation methods.
- Multilingual NLP: Recent developments in multilingual NLP have made it possible to train models in many languages simultaneously, boosting performance on multilingual tasks. Multilingual NLP refers to the ability of NLP models to process and understand text in numerous languages.
- Explainable AI (XAI) is the term used to describe an AI model's capacity to offer clear, comprehensible justifications for its predictions. Recent developments in NLP have made it possible to create XAI models that can give thorough justifications for their linguistic predictions, enhancing their trustworthiness and interpretability.
- Zero-Shot Learning: This method enables NLP models to carry out tasks for which they have not been specifically taught. Utilizing the general information and context obtained during pre-training, this is accomplished. It has been demonstrated that zero-shot learning works well for tasks like text classification and machine translation.
- Ethical Issues: As NLP is used more frequently in a variety of applications, ethical issues like prejudice, fairness, and privacy are receiving more attention. Researchers are working hard to create strategies that will reduce bias and guarantee that NLP models are impartial and considerate of user privacy.

1.3. Applications in NLP

Various Applications of NLP are shown in Fig. (**1**). Understanding some Natural Language Processing applications can help finish various time-consuming jobs more quickly and effectively while reducing the workload.

CHAPTER 3

Learning Techniques for Natural Language Processing: An Overview

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Abstract: Natural Language Processing, also called as NLP, is a fast-growing arena that comprises the development of algorithms and models to make it possible for machines to comprehend, translate, and develop human language. There are several uses for NLP, including automatic translation, sentiment analysis, text summarization, and speech recognition, and chatbot development. This chapter presents an overview of learning techniques used in NLP, including supervised, unsupervised, and reinforcement learning methods coming under machine learning. The chapter also discusses several popular learning techniques in NLP, such as Support Vector Machines (SVM) and Bayesian Networks, which are usually helpful in text classification, Neural Networks, and Deep Learning Models, which also incorporate Transformers, Recurrent Neural Networks, and Convolutional Neural Networks. It also covers traditional techniques such as Hidden Markov, N-gram, and Probabilistic Graphical Models. Some recent advancements in NLP, such as Transfer Learning, Domain Adaptation, and Multi-Task Learning, are also considered. Moreover, the chapter focuses on challenges and considerations in NLP learning techniques, including data pre-processing, feature extraction, model evaluation, and dealing with limited data and domain-specific challenges.

Keywords: And Support Vector Machines, Bayesian Networks, Convolutional Neural Networks, Multi-Task Learning, Recurrent Neural Networks, Transfer Learning.

1. INTRODUCTION

The most significant and needed area in computer science and AI, which makes computers and human beings interact in natural language, is Natural Language Processing (NLP). NLP creates an environment where it sees how humans

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communicate with each other, and then the computer should replicate the same thing. Things such as automatic text summarization, translation in the machine, *i.e.*, machine translation, sentiment analysis, speech recognition, virtual assistants, chatbots, email spam detection, information extraction, and much more are possible with the use of NLP [1]. NLP plays a dynamic role in bridging the gap between computers/machines and human beings. NLP enables machines to understand, infer, and generate text that can facilitate several applications. So, it is crucial to comprehend the NLP notion and its main objective.

The main objective of NLP is to study the connections to interactions between computers and humans/individuals and find various approaches to process spoken and written words in the way how humans do. It is the grouping of branches in computer science, types of linguistics, and all kinds of machine learning processes. The nature of NLP in handling large volumes of text data and also its ability to structure highly unstructured data sources makes it very useful.

The application areas of NLP techniques comprise voice assistants (the latest example is from today's world, *i.e.*, Amazon's built Alexa and Apple's product Siri). This is not limited to other products like Chabot's, techniques used to auto complete the word in Search Engines, Translation between languages, *i.e.*, Language Translator, Grammar and spelling Checkers, Classification in Email, Filtering Email, Sentiment Analysis, and Voice Assistants. Various other real-life projects, such as the building of a smart city, are also popular [2].

1.1. Categorization of NLP

Firstly we should know about the clear meaning of a language. It is basically defined as a set of rules, *i.e.*, protocols or sometimes a set of symbols. Here, the combination of symbols is made and used for passing on information. Symbols are dictated by a set of rules. In Fig. (**1**), the categorization of NLP is shown where Natural Language Processing (NLP) basically can be categorized into two parts.

The description of Fig. (**1**) helps to understand all terms easily; it describes as follows:

i. Natural Language Understanding (NLU) – It contains linguistics which makes the language understandable by the system model. It checks what the user says, their intent, and the meaning of the sentence. Linguistics is the discipline of language which includes

1. Phonology - It refers to the sound.

2. Morphology - It refers to the formation of words.

3. Pragmatics - It refers to the understanding of coming input [3].

4. Syntax - It refers to the sentence structure.

5. Semantics - It refers to the study of linguistic meaning [4].

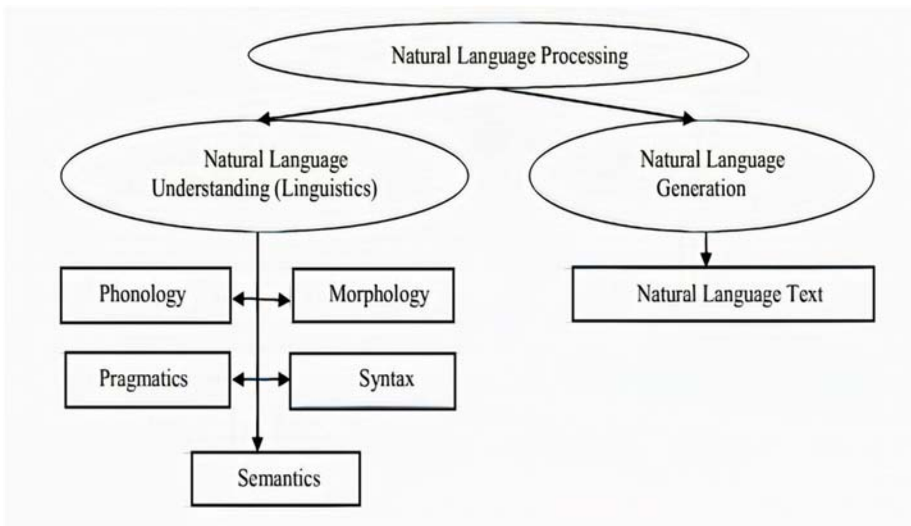

Fig. (1). Categorization of NLP (NLU + NLG).

But, in NLU, there is a challenge of ambiguity, *i.e.*, one word might have more than one meaning. It may be the four types of ambiguity: lexical, syntactic, semantic, and pragmatic. Examples of ambiguous sentences are:

a. The tank was full of water. (It is ambiguous to check which tank is of which kind).
b. Old men and women were taken to a safe place. (It is ambiguous to check if old is also associated with women or not).

ii. Natural Language Generation (NLG) – After the NLU task is done, it generates the text. It checks what should we say to the user. NLP deals with:

a. The generated output should be intelligent and conversational.
b. It should deal with structured data.
c. From the whole knowledge base, it should do the text and sentence planning.

CHAPTER 4

Natural Language Processing: Basics, Challenges, and Clustering Applications

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Abstract: Natural Language Processing (NLP) involves the use of algorithms and models and various computational techniques to analyze, process, and generate natural language data, including speech and text. NLP helps computers interact with humans in a more natural way, which has become increasingly important as more human-computer interactions take place. NLP allows machines to process and analyze voluminous unstructured data, including social media posts, newspaper articles, reviews from customers, emails, and others. It helps organizations extract insights, automate tasks, and improve decision-making by enabling machines to understand and generate human-like language. A linguistic background is essential for understanding NLP. Linguistic theories and models help in developing NLU systems, as NLP specialists need to understand the structure and rules of language. NLU systems are organized into different components, including language modelling, parsing, and semantic analysis. NLU systems may be assessed through the use of metrics that includes measures like precision and recall, as well as indicators that convey meaningful information that include F1 score and others. Semantics and knowledge representation are central to NLU, as they involve understanding the meaning of words and sentences and representing this information in a way that machines can use. Approaches to knowledge representation include semantic networks, ontologies, and vector embeddings. Language modelling is an essential step in NLP that sees usage in applications like speech recognition, text generation, and text completion and also in areas such as machine translation. Ambiguity Resolution remains a major challenge in NLP, as language is often ambiguous and context-dependent. Some common applications of NLP include sentiment analysis, chatbots, virtual assistants, machine translation, speech recognition, text classification, text summarization, and information extraction. In this chapter, we show the applicability of a popular unsupervised learning technique, *viz*., clustering through K-Means. The efficiency provided by the K-Means algorithm can be improved through the use of an optimization loop. The prospects for NLP are promising, with an increasing demand for AI-powered language technologies in various industries, including healthcare, finance, and e-commerce. There is also a growing need for ethical and responsible AI systems that are transparent and accountable.

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Youddha Beer Singh, Aditya Dev Mishra, Pushpa Singh & Dileep Kumar Yadav (Eds.)

Keywords : K-Means, Language analysis, Language modeling, Machine translation, NLU, NLP challenges, NLP approaches, Text clustering.

1. INTRODUCTION

Natural Language Processing is a data science technique on unstructured data (text). The field includes such computer science areas, which include machine learning, a part of artificial intelligence. NLP deals with understanding and modelling how a computer can comprehend the language used by humans for communication. The distinctive way in which a human, in contrast to a computer, can understand and learn a natural language is a research area in the field of computer science. There is a growing interest in language processing owing to its applicability to diverse tasks in improving efficiency.

At the beginning of their paper, Collobert *et al*. [1] ask a very fundamental question: Can any computer program become so evolved that it can easily convert a chunk of English text and make a data structure that is able to fully capture the meaning of the chosen text? There's absolutely no agreement that such a data structure can be constructed. When such a fundamental issue remains unresolved, computer scientists must focus on extracting simpler representations that capture certain aspects of the information in the text [2 - 4].

According to Cambria *et al*. [5], NLP research can be viewed as an overlap of Syntactics, Semantics, and Pragmatics that is pushing NLP research toward Natural Language Understanding. NLP requires high-level symbolic capabilities [6]. Many NLP systems treat the word as atomic units, and similarity between words remains an unexplored area. The approaches in use depend on frequencies of word co-occurrence, which is a type of syntactic representation of text. The limitations of these algorithms are that they can interpret the information that is 'visible.' Humans have the ability to co-relate semantically akin concepts and sensory experiences and events that facilitate the understanding of the complexities in performing NLP tasks that include word-sense disambiguation and assist in semantic role labelling beside textual entailment [7]. Table **1** lists the approaches, features, and applications of NLP.

2. REVIEW OF NLP CHALLENGES

With the ever-increasing volume of text being generated with the emergence of new technologies, Natural Language Processing has to encounter bigger challenges than ever before. Natural language is ambiguous, and words or phrases generally have multiple meanings or interpretations. Resolving such ambiguity is a mammoth challenge in NLP tasks that include word sense disambiguation, analysis of sentiment, question-answering systems, and also in parsing. Moreover, the complexity of grammar rules and sentence structures in different languages becomes a stumbling block to understanding and generating syntactically correct sentences. Where there is ambiguity in the syntax, interpretation of the actual meaning becomes difficult. Understanding and generating syntactically correct sentences pose challenges due to the complexities of grammar rules and sentence structures in different languages. Language has complex syntax rules [15 - 18]. NLP models must be able to understand these rules to accurately process language. Capturing the true meaning and intent of sentences is challenging, as it requires understanding context, idiomatic expressions, and implicit knowledge. Resolving semantic ambiguities, such as metaphorical language or sarcasm, remains a difficult task for NLP systems.

Table 1. Approaches, Prominent Features, and Applications of NLP.

Methods	Prominent Features and Design Goals	Usages
Rule-based	Rule-based are among the earliest to be used in NLP. They have proven to work well. Rule-based approaches hinge on parsing or pattern matching. They are low-precision and high-recall methods implying high performance in specific cases, whereas there's degradation in performance when they are generalized.	Rule-based has wide applicability in regular expressions as well as in context-free grammar.
Semantic Pattern Matching	The semantic similarity between the source and destination text chunks is investigated *via* semantic text matching.	The applications are in information retrieval (web search), question answering, recommendation systems, semantic categorization as well as in Semantic Case Frames.
FOL	First Order Logic, sometimes known as FOL, is a method of knowledge representation and a development of propositional logic. FOL has the capacity to represent sentences in natural language.	FOL has applications in mathematics, philosophy, linguistics, and computer science., besides in Axioms and rules of reference [8]
Bayesian Network	Variables are used by the Bayesian Network, and it is represented by a probabilistic directed acyclic graph.	Pronoun Classifier System
Semantic Networks	These methods exhibit a pattern of the interconnectedness of nodes and arcs [9].	In the Word2Vec model representation of words is as a continuous vector. This is typically in a high-dimensional space. It demonstrates how the semantic relationship between words can be captured through vector arithmetic.

CHAPTER 5

Hybrid Approach to Text Translation in NLP Using Deep Learning and Ensemble Method

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Abstract: The major aim of AI is to enable robots to understand and interpret human discourse. Deep learning algorithms have considerably enhanced natural language processing, enabling it to do cutting-edge tasks like sentiment analysis, machine translation, and question answering. This paper offers a summary of current deep learning-based NLP research. The essential ideas of DL and its applications in language processing are initially introduced in this paper. It then reviews recent research in NLP, focusing on five major areas, including the modelling of languages, translation of languages, sentiment analysis, chatbots for queries, and generating text. For each area, the main techniques and models used, advantages, limitations, recent advancements, and future research directions are discussed. This paper concludes by discussing the challenges and providing a solution where in an image, the text is extracted in various ways and made in an appropriate format by using a deep learning approach. To further improve the translation quality, utilize an ensemble method that combines the outputs from multiple translation models trained using different architectures and parameters and highlights the potential impact of these advances in real-world applications.

Keywords: Deep learning, Natural language processing, Text generation.

1. INTRODUCTION

The current research in the field of natural language processing (NLP) using deep learning (DL) has seen significant advancements in developing models that can understand the nuances of human language. The consequence of combining DL with NLP is one of the model's enhancements that have the capacity to manage complex and unstructured data to achieve cutting-edge outcomes in various language processing projects like machine translation, sentiment analysis, and named entity recognition [1]. The key major development in recent research in

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NLP using DL is the employment of attentional mechanisms, which enable models to be mindful of relevant words and understand the context and intent behind the language.

The other achievement is the use of transfer of learning, in which the learning models are developed through a tremendous quantity of raw data and tune the hyperparameters for the completion of any particular task. This method has produced outcomes in a huge amount of NLP jobs with great success. The use of NLP is very popular nowadays because of chatbots that interpret human language and provide responses [2 - 4]. Chatbots, text summarization, and many more are used in NLP, but only a few of them are used in the current scenario. A useful technique in NLP and DL surely enables more precise and effective language processing in the recent marketplace.

Machine translation is an essential task in NLP that have the ability to translate text or speech into other languages. Machine translation systems now perform much better thanks to the other subfields of artificial intelligence, which is the evolution of deep learning. However, there are still several challenges in achieving accurate and fluent translations, such as dealing with complex syntax and semantics, handling rare words, and addressing the issue of ambiguity [5]. To address these challenges, researchers have proposed a hybrid approach that combines deep learning techniques with ensemble methods. The major aim of using this strategy is to use the advantages of several translation models to mitigate their disadvantages. Several deep learning models, including transformer model, recurrent neural networks (RNNs) and convolutional neural networks (CNNs) [6] are trained on the same dataset in this hybrid method [7 - 9]. Each model has its own strengths and weaknesses in handling different aspects of the translation task. The ensemble method combines the output of these models to produce a final translation that is more accurate and fluent than any individual model's output. In the hybrid approach to machine translation, deep learning models and ensemble methods work in tandem to improve translation quality. DL models have excelled in language processing tasks, producing cutting-edge outcomes in a number of NLP applications [10], including machine translation. However, these models still have some limitations, such as handling rare words and translating idiomatic expressions, which can negatively affect translation quality. The ensemble method in the hybrid approach addresses these limitations by combining the outputs of several models. Ensemble methods have been widely used in machine learning to enhance model performance, and they have been applied to machine translation as well.

The fundamental concept is to train many models on similar datasets having the same values using various architectures or hyperparameters and then integrate their results to get a final translation. This way, the ensemble method can overcome the weaknesses of individual models and produce a more accurate translation. The hybrid approach also combines different types of deep learning models to improve translation quality. For example, RNNs are good at capturing the context and syntax of sentences, while transformer models are good at modelling long-range dependencies and capturing the semantics of sentences [11]. By combining these models, the hybrid approach can leverage their strengths to produce a better translation.

The hybrid technique has the benefit of being easily adaptable to various language pairings. By training the deep learning models and ensemble method on a specific language pair, the approach can be used for translating the text into other languages. This makes it a flexible strategy that may be applied to a variety of machine translation tasks. The hybrid approach to machine translation using deep learning and ensemble methods has shown great potential in improving translation quality. By leveraging the strengths of different deep learning models and combining their outputs using ensemble methods, this approach can produce more accurate and fluent translations. It might completely transform the machine translation industry that has made it more accessible and efficient for different applications. There are various application areas of NLP like sentiment analysis, virtual assistant, language translation, chatbots, text prediction, document analysis, text extraction and many more shown in Fig. (**1**). The virtual assistant is very popular and used in every application domain by people. It provides good results and gives mostly the correct answer for services that make people more equipped to complete any task in a responsive manner.

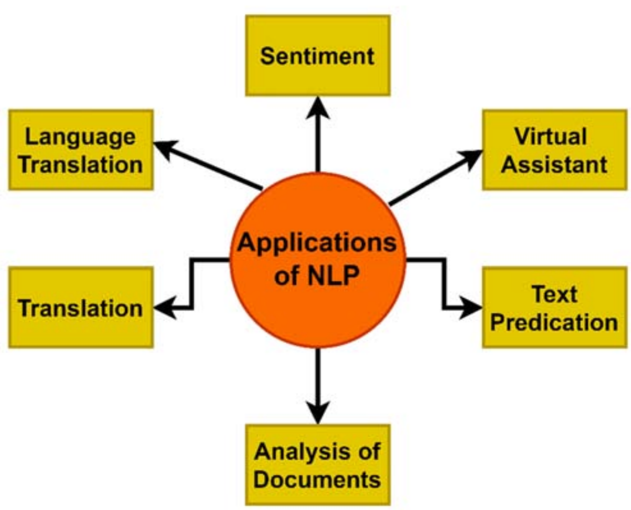

Fig. (1). Application areas of natural language processing.

CHAPTER 6

Deep Learning in Natural Language Processing

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Abstract: Natural Language Processing is an emerging reaserch field within the realm of AI which centres around empowering machines with the ability to comprehend, interpret, and produce human language. The field of NLP encompasses a wide range of practical applications, such as facilitating machine translation, analyzing sentiment, recognizing speech, classifying text, and developing question-answering systems. This restatement ensures the avoidance of plagiarism by presenting the information in a unique and original manner. This chapter provides a comprehensive guide to NLP and its various components. Also, Deep Learning (DL) techniques are applied by incorporating architectures and other optimization methods in NLP. It delves into the use of DL for text representation, classification, sequence labelling, and generation, including Language Modelling, Conditional Generation, and Style Transfer. Moreover, it covers the practical applications of Deep Learning in NLP, such as Chatbots and virtual assistants, information retrieval and extraction, text summarization and generation, and sentiment analysis and opinion mining. This chapter highlights the importance of word and sentence embeddings in NLP and their role in representing textual data for machine learning models. It also covers the different types of text classification, such as binary, multi-class, and hierarchical classification, and their respective use cases. Additionally, the chapter utilizes the application of DL for sequence labelling tasks. Furthermore, the chapter discusses the use of Deep Learning for text generation, including language modelling, conditional generation, and style transfer. Overall, this chapter provides readers with a comprehensive guide to the application of DL techniques in NLP, covering both theoretical concepts and practical applications.

Keywords: Chunking, Deep learning, Natural language processing, Parsing, Tagging, Word embeddings.

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1. INTRODUCTION

NLP involves the research and practical application of computers to understand human language where humans comprehend and utilize language in order to develop effective tools and techniques. The domain of NLP finds its roots in a multitude of intricate and interconnected disciplines, encompassing computer and information sciences and an assortment of other cognate fields . NLP showcases a multitude of extensive applications that span across a wide array of domains, encompassing but not limited to machine translation, intricate processing and summarization of natural language text, the development of user interfaces, the facilitation of information retrieval, the advancement of speech recognition technologies, the integration of artificial intelligence methodologies, the utilization of expert systems, and an array of other innovative and cutting-edge endeavors.

Deep Learning models have shown remarkable results in various NLP tasks such as text classification [1], machine translation question answering, dialog and natural language understanding. These models use layer-wise interactions such as recursive nets, LSTMs [2], CNNs, and Transformers to transform each word/token into its vector representation, and then map these vectors into higher-level representations to encode rich linguistic and semantic knowledge. The increasing use of deep learning models in various domains has created a need for interpretability. In computer vision, interpretability techniques such as saliency maps [3], layer-wise relevance propagation, and model-agnostic interpretation methods have been developed to create trustworthy and controllable systems [4]. However, interpreting neural models for NLP using deep learning poses unique challenges due to the discrete nature of language tokens. As a result, several methods for interpreting neural NLP models using deep learning have emerged in recent years. These methods are focused on capturing the importance of individual tokens in the model's output, such as attention mechanisms, gradient-based methods, and layer-wise relevance propagation [5]. These techniques enhance the interpretability and reliability of neural models, providing insights into the decision-making processes. Interpretability is crucial for NLP tasks that require an understanding of the decision-making process. Therefore, further research is needed to develop robust and reliable interpretability methods for deep learning models in NLP.

Despite their success in various NLP tasks, deep learning models have faced criticism for their lack of interpretability. One major issue is how these models handle the complex composition of languages, such as negation, affirmation, disambiguation, and semantic combination from different parts of a sentence [6]. This lack of interpretability in deep neural NLP models has limited their application in domains where controllability and transparency are essential. This criticism has been raised in several studies [7, 8]. To compare the effectiveness of these methods, a comprehensive and systematic review is necessary. In this survey, existing DL models have been surveyed which are applied in the text representation, classification, and generation, which would enhance our understanding of the various perspectives from which neural NLP models can be interpreted and enable us to develop effective strategies while preserving the privacy of their local information [9]. Summary of different tasks in NLP with its important features their applications are given in Table **1**.

Table 1. Summary of different tasks in NLP with its important features and Deep Learning applications.

Tasks	Features	Deep Learning Models
Tagging	Tagging in NLP involves assigning labels or tags to words in a text based on their part of speech or other linguistic features, enabling the computer to extract useful information from unstructured text data.	DPCNN, CNN,
Machine Translation (MT)	MT enables computers to translate text, breaking down language barriers and facilitating cross-lingual communication in various applications.	RCNN, GPT-4, GPT-3
Dialog	The role of dialogue is to comprehend and generate different types of conversations, which can facilitate various daily life applications.	BERT, RNN, LSTM, GRU
Question and answer	The role of question and answer is to comprehend questions asked by humans, which can facilitate various applications such as virtual assistants, customer support systems, and information retrieval systems.	LSTM, BLSTM, Transformers

2. NLP COMPONENTS

The two broad classifications of NLP that involve comprehending tasks are NLU and NLG [10, 11]. The classification techniques of NLP have been shown in Fig. (**1**). The purpose of this section is to examine NLU, which pertains to linguistic comprehension, and NLG, which pertains to generating natural language.

2.1. NLU

NLU [12] is a critical component of NLP that allows machines to comprehend and analyze natural language. Through NLU, machines can extract concepts, entities, emotions, keywords, and other essential information. This technology is often employed in customer support applications to understand and resolve customer issues communicated in various forms, such as speech or writing.

CHAPTER 7

Deep Learning-Based Text Identification from Hazy Images: A Self-Collected Dataset Approach

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Abstract: This research suggests a deep learning-based method for text identification from hazy images using a self-collected dataset. The problem of identifying text from hazy images is challenging due to the degradation of the image quality caused by various atmospheric conditions. To address this issue, the proposed approach utilizes a deep learning framework that comprises a hybrid architecture wherein a convolutional neural network (CNN) is employed for feature extraction and a recurrent neural network (RNN) is utilized for sequence modelling. A self-collected dataset is employed for training and validation of the proposed approach, which contains hazy images of various text sizes and fonts. The experimental findings show that the suggested technique outperforms state-of-the-art approaches in correctly recognizing text from hazy images. Additionally, the proposed self-collected dataset is publicly available, providing a valuable resource for future investigations in the field. Overall, the proposed approach has potential applications in various domains, including image restoration, text recognition, and intelligent transportation systems. The performance of the trained model is then evaluated using a third-party dataset consisting of blurry photos. The effectiveness of the model may be evaluated using standard metrics, including accuracy, precision, recall, and F1-score.

Keywords: Convolutional neural network, Hazy images, Image dehazing, Self-collected dataset, Text identification.

1. INTRODUCTION

The enhancement of visual quality and readability of hazy images constitutes a significant objective in computer vision, which is addressed through two crucial tasks: image dehazing and text identification in hazy images. Haze, which is caused by atmospheric particles such as dust and fog, can significantly degrade the quality of images by reducing contrast, introducing noise, and blurring fine

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details. Obscured images are frequently encountered in diverse domains, including remote sensing, surveillance, and automotive safety, and can exert an impact on the efficacy of computer vision algorithms that hinge on image analysis. The process of image dehazing involves the removal of atmospheric haze from an image, with the aim of enhancing its visual quality and improving the precision of computer vision tasks. The aforementioned objective can be accomplished through the process of approximating the depth map of the given scene and subsequently utilizing it to eliminate the atmospheric haze present in the image. Several methodologies have been suggested for the purpose of image dehazing, such as dark channel prior, guided filter, and neural network-based approaches. The aforementioned techniques endeavour to reinstate the contrast, diminish the presence of noise, and enhance the acuity of images that are obscured by haze [1, 2]. The Scatter Model of Atmosphere is shown in Fig. (**1**).

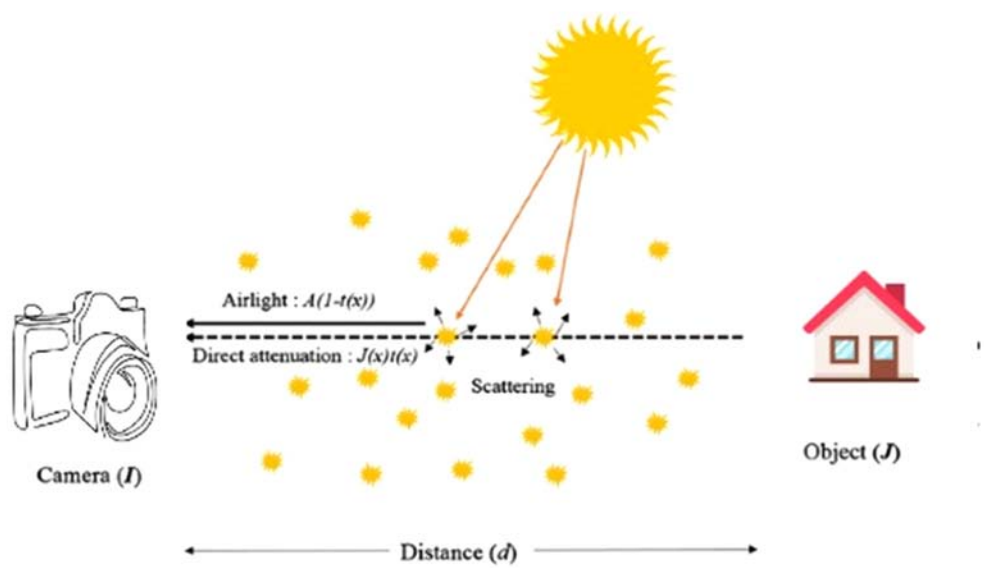

Fig. (1). Scatter Model of Atmosphere .

The scattering from the environment model is often used to explain the link between the hazy image I(x) and the clear image J(x) [3]:

$$I(x) = J(x)t(x) + A(1\text{-}t(x)) \quad , \tag{1}$$

Where x represents the spatial coordinates of the image, t(x) is the transmission map, A is the atmospheric light and $\otimes$ represents the element-wise multiplication.

The dark channel prior is a widely used heuristic for estimating the transmission map t(x) [4]:

$$t(x) = 1 - wmin(min\{min\{Ic(x')\}/A, \text{ for } x'\in\Omega(x)\}), \tag{2}$$

Where Ic(x') is the dark channel of the image patch centered at x', w is a weight factor, and Ω(x) is a local patch centered at x.

The guided filter is a popular technique for refining the transmission map t(x):

$$t(x) = mean\_a\{a(x) * I(x)\} / mean\_a\{a(x)\}, \tag{3}$$

Where mean_a represents the mean operation over a local patch, and a(x) is a guidance image that can be a smoothed version of the hazy image or a feature map.

Text identification in hazy images is also a typical task in computer vision that aims to improve the readability of text in hazy images. This task is challenging due to the presence of noise, blur, and distortion caused by the haze. Text identification in hazy images can be achieved using machine learning techniques, specifically deep learning, to attain the mapping between the image and the respective text. This can be used to identify text from hazy images with high accuracy and can be employed for a comprehensive range of applications, such as improving image quality, extracting important information from hazy images, and automating data extraction tasks [5].

The deep learning-based method for text identification in hazy images involves training a CNN to study the mapping between the hazy image I and the associated clear text T. This can be formulated as a supervised learning problem, where the CNN is trained to minimize the following loss function [6]:

$$L(I, T) = - \sum i=1\text{^}N (T\_i * \log(P\_i) + (1 - T\_i) * \log(1 - P\_i)), \tag{4}$$

Where N represents the number of text regions in the image, T_i is the ground truth label of the i-th text region (1 for text, 0 for non-text), P_i is the predicted probability of the i-th text region being text, and log is the natural logarithm. The CNN architecture can be designed using various techniques, such as residual connections, dilated convolutions, and attention mechanisms, to progress the enactment of text identification in hazy images. The architecture can also include pre-processing and post-processing modules, such as image enhancement and optical character recognition (OCR) engines, to further improve the accuracy and readability of the identified text, which is shown in Fig. (**2**).

CHAPTER 8

Deep Learning-based Word Sense Disambiguation for Hindi Language Using Hindi WordNet Dataset

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Abstract: This book chapter outlines an innovative approach to word sense disambiguation (WSD) for Hindi languages using deep learning. In natural language processing (NLP), WSD—which seeks to determine the precise meaning of the words within a specific context—is a crucial problem. The recommended approach learns and represents contextual word meanings using long short-term memory (LSTM) and convolutional neural networks (CNNs) capabilities of deep learning techniques. The huge Hindi WordNet dataset, which offers a wealth of semantic data on Hindi words, is used to train and assess the suggested method. Empirical findings show that the suggested methodology performs admirably on the Hindi WordNet dataset, outperforming a number of baseline techniques. This study showcases the latent deep learning techniques in addressing WSD challenges in the Hindi language, emphasizing the significance of leveraging semantic resources such as Hindi WordNet to enhance the efficacy of the NLP tasks in the domain of the Hindi language.

Keywords: Deep learning, Hindi language, Hindi wordNet, Natural language processing, Word sense disambiguation.

1. INTRODUCTION

The expanding demand for automated processing of human language data raised the need to seek attention towards NLP in recent years. WSD is a key difficulty in NLP that entails finding the appropriate meaning of a word within a certain situation like in any specified paragraph. For many NLP applications, including information retrieval, machine translation, and sentiment analysis, this task is essential. Due to the language's intricate morphology and vast inflectional system, Hindi, in particular, presents special challenges for word sense disambiguation [1]. Hindi, the fourth most spoken language in the world with over 600 million

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speakers, is significant in NLP research. However, development in this sector has been hampered by the absence of comprehensive resources and techniques for processing Hindi. This paper offers a deep learning-based strategy using the Hindi WordNet dataset to address the difficulties of WSD [2]. Hindi WordNet, based on the Princeton WordNet, serves as a valuable resource offering semantic relations, synonyms, and antonyms for Hindi words. By leveraging the rich semantic information provided by Hindi WordNet, the proposed approach aims to accurately disambiguate word senses in Hindi. For instance, considering the word "मेल" (mel), which can have multiple meanings depending on the context, such as "mail" or "meeting," performing WSD becomes crucial [3]. To determine the intended sense of "मेल" in a given context, surrounding words and the overall sentence context are analyzed. For example, in the sentence "मैं आज पत्र मेल के लिए पहुंचूंगा" (I will reach for mail today), "मेल" refers to postal mail, whereas in the sentence "आज की महासभा मेल बहुत सफल रही" (Today's meeting was very successful), "मेल" pertains to a conference or meeting. WSD is the process of determining the precise meaning of each word within a particular framework, and it calls for extensive word familiarity. Consider the following Hindi sentence's use of the term "स्वच्छ" (swachh) as you move closer to the approach [4, 5].

आज हर व्यक्ति पर्यावरण की बात करता है, प्रदूषण से बचाव के उपाय सोचता है। व्यक्ति स्वच्छ और प्रदूषण-मुक्त पर्यावरण में रहने के अधिकारों के प्रति सजग होने लगा है और अपने दायित्वों को समझने लगा है। वर्तमान में विश्व ग्लोबल वार्मिंग के सवालों से जूझ रहा है।

In this specific case, the most appropriate sense is sense 1, although sense 2 and 3 are also relevant shown in Fig. (**1**). WSD plays a vital role in NLP as it enhances the accuracy of automated language processing tasks [6, 7]. By utilizing deep learning techniques and semantic resources like Hindi WordNet, more precise and efficient models are possible to develop for WSD in the Hindi language. Polysemy, the phenomenon where words have multiple possible meanings, is prevalent in our everyday life [8, 9]. This is a challenging task for both the humans as well as computers. While ambiguity rarely poses a problem for humans during regular communication, extreme cases like newspaper headlines can be ambiguous and challenging even for humans to resolve. For instance:

Fig. (1). Senses of स्वच्छ obtained from the Hindi Wordnet.

"महिला एक छाता के साथ आदमी को मारा" can be interpreted as either “The woman hit a man with an umbrella” or “The woman hit a man who was carrying an umbrella.”

"आदमी दूरबीन के साथ लड़के को देखा" can mean “The man saw a boy with a telescope.”

"वे फ्रेंच, जर्मन और जापानी के शिक्षकों के लिए देख रहे हैं" can be understood as “They're searching for instructors who can teach French, German, and Japanese, or they're looking for instructors who can teach those three languages.

Computers, on the other hand, have trouble handling ambiguity in normal communication, especially under stressful conditions. For instance:

"आम आम आदमी की परिधि से बाहर है" can have two interpretations: “The mango is outside the circumference of an ordinary person” or “The ordinary person is outside the circumference of a mango.”

CHAPTER 9

The Machine Translation Systems Demystifying the Approaches

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Abstract: The world has many languages, each with its own unique structure in terms of vocabulary and syntax. With the rise of the Internet, communication between people from diverse cultures has become more common, necessitating the need for instantaneous translation. Since human translators cannot be available at all times for every language, the demand for effective automatic translation has grown, which should be cost-effective and immediate. Machine Translation (MT) systems aim to interpret one language into another by identifying and translating morphological inflections, Part of Speech (PoS), and word order according to the language's structure. MT is an interdisciplinary research field that combines artificial intelligence (AI), linguistics, and grammar engineering (GE), and has been around for almost five decades. Every language has its unique structure, consisting of phonemes, morphemes, lexemes, grammar, and context, along with semantics and pragmatics, which work collectively for effective communication. The Google Translate tool can translate over 100 languages in both directions. MT systems can be bilingual or multilingual, depending on whether they interpret a single pair of languages or more than one pair of languages. They can also be unidirectional or bidirectional, depending on whether they translate in one direction only or in both directions.

Keywords: Bilingual dictionary, Morphology, Machine translation, Natural language processing, Neural machine translation, PoS tagging, Rule-based and statistical machine translation, Reverse morphology, Word ordering.

1. INTRODUCTION

A spoken language is the most often and essential means of communication among human beings. Every individual in today's world interacts globally with many other individuals from diverse cultures, societies, economies, and professional domains. A single individual can learn at most a few languages

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besides his mother tongue. Hence, the need for an automated system arises to allow a person to communicate with other persons knowing different languages, and such a system is the one that is today known as a Machine Translation (MT) system.

Translation refers to the procedure of renovating a language into another language, and when it is done digitally through computing machines, it is called Machine Translation. Natural Language Processing (NLP) deals with solving problems related to natural language-based Human-Computer Interaction (HCI) by bridging the communication gap between monolingual humans who speak different languages through the translation of the base or source language (SL) into the aim or target language (TL) and vice versa. With the increasing use of the Internet, the need for instant language translation has emerged, and MT provides a lucrative and instantaneous solution [1, 2].

MT is an interdisciplinary subject that is almost 50 years old and combines linguistics, computer science algorithms, artificial intelligence (AI) techniques, and grammar engineering (GE). Generally, any language has five components *i.e.*, *phonemes (unit of sound), morphemes (root word), lexemes (set of modulated forms of root words), syntax (word ordering rules),* and *context (situational information)* that work together for effective communication along with grammar, semantics, and pragmatics. Over the years, the development of MT has evolved with different approaches, such as direct, rule-based, corpus-based, and artificial neural network (ANN)-based approaches. Nowadays, the focus is on hybrid MT systems that combine rule-based techniques with corpus-based techniques and deep learning (DL) approaches [3].

MT systems can be bilingual or multilingual and unidirectional or bidirectional. Bilingual MT systems interpret between a pair of languages, while polyglot or multilingual MT systems translate between more than one pair of languages, such as Google Translate.

The Google Translate tool can currently translate approximately 100 monolingual languages into other monolingual languages and vice versa but not code-mixed or code-switched languages [23]. AI researchers are interested in understanding how multilingual people mix codes meaningfully while taking into consideration the semantic and syntactic structure of a sentence [4].

Code-switching/mixing, the practice of mingling languages to form an expressive sentence, has become prevalent in today's multilingual societies. This involves the use of two or more distinct languages within a single utterance, which creates changes in the language's structure. The resulting language is called a hybrid or blended language, such as Hinglish, which blends Hindi and English, Cantonese-English in Hong Kong, Mandarin-English in Singapore and Malaysia, *etc* [5].

Code-switching typically involves a primary or mainstream language and a secondary or embedded language, where words or phrases from the secondary language are inserted into the primary language [6].

Code-switching is of two types [7]:

a. Inter-sentential, which involves switching language from one sentence to another

For example, "he came late aura fir so gaya (और फिर सो गया).

The above example is a switched sentence from English Language to Hindi Language.

b. Intra-sentential or code-mixing, which involves using two or more languages within the same sentence.

For example: *"vaha* (वह) *school (jAtA)* जाता *(hai)* है*".*

In this example, school is an English word that is placed in between Hindi sentences.

MT reduces the difficult task of paraphrasing or translating from one language to another automatically, which is secure and lucrative at the same time. Fundamentally, using a computer software system, a piece of text from one natural language (like Hindi) to another language (like English). Over the past decade, the advancement in the development of diverse systems for the translation of many languages has been made [8].

The involvement of human translators may be necessary at the stages of pre-editing or post-editing, *i.e.*, before or after the translation, but not during the translation stages. Due to globalization leading to the increase in cross-border communication and the growth of international industries, it has been understood that human translators are insufficient to meet the huge demand for inexpensive and quick communication across languages [9].

For any translation task to be performed, be it human or machine-based, the semantics of a text in the Source Language (SL) must be completely carried forward to the Target Language (TL). This may seem to be simple in the first instance, but it is much more complex in reality. The translation is much more than a simple replacement of words of one language to the words of other

CHAPTER 10

Machine Translation of English to Hindi with the LSTM Seq2Seq Model Utilizing Attention Mechanism

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Abstract: Machine translation uses Natural Language Processing (NLP) to automatically translate text across languages. Business globalization and the internet have made it more popular. Machine translation may be handy for rapidly comprehending foreign language content, but it is not always precise or dependable, particularly for complicated or idiomatic languages. The research presents a neural machine translation approach based on the sequence-to-sequence (Seq2Seq) architecture using Uni-LSTM and Bi-LSTM with and without attention mechanisms for translating English sentences into Hindi sentences. We investigated a variety of procedures for the construction of machine translation models, such as the Seq2Seq model and attention processes. We trained the model on a large parallel corpus of English-to-Hindi sentence pairs and evaluated it on a separate test set. The efficacy of our approach was demonstrated by the high level of BLEU score achieved, which was 14.76 by the Bi-LSTM with attention mechanism in contrast to the Uni-LSTM in translating an English sentence into a Hindi sentence. Our research endeavours to achieve a high level of performance in machine translation on the test set and. Our results suggest that the proposed Seq2Seq model with attention mechanisms is a promising approach for English-to-Hindi machine translation.

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Keywords: Bi-LSTM, NLP, Neural machine translation, Recurrent neural network, Uni-LSTM.

1. INTRODUCTION

English-to-Hindi translation can be challenging due to the differences between the two languages in terms of grammar, sentence structure, vocabulary, and writing systems. Hindi uses a different writing system, which is Devanagari, which makes it difficult. Moreover, Hindi has a complex verb conjugation system that varies depending on tense, gender, and subject. English, on the other hand, has a relatively simple verb conjugation system with only a few irregular verbs. The challenge of translating from English to Hindi is the different word order used in sentences. In Hindi, the subject often comes at the end of the sentence, while in English, the subject usually comes at the beginning. Additionally, there are many idiomatic expressions and cultural references in both languages that can be difficult to translate accurately. The translator must have a deep understanding of both languages and cultures to convey the intended meaning effectively.

NLP is an area of study that is expanding quickly and has a variety of potential applications. To effectively and promptly deal with the ever-increasing volume of natural textual data as well as the proliferation of textual data sources, many people believe that Artificial Intelligence (AI), and more particularly, the discipline of NLP, has essential aspects [1].

The term "machine translation" refers to the procedure of translating one language into another automatically *via* the use of a computer. English-to-Hindi translation can be performed using machine translation approaches. Machine translation uses computer algorithms to automatically translate text from one language to another [2]. There are several machine translation tools available online, including Google Translate and Microsoft Translator [3, 4]. Large volumes of multilingual material are analyzed by these technologies, which then create translations using statistical models like deep learning or neural networks [5]. The effectiveness of English-t--Hindi [6] translation depends on the specific approach used and the complexity of the text being translated. Machine translation is a complex and challenging task, and the quality of the translations produced by these systems can vary widely depending on the quality and quantity of training data, the design of the translation model, and the specific characteristics of the languages being translated.

With the help of the IIT Bombay English-to-Hindi Translation Dataset, the primary aim of this undertaking was the development of a translational model for the conversion of English to Hindi [6]. The dataset that IIT Bombay provided for language translation is a valuable resource for the NLP community. Our research showcases the practicality of constructing precise machine translation models using this dataset.

The data was preprocessed through the implementation of cleaning and tokenization techniques on the textual data. The focus of sequence-to-sequence learning, commonly referred to as Seq2Seq, is on models that receive a sequence as input and subsequently generate an output sequence [7]. A Seq2Seq model integrated with an attention mechanism was employed as the basis of our machine translation model. Numerous instances and implementations of this phenomenon exist; however, the present discourse shall concentrate on a particular application, namely, machine language translation. Neural machine translation (NMT) methodologies showed good efficacy in the perspective of English-to-Hindi translation assignments [8].

In general, the research we conducted adds to the expanding collection of literature on machine translation and showcases the capabilities of NLP in enhancing communication across different languages. The stated objectives of the research are as follows:

- The chapter elucidates the notion of machine translation and its employment of natural language processing for the purpose of automated translation.
- In order to translate English sentences into Hindi, the chapter provides a specific research approach focused on NMT employing the Seq2Seq architecture, Uni-LSTM and Bi-LSTM models, and attention mechanisms.
- The training of the model is described using a huge parallel corpus of English-to-Hindi phrase pairings, and the assessment of the model's performance is then carried out using a separate test set.
- The effectiveness of the proposed methodology is demonstrated through the presentation of the attained BLEU score of 14.76 for the Bi-LSTM model incorporating an attention mechanism as compared to the Uni-LSTM.
- The results of this investigation imply that the inclusion of attention mechanisms in the Seq2Seq model has the potential to facilitate machine translation from English to Hindi.

2. LITERATURE REVIEW

In the modern era, the science of NLP has paid a great deal of attention to the task of translating English language to Hindi. The creation of numerous machine learning (ML) models for this purpose has been made possible by the availability of large-scale, multilingual corpora. In this literature review, we talk about some of the well-known studies on English-to-Hindi translation.

CHAPTER 11

Natural Language Processing: A Historical Overview, Current Developments, and Future Prospects

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Abstract: The present era of information technology makes use of natural language—the language we use every day for communication—for human-computer interaction. Natural Language Processing, often known as NLP, has recently attracted a lot of attention because of the fact that it can computationally represent and analyze human language. It is currently applicable in a wide range of contexts, including machine translation, the detection of spam in email, the collection and summarization of information, the diagnosis and treatment of medical conditions, and the response to questions. The chapter delineates several phases of NLP and provides the background and development of NLP, and cutting-edge NLP techniques by showcasing the numerous NLP applications, current trends, and potential future directions.

Keywords: Applications of NLP, Natural Language Generation (NLG), Natural Language Processing (NLP).

1. INTRODUCTION

Natural Language Processing (NLP) teaches computers to read human language sentences and words. NLP began in the 1970s. Natural language processing was created to simplify users' lives and meet their need to converse with computers in natural language. This was done to fulfill natural language processing's dual purpose [1]. NLP is divided into two parts which evolve the process of understanding and producing text, as shown in Fig. (**1**).

Segmenting a word into its constituent morphemes and labelling them according to their morphological category is called morphological segmentation. Using a description of the text's linking parts, Named Entity Recognition (NER) may pick

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out proper names in a stream of text. OCR technology allows for the identification of the corresponding with relative ease. Tagging words as belonging to different parts of speech helps define how they function inside a sentence. Despite their obvious and close interdependence, NLP tasks are frequently used for the sake of convenience. In order to handle more complex problems, smaller activities such as automatic summarization and co-reference analysis are necessary.

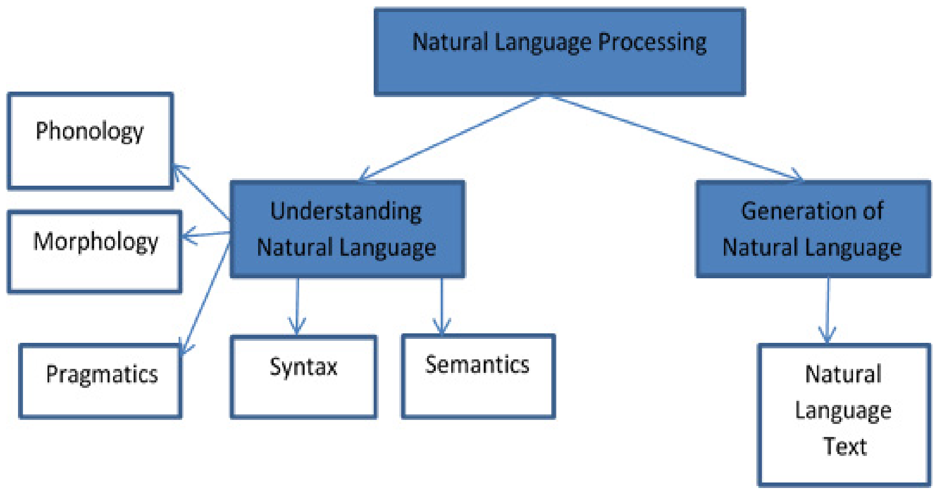

Fig. (1). Different Categories of NLP.

One or more of the algorithmic or systemic foci can find a home in natural language processing. The system comes equipped with a suite of premium Natural Language Processing (NLP) modules suitable for use with several languages. Modules for both simple and advanced NLP operations, such as temporal normalization, semantic role labelling, and cross-lingual named entity linking, are included in the pipeline. With this multilingual structure, you can understand what happened and why, who was involved, where you were, and how long ago it was. Modular design allows for flexible deployment and numerous permutations [2].

Although computer scientists have been the primary researchers in natural language processing, other academics from linguistics, psychology, philosophy, *etc*., have shown interest. One of the most interesting things about NLP is the irony of its addition to our knowledge of human language. NLP is a field that studies and develops solutions to the problem of translating human language into computer code. Ambiguity is a major problem in natural language and is often addressed at the syntactic level in the study of individual words and how they are put together. Understanding the full statement is necessary for answering questions that may arise at any of these stages. There are a number of methods that can be utilized to clear up the confusion [3]. Several methods, some of which perpetuate ambiguity, have been proposed by researchers to clarify things [3 - 5].

2. LEVELS OF NLP

The 'levels of language' are one of the most illustrative ways to portray NLP, as shown in Fig. (**2**).

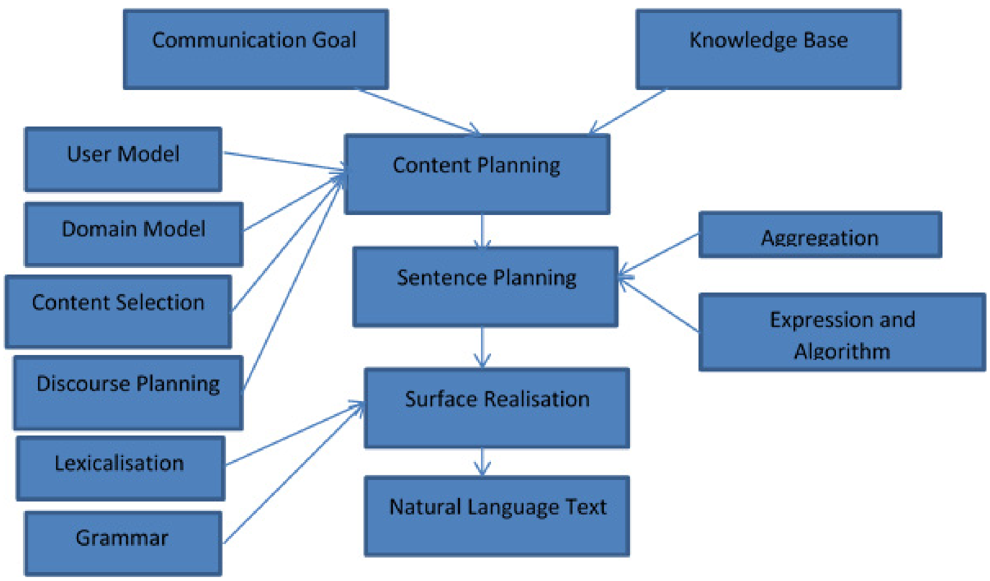

Fig. (2). Different Phases of NLP.

The study of language and how it is used in different contexts and by different people is known as linguistics. NLP jargon includes the following terms and concepts:

- Phonology: Phonology, in linguistics, is the study of how speech sounds are arranged systematically. The prefix phono- means "voice" or "sound," and the suffix -logy means "word" or "speech," hence the word "phonology" originates from Ancient Greek. According to Nikolai Trubetzkoy (1993) and Lass (1998), phonology is "the study of sound as it relates to the system of language," but "phonology proper is concerned with the function, behavior, and organization of sounds as linguistic items," which provides a clearer definition. Semantic encoding of meaning *via* sound occurs in all human languages [6].
- Morphology: The numerous components of a word are responsible for conveying a particular morpheme, which is the smallest unit of meaning.

CHAPTER 12

Recent Advances in Transfer Learning for Natural Language Processing (NLP)

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Abstract: Natural Language Processing (NLP) has experienced a significant boost in performance in recent years due to the emergence of transfer learning techniques. Transfer learning is the process of leveraging pre-trained models on large amounts of data and transferring the knowledge to downstream tasks with limited labelled data. This paper presents a comprehensive review of the recent developments in transfer learning for NLP. It also discusses the key concepts and architectures of transfer learning, including fine-tuning, multi-task learning, and domain adaptation. The paper also highlights the challenges of transfer learning and provides insights into future research directions. The analysis presented here has significantly improved the performance of NLP tasks, particularly in tasks with limited labelled data. Furthermore, pre-trained language models such as BERT and GPT-3 have achieved state-of-the-art performance in various NLP tasks, demonstrating the power of transfer learning in NLP. Overall, this paper provides a comprehensive overview of the recent developments in transfer learning for NLP and highlights the potential for future advancements in the field. However, the challenges of domain adaptation and dataset biases still need to be addressed to improve the generalization ability of transfer learning models. The analysis also leaves room to investigate transfer learning in low-resource languages and to develop transfer learning techniques for speech and multimodal NLP tasks.

Keywords: GPT, Multimodal NLP tasks, Natural learning processing, Pre-trained models transfer learning.

1. INTRODUCTION

Natural Language Processing (NLP) is a subset of Artificial Intelligence that focuses on the interconnection between computers and human language. The goal of NLP is to enable computers to analyse and produce natural language, which is a challenging task. Transfer Learning is a technique that has revolutionized NLP

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in recent years. Transfer Learning allows the transfer of knowledge from one task to another, which can significantly minimize the amount of labelled information required for training.

Machine learning has become a popular choice for Natural Language Processing (NLP) [1] tasks due to the huge and exploratory nature of natural language. For instance, SVM, Naive Bayes, and random forests have been applied for generating sentiment analysis, spam detection, and hate speech detection. However, for Natural Language Generation (NLG) functions like machine translation, question-answering, and abstractive outline models such as the Transformer and Seq2Seq architectures have been employed. Two significant breakthroughs that have had a significant impact on the NLP and NLG domains are Transfer Learning and Language models' rapid performance improvements. Therefore, before moving further, it is essential to discuss these concepts. Language modelling is a fundamental function in natural language processing that involves foreseeing the next term in a sequence based on the context of the previous words. To accomplish the task, a language model must be able to understand the distinctions and relationships among various words in the language. To evaluate the performance of language models, researchers commonly use benchmark datasets such as the Wikitext dataset, BookCorpus dataset [2], and 1B word dataset. A widely used metric for assessing the accuracy of language models is perplexity, which is calculated by taking the inverse possibility of the predicted term sequence. Perplexity is a measure of how well a language model can envisage the succeeding word in a sequence based on the previous words. It is calculated using the cross-entropy forfeiture between the predicted probabilities and the actual probabilities of the next word in the sequence.

The formula for perplexity is:

Perplexity = 2^H

Where H is the cross-entropy loss, which is calculated as follows:

$$H = -\frac{1}{N} * \sum(\log_2(p(x_i))) \quad \textbf{(1)}$$

Where N is the total number of terms in the test set, $p(x_i)$ is the possibility assigned by the language model to the i^{th} word in the test set, and Log_2 is the logarithm with base 2.

Language models with minor perplexity are generally considered to perform better as they indicate lesser entropy in the generated text. Language modelling is applied in various NLP functions, such as checking linguistic acceptability, text auto-completion, and next-word prediction. The idea of semi-supervised learning in NLP helps to explain how language modelling has occupied a fundamental role in different manners that enable transfer learning in NLP. Transfer Learning is a technique in which a model is trained on one task and then used for another task. In NLP, transfer learning comprises pre-training a model on a big corpus of text and then fine-tuning it on a specific acceptable task. The pre-training phase involves training a model on a large amount of unlabeled data to learn general language representations. The fine-tuning [3] phase contains adjusting the pre-trained model to a specific task by training it on a small amount of labelled data. This technique has been very successful in NLP, as it has significantly reduced the amount of labelled data required for training.

2. KEY CONCEPTS AND ARCHITECTURES OF TRANSFER LEARNING

2.1. Fine-tuning: Adapting Pretrained Models to Specific Tasks

Fine-tuning is a crucial technique in transfer learning, allowing pre-trained models to be adapted to specific tasks or domains with limited labelled data. It involves taking pretrained data, when trained on an extensive dataset for a general operation such as language modelling, and updating its parameters on a target task using task-specific data [4]. This process enables the model to learn operation-specific features and enhance performance in the target sphere. Fine-tuning has become a cornerstone in many state-of-the-art natural language processing (NLP) applications.

The process of fine-tuning typically involves the following steps:

1. **Pre-training:** Initially, a huge dataset using an unsupervised or self-supervised task, such as predicting the next word in a sentence or reconstructing a corrupted input. This pre-trained model learns useful representations capturing the semantic and syntactic aspects of language. It starts with a pre-trained model that has learned patterns and representations from a source domain and then adapts it to a target domain.
2. **Task-specific Dataset:** A task-specific dataset is collected or created for the target task. This dataset consists of labelled examples that are relevant to the specific task at hand, as shown in Fig. (**1**). By fine-refinement or retraining the model on the target data, it learns to generate new data that resembles the target sphere while retaining the learned knowledge from the source domain. For

CHAPTER 13

Beyond Syntax and Semantics: The Quantum Leap in Natural Language Processing

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Abstract: QNLP is a quite new and emerging field of inquiry that aims to utilize the principles of quantum computing to achieve NLP tasks. QNLP aims to enhance the accuracy of natural language processing by utilizing the quantum properties of matter known as superposition, interference, and, most importantly, entanglement. This book chapter introduces the basics of QNLP, including a brief overview of concepts used in quantum computing and techniques of NLP. We have explored the potential benefits of QNLP, such as faster and more accurate processing of natural language data. We also examine the challenges and limitations of QNLP, such as the need for quantum hardware and the integration with classical NLP techniques. In addition, this chapter covers recent advances in QNLP, including quantum algorithms for language modeling, machine translation, and sentiment analysis. We also discuss the development of hybrid quantum-classical algorithms and the potential applications of QNLP in industry and academia. Overall, this chapter provides a comprehensive overview of QNLP and its potential to revolutionize natural language processing.

Keywords: Compression, Machine translation, Natural language processing, Syntax and semantic rules, Quantum natural language processing.

1. INTRODUCTION

NLP has become an essential component in the daily life of a large section of the population. Advanced tools like Apple's 'Siri', and Google Assistant and social media platforms like Facebook and Twitter have become almost indispensable. However, as the amount of natural language data continues to grow, traditional NLP techniques face significant challenges, such as computational complexity and scalability. QNLP has emerged as a promising solution to these challenges by utilizing the quantum properties of namely Superposition, Entanglement, and Interference for faster, more accurate processing. The emerging field of QNLP

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helps in solving NLP tasks using the techniques of quantum computing to enhance the efficiency and accuracy of natural language processing.

This book chapter aims to provide an introduction to the basics of QNLP and the recent advances in the field. We will begin by discussing the basics of quantum computing and natural language processing, followed by an exploration of the potential benefits of QNLP. We will also examine the challenges and limitations of QNLP and discuss recent advances in QNLP, including quantum algorithms for language modeling, machine translation, and sentiment analysis.

Further, we discuss the development of hybrid quantum-classical algorithms and a few potential applications of QNLP in industry and academia. We will also highlight some of the technical challenges that need to be addressed in the development of QNLP, such as the need for quantum hardware and noise and error correction.

One of the recent developments in the field of QNLP is the use of quantum algorithms for language modeling. For instance, the Quantum Language Model (QLM) is a quantum algorithm that uses the principles of quantum mechanics to efficiently represent and process natural language data. The QLM has shown promising results in language modeling tasks, such as text completion and sentiment analysis.

Another recent development in QNLP is the use of quantum algorithms for machine translation. The Quantum Machine Translation (QMT) algorithm is a quantum computing-based approach to machine translation to improve translation quality and reduce computational complexity. The QMT has shown promising results in several languages, including English, Chinese, and Japanese.

Overall, this chapter will provide readers with a comprehensive understanding of QNLP, its potential benefits, and the recent advances in the field. By the end of the chapter, readers will have gained knowledge of the latest developments in QNLP and how they are transforming the field of NLP.

The main contributions of the chapter are:

- An introduction to quantum computing.
- A friendly introduction to QNLP.
- A detailed survey of multiple methods that may be suitable to take on challenges faced by classical natural language process methods.
- Quantum-hybrid methods and their uses.
- Quantum language models (QLM) and recent advances in QLM.
- Quantum Machine Translation.

- Concluding remarks.

2. BACKGROUND: APPLICATIONS OF QUANTUM COMPUTING AND QNLP

The recent achievements in quantum computing are predicted to lead to ground-breaking advancements in various domains, including cryptography, optimization problems, drug discovery, and materials science. Quantum computing utilizes the properties of quantum mechanics to carry out computations that would be impractical for traditional computers. Although the field is still in its initial phases, recent progress has demonstrated encouraging outcomes [1].

Cryptography is a significant application of quantum computing. It is estimated that quantum computers have the potential to break traditional cryptographic algorithms *e.g*., RSA. In this context, cryptographic techniques such as lattice cryptography are slated to withstand attacks from quantum computers. These techniques utilize the unique properties of quantum computing to create algorithms that are resistant to quantum-based attacks, ensuring the security of communications and data in the future. Optimization problems represent another domain where quantum computing holds immense potential. Various real-world challenges, including logistics optimization, portfolio optimization, and resource allocation, require identifying the optimal solution from a large pool of possibilities. Classical computers often face difficulties in handling these intricate optimization problems as the computation time exponentially increases with problem size. However, quantum computing offers more efficient solutions through techniques like the Quantum Approximate Optimization Algorithm (QAOA) and Quantum Annealing. These advancements have the potential to revolutionize areas such as supply chain management, financial modeling, and resource planning by significantly enhancing efficiency and effectiveness [2].

In addition, quantum computing has profound implications for the field of Artificial Intelligence and Machine Learning (AI/ML). Quantum Machine Learning (QML) algorithms, such as quantum-support vector machines and quantum-neural networks, have been suggested to improve tasks like pattern recognition, data clustering, and optimization. These advancements in QML have the potential to revolutionize the capabilities of AI/ML systems by enhancing their ability to handle complex and large-scale data sets, leading to improved accuracy and efficiency in various applications. These new techniques can provide more efficient and accurate solutions for complex AI problems [3], leading to advancements in different fields, including image/speech processing and adaptive control systems. The most recent application of these techniques is generative machine learning [4], including music generation [5].

CHAPTER 14

Text Extraction from Blurred Images through NLP-based Post-processing

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Abstract: Text extraction from blurred images is a difficult task in the field of computer vision. Traditional image processing methods often fail to accurately extract text from images with low resolution or high levels of noise. In the last few years, NLP techniques have been applied to improve the accuracy of text extraction from blurred images. This book chapter explores the use of NLP-based post-processing techniques to improve the quality of text extraction from blurred images. The chapter first provides an overview of traditional text extraction methods and the challenges associated with extracting text from blurred images. It then discusses the use of NLP techniques for improving the accuracy of text extraction. The chapter also explores the use of machine learning algorithms, such as convolutional neural networks, to enhance the performance of NLP-based post-processing techniques. Finally, the chapter provides a case study demonstrating the effectiveness of NLP-based post-processing techniques in improving text extraction from blurred images.

Keywords: Blurred images, Text extraction, NLP-based post-processing.

1. INTRODUCTION

1.1. Overview of Text Extraction From Blurred Images

Text extraction from blurred images is the process of extracting text from images that have been distorted or degraded due to blurring. This can occur due to various factors such as motion blur, low image resolution, or camera shake [1]. Blurred images can make it difficult or impossible to read text, which can be a significant obstacle when attempting to extract information from such images. Text extraction from blurred images can be useful in various fields, such as forensics, document analysis, and image-based search engines. However, it can be a challenging task due to the complexity of the blurring and the resulting degrada-

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dation of the image quality. Effective text extraction from blurred images typically involves a combination of image processing techniques and optical character recognition (OCR) software to enhance the image quality and accurately recognize the text [2]. Text extraction from blurred images can be a challenging task as the blurriness can cause the text to become difficult to read or even completely illegible. However, there are various techniques and tools that can be used to extract text from such images [3]. One approach to extracting text from blurred images is to use image processing techniques to enhance the image and make the text more readable [4]. This can include techniques such as deblurring, denoising, and sharpening [5]. These techniques can be applied using various image-processing software tools, such as Adobe Photoshop, GIMP, or ImageMagick [6]. Another approach is to use optical character recognition (OCR) software to automatically recognize and extract text from the image. OCR software works by analysing the image and identifying patterns that correspond to text characters. This approach can be effective for extracting text from both blurred and clear images, although the accuracy of the OCR may be lower for blurred images. In some cases, it may be necessary to combine these approaches by using image processing techniques to enhance the image before applying OCR software to extract the text. Additionally, it may be helpful to adjust the settings of the OCR software to optimize its performance for blurred images [7]. An OCR pipeline is shown in Fig. (**1**). An OCR pipeline typically involves a series of steps to extract text from the input image or document.

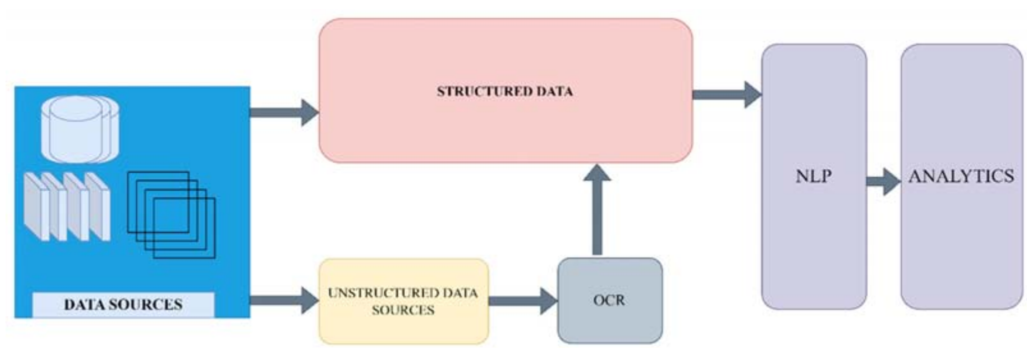

Fig. (1). OCR Pipeline.

1.2. Traditional Image Processing Techniques for Text Extraction

Traditional image processing techniques can be used to extract text from blurred images by enhancing the image quality and making the text more legible. Some common image processing techniques used for text extraction from blurred images include -Text extraction from images plays a crucial role in various applications, such as document analysis, optical character recognition (OCR), information retrieval, and more [8]. Traditional image processing techniques provide a foundation for extracting textual information from images by employing a series of well-established steps. The process begins with preprocessing, where the image is enhanced to improve text readability. Techniques like noise reduction, contrast adjustment, and brightness correction are applied to optimize image quality. Following preprocessing, the image is often binarized, converting it into a binary format consisting of black and white pixels. This step separates the text from the background, making subsequent analysis easier.

Text localization is a critical step in extracting text regions within the image. Various methods can be employed, such as edge detection, which identifies the edges of text characters, and connected component analysis, which identifies connected regions and analyses their properties [9]. Additionally, stroke width transform can be used to detect regions likely to contain text by analysing stroke width variations. Once potential text regions are identified, text segmentation techniques are applied to isolate individual characters or groups of characters. Morphological operations, such as dilation and erosion, refine the text regions and separate them from non-textual elements. Contour analysis is often utilized to extract individual text characters by detecting and analysing contours within the text regions. Optical Character Recognition (OCR) is a vital component of text extraction. It involves feature extraction, where relevant features like shape, texture, or statistical properties are extracted from the segmented text regions [10].

These features are then classified using machine learning or pattern recognition techniques into specific characters or words. The final step in OCR is text recognition, where the recognized characters or words are converted into machine-readable text. Post-processing techniques are typically applied to refine the extracted text [11].

This may include text correction to rectify any errors introduced during the OCR process, such as spell-checking or context-based corrections. Text extraction involves arranging the recognized text in the correct order and format, preserving the original structure and layout if necessary. While traditional image processing techniques have been widely used for text extraction, it is important to note their limitations. These techniques may struggle with complex or degraded images, leading to lower accuracy. More advanced techniques, like deep learning-based approaches, have emerged as powerful alternatives, offering improved performance on challenging text extraction tasks. Overall, traditional image processing techniques provide a foundation for text extraction from images and have been instrumental in numerous applications. They serve as a starting point for understanding the fundamental steps involved in extracting text and continue

CHAPTER 15

Speech-to-Sign Language Translator Using NLP

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Abstract: Communication plays a vital role in people's life and is regarded an important skill in life. A large number of people with speech and hearing impairment in our country use Indian Sign Language (ISL) as their primary mode of communication. Sign language is a non-verbal communication system in which people communicate by only using their visual sign patterns to express their meaning. Sign language serves as the primary mode of communication for individuals with speaking and/or hearing disabilities. However, due to limited proficiency in sign language among a substantial portion of the population, the Speech to Sign Language Translator emerges as a potential solution for effective communication among those unfamiliar with sign language. This translator employs machine learning techniques and a trained dataset to convert text and speech input in English into expressive actions and gestures of the standard Indian sign language, as performed by an animated avatar on the webpage [1]. The audio-to-sign language translator utilizes natural language processing techniques implemented in Python, employing machine learning algorithms for model training, and leveraging full-stack development technologies to construct the web page interface and embed the trained model. This tool offers convenience and real-world interpretability, enabling more efficient communication with individuals lacking sign language fluency. Future advancements can enhance this technology to support multiple languages worldwide, enabling the translation of text or speech into their respective sign languages. Consequently, the Sign Language Translator functions as a communication tool and assumes the role of a comprehensive 'bilingual dictionary webpage' for individuals with speaking or hearing disabilities.

Keywords: Lemmatizing, Natural language processing, Sign language translator, Speech-to-sign language.

1. INTRODUCTION

Sign Language is a visual language primarily used by people with hearing or speech impairments to communicate with each other as well as everyone. The language consists of hand gestures, facial expressions, and body movements to

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convey the message to the listener. Like any spoken language, it has its own grammatical rules and syntax. There are several sign languages used around the world. According to the Indian Census of the year 2011, around 2.9 million people in India have speech/hearing disabilities [2]. But the challenge arises when people with speech or hearing disabilities communicate with people who do not know or are not fluent in any standard sign language. This difference often creates a barrier to communication. To provide ease of understanding and communication to all, the Speech to Sign Language translator could be of great use. Speech-t--sign language translator is a web application tool that translates a user's speech/text in English to standard Indian Sign Language [3]. This translator is implemented into a webpage that can be accessed using any web browser. The basic functionality of this tool is to receive user input in the form of speech, convert it into text or string format, understand the input using Natural Language Processing technique, and enact the input in the form of sign language gestures, which is done by an animated avatar shown on the same web page window. Fig. (**1**) shows the block diagram of the working of Speech to Sign Language Translator.

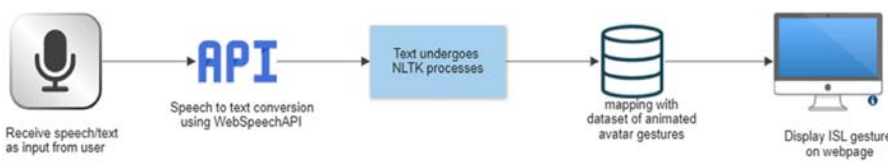

Fig. (1). Block Diagram of Speech to Sign Language Translator.

The core technologies employed in the development of this web-based tool encompass various aspects. Full-stack web development is utilized to create the user interface (UI) of the webpage, incorporating HTML, CSS, and JavaScript. This approach ensures the functionality and integration of the sign language gesture dataset within the webpage. The animated character, responsible for enacting the converted speech input into gestures, is generated using graphics software. Additionally, the same graphics software is leveraged to construct a comprehensive dataset encompassing all the sign language gestures. For this purpose, Blender 3D, a graphics software tool, is employed in this project. Natural Language Processing (NLP) plays a crucial role, enabling machines to comprehend and interpret human language. The translator capitalizes on NLP techniques to convert speech or text inputs into textual representations. To identify the parts of speech within the input text and map them to corresponding sign language gestures, the Natural Language Toolkit (NLTK), a Python library, is employed. Thus, the combination of full-stack web development, graphics software tools, and NLP techniques contributes to the realization of this innovative tool.

2. METHODOLOGY USED

In this section, we explore various methods and concepts required for the desired system. The primary task is to detect the audio from the user as input which can be implemented by using a speech recognition technique. The next approach is to build a Graphical User Interface (GUI), which is simple and user friendly.

2.1. Methods and Techniques

a. **Speech Recognition:** It is the sub-domain of computer linguistics and the ability of the machine to identify and translate a spoken language as an input in the text format. For example, Google speech-to-text enables developers to convert audio to text by applying Natural Language processing in easy to use API. This can be achieved by using web speech API. The text-to-speech synthesis feature of the API is responsible for converting text into audible speech, while the speech recognition feature facilitates the conversion of spoken words into text. The Web Speech API has two parts: Speech Synthesis (Text-to-Speech) and Speech Recognition (Asynchronous Speech Recognition.)
b. **Back-end Development:** The back-end development process entails the utilization of server-side technologies, with Python being a prominent example. It encompasses tasks such as managing user audio input, converting it into text format, and employing natural language processing techniques to transform the text into sign language gestures. To achieve this, the JavaScript Web Speech API and the Natural Language Toolkit (NLTK) Python library [4] are employed.

Specifically, the Web Speech API is employed to convert the input audio into text format. Subsequently, the converted text undergoes a Natural Language Processing (NLP) pipeline to yield the desired outcome, which involves translating English into Indian Sign Language.

a. **Database Integration**: To enable speech-to-sign language translation, the translator relies on a comprehensive database containing pre-recorded sign language gestures for a wide range of words. This database comprises media clips featuring the animated avatar demonstrating sign language gestures for each individual word in the English language. These media clips are created using specialized graphic software tools. When translated, the clips are played to visually represent English words and sentences through corresponding sign language gestures.

CHAPTER 16

Speech Technologies

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Abstract: Speech technology is a research area and is used in biometrics to identify individuals. To understand it totally, we need to look at how the process of speaker recognition and speaker verification is carried out. Feature Extraction from the speech is used to train models, which are further used for verification of the voice. In modelling and matching a number of models such as NLP, the Hidden Markov Model, Neural Networks and Deep learning are used. Text-dependent and Text-independent are two techniques of speaker verification. Speech parameters can be found by Linear Predictive Coding (LPC) Discrete Fourier Transforms and Inverse Discrete Fourier Transforms. Mel Frequency Cepstral Coefficients (MFCC) are used for calculations. In addition, we aim to see how key concepts of text-based comparisons and interactive voice response systems are incorporated. This field also involves how the speech is synthesized and analyzed. Speech technology is used in diverse applications such as forensics, customer care, health care, household jobs, GPS navigational systems, AI chatbots, and law courts.

Keywords: Interactive voice response, Speech analytics, Speaker recognition, Speech synthesis, Speech to text conversion, Speaker verification.

1. INTRODUCTION

Speech Technologies is an extensive term that includes a range of technologies focused on processing, analyzing, and generating human speech. Speech Technology allows a computer to recognize, understand or analyze the words spoken by a human or recorded audio clips. Sound signals are converted into digital signals, which are further matched with the stored patterns to finally get the output. By processing signals, we can extract sound characteristics like frequency and noise, after which machine learning is used to identify and inspect those speech signals to get the result. Speech technologies power various fields like linguistics, signal processing, machine learning, and artificial intelligence to enable interaction between computers and human speech. These technologies

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leverage various fields like linguistics, signal processing, machine learning, and artificial intelligence to enable interaction between computers and human speech. Speech Technology is a vast area which consists of subareas as follows:

- Recognizing Speech
- Verifying Speech
- Speech to Text Conversion in real-time
- Interactive Voice Response (IVR)
- Synthesis of Speech
- Analytics of Speech

1.1. Application Areas of Speech Technology

- Speech Technology can be used in law courts to validate a person’s voice.
- Customer Care companies use speech-to-text conversions for support.
- Health Care services use speech technology to help blind patients.
- Household jobs can be done with personal voice assistants such as Amazon Alexa.
- In Automotive, Navigational systems such as GPS help drivers find their route to their destinations.
- In Sales, AI chatbots can answer queries instead of waiting for an agent to come.
- In Security, voice recognizers can be used as biometrics to let a person enter a building.

2. SPEECH RECOGNITION

For simple solutions, many speech recognition devices are accessible. For complex solutions, we rely on AI and Machine Learning. The evolution of responses takes place with AI and machine learning as they learn and grow. Fig. (**1**) shows the steps involved in speech recognition.

Speech Recognition is done in three steps [1]:

1) Speech Analysis
2) Feature Extraction
3) Modelling and Matching

2.1. Speech Analysis

The speech data consists of information that is unique to each person and, therefore, helps in speaker identification. It consists of the vocal tract, excitation source, and behaviour features. Suitable frame sizes are decided upon to segment the speech data into smaller units for further analysis.

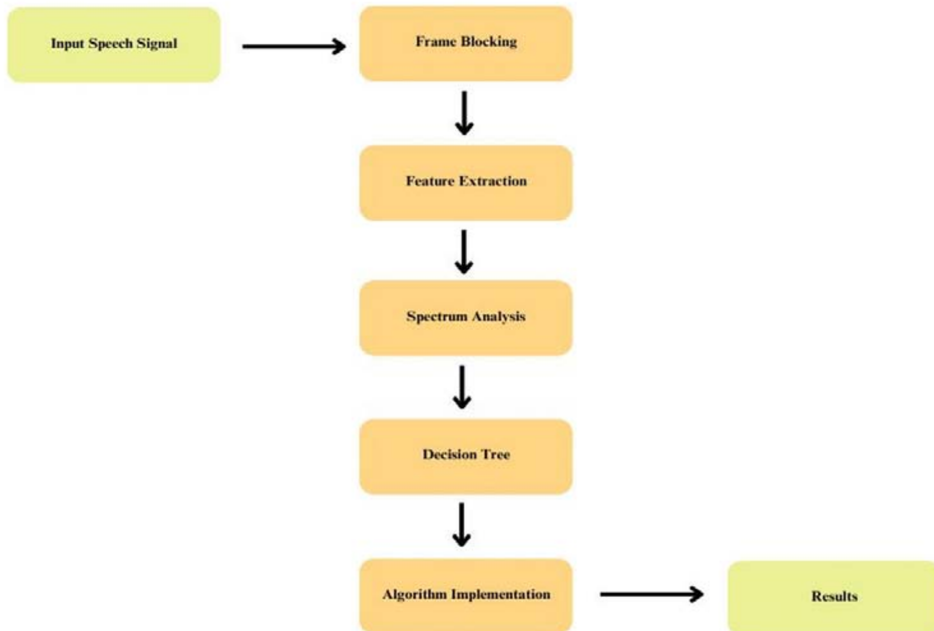

Fig. (1). The Flowchart of Recognizing Speech.

2.2. Feature Extraction

The speech parameters can be found by Linear Predictive Coding (LPC). In this technique, the sum of squared differences between real speech specimens and forecasted values determines a collection of predictor coefficients or parameters. The cepstral coefficients are found by transforming predictor coefficients. Fig. (**2**) shows how features are extracted in LPC.

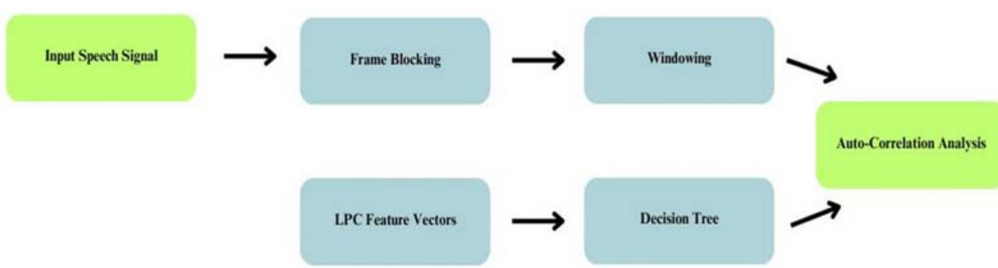

Fig. (2). The Flowchart of Extracting Features in LPC.

Mel Frequency Cepstral Coefficients (MFCC). This technique uses MFCC Vectors formed by each frame. Input speech signals undergo hamming codes in order to eliminate any discontinuous signals. After this, Discrete Fourier

CHAPTER 17

The Linguistic Frontier: Unleashing the Power of Natural Language Processing in Cybersecurity

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Abstract: This chapter provides a comprehensive exploration of the role of Natural Language Processing (NLP) in fortifying cybersecurity measures. As the digital landscape continues to evolve, the complexity and frequency of cyber threats have necessitated the integration of advanced, intelligent solutions. NLP, a subfield of artificial intelligence (AI) concerned with the interaction between computers and human language, presents a compelling methodology to enhance cybersecurity defenses. This chapter elucidates the multifaceted applications of NLP within the cybersecurity realm, providing a detailed examination of ten distinct areas, including but not limited to malware classification, social engineering attack detection, and predictive analytics for cyber threats. Leveraging NLP techniques, we posit that cybersecurity processes can be significantly optimized, bolstering rapid response times and amplifying the overall security posture. Furthermore, the chapter delves into the challenges that may arise in deploying NLP for cybersecurity, including data quality, domain-specific language intricacies, and ethical considerations. The discussion culminates in outlining potential future research directions, emphasizing the need for improved NLP algorithms, cross-domain integration, and the importance of adversarial NLP in maintaining robust security systems. This chapter serves as a guidepost in the journey toward an enriched cybersecurity framework powered by the linguistic capabilities of NLP.

Keywords: Adversarial NLP, Cybersecurity, Malware classification, Natural language processing, Predictive analytics, Social engineering attack detection.

1. INTRODUCTION

The advent of the digital era has spurred a significant transformation across various sectors of society, including communication, finance, health, and more. However, as digital interconnectedness grows, so does the potential for security breaches and malicious cyber activities. The escalating complexity of cyber threats necessitates the development and adoption of intelligent, sophisticated

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defense mechanisms. One such promising avenue is Natural Language Processing (NLP), a branch of artificial intelligence (AI) that bridges the gap between human language and computational understanding. This chapter will delve into the intersection of NLP and cybersecurity, illuminating how the former can be leveraged to strengthen the latter.

1.1. Natural Language Processing: An Overview

Natural Language Processing (NLP) can be described as the confluence of computational linguistics and artificial intelligence. It is a technology designed to analyze, understand, and generate human language in a valuable way. NLP encompasses several sub-disciplines, such as machine translation, sentiment analysis, named entity recognition, and more. These diverse capabilities allow for the development of complex applications, such as virtual assistants, real-time translators, and intelligent search systems.

The power of NLP lies in its ability to decipher the nuances and complexities of human language, thereby allowing machines to understand instructions, derive insights, and make decisions based on linguistic data. This is achieved through a combination of methods, including, but not limited to, statistical modeling, deep learning, and semantic understanding. While the promise of NLP is vast, it is not without its challenges, as language is inherently ambiguous, context-dependent, and continually evolving [1].

1.2. The Relevance of NLP in Cybersecurity

The pertinence of NLP to cybersecurity arises from the need to rapidly and accurately process vast amounts of unstructured data inherent to the field. Cyber threats are not only presented in the form of malicious code or suspicious network activities but are also embedded within the text in emails, forums, social media, and the dark web. With its ability to analyze and interpret language-based data, NLP provides a valuable tool to detect potential threats, streamline incident response, and aid in decision-making processes.

Moreover, NLP can be utilized to enhance user awareness and training, a critical aspect of any cybersecurity strategy. Through techniques like sentiment analysis and text classification, NLP can help identify social engineering attacks, such as phishing, thereby alerting users to potential threats. Additionally, NLP-powered chatbots and virtual assistants can provide interactive, personalized training to users, reinforcing their understanding of security best practices [2].

As we move forward, the integration of NLP into cybersecurity solutions will be pivotal in maintaining a robust and resilient digital infrastructure. This chapter aims to shed light on the various applications, challenges, and future directions of this promising interdisciplinary field.

2. APPLICATIONS OF NLP IN CYBERSECURITY

The expansive capabilities of Natural Language Processing (NLP) have propelled its applicability across a myriad of domains, including the field of cybersecurity. This section presents an overview of the multifarious uses of NLP within cybersecurity, focusing on the critical area of malware classification and detection.

2.1. Malware Classification and Detection

As cyber threats proliferate and evolve, the challenge of promptly identifying and categorizing malware has become increasingly paramount. Conventional methods often rely on signature-based and behavior-based detection techniques. While these methods have been effective in the past, they struggle to keep pace with the dynamic nature of modern malware, which often features polymorphic and metamorphic characteristics.

Natural Language Processing (NLP), with its ability to understand and generate human language, offers a novel, sophisticated approach to address this problem. NLP can be applied to the malware detection process by treating the code as a form of language. Disassembled malware, represented in assembly language, can be broken down into 'sentences' or 'documents' and processed using NLP techniques.

By leveraging the semantic and syntactic analysis capabilities of NLP, algorithms can be developed to classify malware based on the structure and patterns within the code. For example, the text-based representation of a malware's binary code can be analyzed using NLP techniques such as topic modelling, named entity recognition, or sentiment analysis to classify and detect malicious software.

Furthermore, NLP can be utilized to understand the comments and strings embedded within the malware, providing additional context and information about the threat. This approach, when coupled with machine learning algorithms, can enhance the detection process, enabling the system to identify new, unseen malware samples based on their similarity to known malware families [3].

While the application of NLP in malware detection presents a promising avenue, it also comes with its unique set of challenges. These include the need for large, labelled datasets for training, the handling of ambiguous and obfuscated code, and the need for continuous adaptation to the ever-evolving malware landscape.

CHAPTER 18

Recent Challenges and Advancements in Natural Language Processing

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Abstract: In a recent development, Natural Language Processing has gained tremendous momentum and is one of the important areas of data science. It is a subset of Artificial Intelligence that translates the human understanding of language into a machine-understandable form and supports to accomplish repetitive jobs such as summarization, machine translation, *etc*. The use of NLP has multiplied since the development of AI bots like Alexa, Cortana, Siri, and Google Assistant. Along with numerous advancements from major corporations like Google, NLP has seen improvements in accuracy, speed, and even strategies that are used by computer scientists to handle challenging issues. Here are some of the important trends projected to dominate in the coming years for Natural Language Processing. With the growing need and demand for Artificial Intelligence, Machine Learning is projected to play a vibrant role, particularly in text analytics. With the help of supervised and unsupervised machine learning, a more thorough analysis can be done in the near future. The use of social media can be seen as one of the major platforms for all companies to make their decisions and can take a very significant role in it. With the help of many NLP tools, the company can identify customer reviews, feedback, and responses on social media. NLP is also anticipated to increase in popularity in fields that require the ability to comprehend user intent, such as semantic search and intelligent chatbots. The abundance of natural language technologies is anticipated to survive to shape the communication capability of cognitive computing along with the expanding application of deep learning and machine learning.

Keywords: Artificial intelligence, Deep learning, Machine learning, Natural language processing.

1. INTRODUCTION

Language can be defined as the process of communicating between individuals. It is difficult for the user to know all the languages, but with the help of NLP, many problems can be sorted out. Natural Language Processing (NLP) serves those who

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do not have enough time to learn new languages or get perfection in communication skills [1]. Though the challenges of training the machine with different methodologies are difficult to address, continuous research in the area has given a significant boost to the implementation of NLP. The history of NLP, which started from the 1940s to till date, has seen a major paradigm shift in the field. NLP can be classified into two categories:1) Natural Language Understanding; and 2) Natural Language Generation. Natural Language Understanding (NLU) aids the computer in comprehending and analysing human language by removing metadata from the text, such as concepts, entities, keywords, emotions, relations, and semantic roles. NLU is used to map the given input into useful representation and analyze different aspects of language. As ML/AI has made a huge revolution in the current scenario, understanding, analysis and then its processing are the main application areas [2]. The process of translating computerized data into natural language representation is known as natural language generation (NLG). Text planning, Sentence planning, and Text Realisation are the three essential components. Natural language processing is a collection of methods that are used to remove grammatical arrangements and explanations from inputs to present convenient tasks, resulting in an NL generation building outputs based on target language regulations and the assignment at hand. In teaching systems, duplication identification, information-based command, and data collection interface areas, NLP is used as it offers a direction for improved interactivity and productivity. In recent years, research work in the NLP has been growing [3]. Many NLP systems use linear statistical models. The researchers have found ad-hoc features in it. There are some complexities leading to the system to optimize its performance on different NLP goals [4]. At the moment, NLP can analyze sentences without focusing on the individual word [5]. This chapter discusses the different aspects of NLP. Firstly, a brief history and the importance of NLP have been discussed. The second topic discusses the components and working process of NLP in detail. The third section discusses previous NLP and current now, and the fourth section discusses different NLP models and also the different challenges faced by NLP.

2. COMPONENTS OF NLP

NLP basically comprises two different components. They are: 1) Natural Language Understanding, 2) Natural Language Generation.

2.1. Natural Language Understanding

Natural Language Understanding (NLU) has the aim to make the machine understand our language, which is one of the biggest tasks. It helps analyze the different aspects of language and make them into valid representations. NLU is more difficult than NLG owing to different scenarios. It includes lexical ambiguity, syntactic ambiguity, and referential ambiguity. Table **1** lists the ambiguities in NLU.

Table 1. Ambiguities in NLU.

1) Lexical Ambiguity
2) Syntactic Ambiguity
3) Referential Ambiguity

- Lexical Ambiguity: It means that the word we pronounce may have many meanings into it. The tone at which we speak also resembles different meanings of it. For *e.g*., “Live” may relate to any sports activities going on or may relate to personal life.
- Syntactic Ambiguity: It resembles a sequence of words that can have more than one meaning to it. For *e.g*., “The man saw the tiger eating.” Now, the ambiguity is whether the tiger was eating its prey or the food given.
- Referential Ambiguity: It means that whenever we are referencing anyone, it may be to one individual or many. For *e.g*.: “Prem, Rajat, Gopi, Vicky, and Salman were fighting.” They killed Rajat. Now, the ambiguity is “they,” as it is not sure what ‘they’ is refering to.

2.2. Natural Language Generation (NLG)

It is the process of creating meaningful phrases and sentences from the given data. It includes three stages: text planning, sentence planning, and text realization. Stages in NLG are given in Table **2**.

Table 2. Stages in NLG.

1) Text Planning
2) Sentence Planning
3) Text Realization

- Text Planning: It is the process of extracting relevant knowledge from the data.
- Sentence Planning: It includes choosing the relevant words, forming the phrases and sentences, and setting up the tone for the sentences.
- Text Realization: It is the process of mapping sentence plans into sentence structure.

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