A SURVEY OF RECENT ADVANCES IN THE AUTOMATIC SPEECH TEXT GENERATION

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Umar Hussein[1]*, Emeka Ogbuju[2,3], Abraham Ayegba Alfa[4] and Francisca Oladipo[5]
[1]Department of Computer Science, Federal University Lokoja, Nigeria,
[2]Department of Computer Science, Federal University Lokoja, Nigeria,
[3]Department of Computer Science, Miva Open University, Abuja,
[4]Department of Computer Science, Confluence University of Science and Technology Osara, Nigeria,
[5]Department of Computer Science, Thomas Adewumi University, Oko, Nigeria,
***Corresponding author:** Email: hussein.umar-pg@fulokoja.edu.ng

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Abstract: NLG has been used in a variety of areas such as report generation, machine translation, information generation, and word summarization. These problems require the creation of long essays from short essays, which are very interesting and difficult. This requires strong thinking and reasoning skills that match human performance. The generation of macroeconomic news and short-term news was done through deep neural network techniques. Automatic text generation is important in natural language processing and artificial intelligence. Articles can be made to write stories, weather reports, and even poems. It is also important for machine translation, text summarization, query answering, and information systems. NLP relies on cognitive representation studies to understand how people communicate using patterns in language and text. The main goal is to create algorithms that can translate human language between machines and humans. In this article, the latest developments in document publishing and automated publishing from 2009 to 2022 were reviewed. As a result, the characteristics of the research area are said to have evolved significantly over time. Common datasets, methods, and capabilities of integration are discussed. Several research areas from various types of research were proposed to inspire future research in thematic areas, especially for essay writing. It is good to develop an effective NLP solution for producing essays, articles, publications, and future content. In particular, the most important applications are publishing articles, publishing political articles, formulating and marking test questions, robots, and conference reports.

Keywords: Political Speech, Text Generation, NLP

Introduction

In social relations, the mode of communication requires high competencies in the process of speech-making, which involves the exchange of thoughts in different scenarios. This entails the accurate use of language and norms of speech-making. Consequently, there is a poor quality of speech writing and public speaking presentation due to low thinking and creative capabilities as well as low quality (Saidjajalova, 2022). There is a consensus about low functional writing skills among people especially the younger population for social and personal expressions (Koross, 2022).

NLP can generate coherent semantically correct and meaningful text employing diverse applications including machine translation, dialogue generation, and image captioning. Traditionally, the majority of task-specific applications occur in supervised settings, and the generic unsupervised text generation (that is, target the distribution over real text from the corpus in more recent studies). Generating text by mimics of expressions of humans has been undertaken for poem generation, and image captioning (Guo *et al.,* 2018).

Topic-to-Essay Generation (TEG) tasks generate a fluent, topic-related, topic-integrate, and coherent text based on the topics provided. One similar task to TEG is poetry generation which is a type of sequence-to-sequence learning task. Conventional methods that utilize rules and templates can generate poems but are incapable of understanding the meaning of the text. Scholars are leveraging the neural network in poetry generation especially the Residual Neural Network (He & Rao, 2022).

The text-to-text generation of NLG has been applied in various fields such as report generation, machine translation, dialogue generation, and text summarization. These problems require that long texts be generated from short text, which is highly tasking and complex. This requires a high level of inference and reasoning capabilities that can match the efforts of humans. Macro financial report generation was carried out with short breaking news through the hybrid deep generative `neural network method (Ren *et al.,* 2021).

The quest to overcome the problem of human influence in speech production and text generation about historical preconditions and individual properties has been a serious area of research in recent years. Yergaliyeva *et al.* (2022) attempt to identify personal and textual script generation parameters for English and Kazakh political Internet commentary in virtual spaces to engage citizens in political interactions.

Automatic text generation is important in natural language processing and artificial intelligence. Text generation is applicable in writing comments, weather reports, and even poems. It is also essential to machine translation, text summarization, question answering, and dialogue systems (Wang, Qin & Wan, 2018). NLP relies on precise representation learning to understand how humans communicate using voice- and text-based patterns. Essentially, its ultimate goal is to create algorithms capable of interpreting human language and between machines and humans (De Rosa and Papa, 2021). Bach *et al.* (2018) introduced the Alibaba speech translation system that was built as part of the Speech Translation Task in IWSLT 2018. The task involved translating English audio to German text in which English audio is from lectures and TED talks. The backbone of the system employs a pipeline approach that includes an automatic speech recognition system (ASR) and a machine translation (MT) system (composed of fully-connected DNN (FDNN), time-delay deep neural network (TDNN), and latency-controlled bidirectional long short-term memory (BLSTM)).

Public speaking is considered a practice of assembling meaningful interpretations in specific scenarios. In political discourse, hermeneutic dimensions are often taken into account, which are the qualities of activity of assembling and re-assembling the meaning of a situation. Again, political discourse can be in the form of abstraction to the general domain of symbols and signs exchanges through rhetoric or devices, strategies, and techniques. In particular, speakers are expected to pay close attention to occasions' practical purposes, their specific conventions, and the audiences' character, which generally impact the proper organization of discourse (Martin, 2020). The problem of mispronunciation is a common phoneme sequence in real-work public speeches (Zhang *et al.,* 2022).

Though neural network-based models have demonstrated a high recognition rate, they consumed huge computational resources. Recently, several studies were proposed to avoid the neural network because of their inability to recognize rough sets and numerical feature extraction. To this end, the accuracy of textual information can be improved with higher-performing models such as RNN, Bi-LSTM, etc., which support sequence data at the character level (Mookdarsanit & Mookdarsanit, 2021).

The ability to generate coherent and semantically meaningful text plays a key role in many NLP applications such as machine translation, dialogue generation, image capturing, and text speech generation (Guo *et al.,* 2018). More so, there are still problems with generating long texts from short texts capable of matching human logic (Cho *et al.,* 2019; Ren *et al.,* 2021). The process of creating readable and coherent personalized text for a specific user is daunting. However, deep learning approaches are probable solutions (Navali *et al.,* 2019). This paper provides the following contributions:

i. to provide the trends in automatic text generation tasks.
ii. to provide insights into common datasets utilized for text generation problems.
iii. To construct taxonomy on NLP texts and speeches automatic generation
iv. To discuss the methods and strengths of automatic text generation tasks.
v. To highlight the research gaps and weaknesses in automatic text generation texts.

Natural Language Processing

In the past decades, the target of computer science and AI research has been Natural language generation. In the 1960s, the ELIZA (Weizenbaum, 1966) chatbot was developed by the MIT Artificial Intelligence lab for the simplest language processing tools, pattern matching, rules, and scripts. The ELIZA software agent was capable of interacting with humans effectively with human-like feelings and emotions. Several years later, NLG applications progressed beyond simple chatbot programs to human writing tasks such as weather, sports, and financial reporting, translation, patient healthcare summaries, and document summarization.

Generally, the NLG process involves a three-stage pipeline: document planning, microplanning, and sentence writing (Reiter & Dale, 2000). Usually, these systems utilize a huge set of complicated rules built by domain experts, that is, the creation of document plans using a knowledge base. Though, NLG systems are applicable in a highly constrained domain but are expensive to build and incapable of properly generalizing in other domains. Consequently, there is a need to build new systems and sets of rules for every new domain requiring writing tasks. It is a more amplified problem for sub-domains of the medical field which have special text formats, styles, and sub-languages. Recent NLG advancements are leveraging statistical and machine learning schemes to minimize the fragility of traditional NLG systems. Statistical systems are less expensive, easily adaptable, and have better coverage of the language features in the corpus; but, suffer from low coherence in the synthesized text, and high error rates (Brown, 2019).

The concept of automatic text generation came to common usage as a description of a computer-generated natural language based on a certain collection of data content. The NLG technology started in the 1970s (BrDotzillion, 1999). The template-based generation is the foremost deployment of text automatic generation technology. Then, the theory of RST (Rhetorical Structure) based solutions evolved including the schema generation technology (or schema-based generation) and phrases planning technology (phrase/plan expansion). Recently, text-to-text generation technology aims at converting any given text content into another text in the forms of sentence compression, summarization, sentence fusion, and text retelling (Y. Zhang, 2021). These concepts have been applied in diverse fields of information summarization, system dialog, news writing, and machine translation as illustrated in Figure 1.

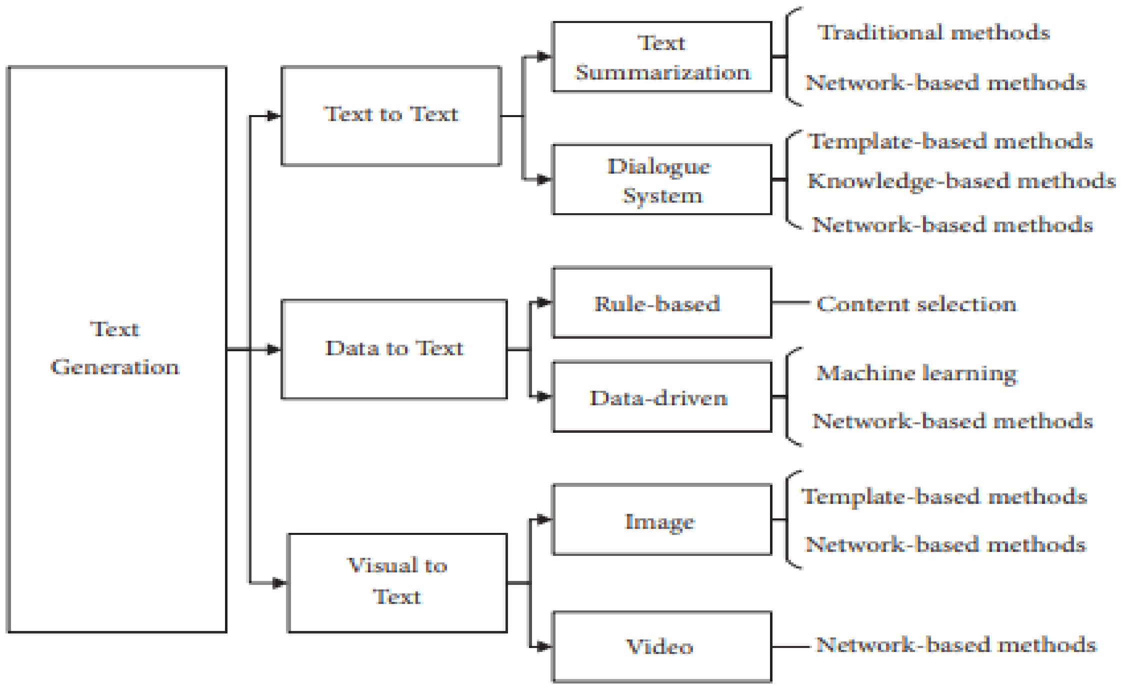

Figure 2.1: The methods for text generation (Zhang, 2021).

In Figure 1, the main descriptions of the text generation solutions are provided as follows:

Text Summarization utilizes computers to extract simple coherent text content from the original text, which can be fully and accurately expressed. The central idea of the whole text summarization can be classified into extractive and abstractive forms; the extractive form consists of important sentences in the original text, while the abstractive form consists of new sentences. In the original text, summary approaches, sentences are rated, sorted, and selected using word frequency, keywords, and sentence position (first and last sentence).

Knowledge-based models utilize an indexed dialog database and NLP technology to analyze the statements of the user and then perform fuzzy matching within the statement database to choose the response statements having the best matching degree. It is most applicable in question-and-answer systems entertainment chat. The knowledge base is easily expandable, but, a large amount of data reduces the context connectedness. Deep learning-based models are most effective for dialog generation because no template or knowledge base is needed. The end-to-end technology of deep learning takes advantage of organizational ability and directly learns natural language through a large amount of corpus. The synthesized texts are intelligent and flexible (Y. Zhang, 2021).

In the last five years, unsupervised pre-training and supervised fine-tuning have offered huge successes in NLP tasks. The language modeling methods and its variant have served as the pre-training task and task-specific parameters on labeled data (Wang, Zhao, Jia, Li, & Liu, 2019). The state-of-the-art performances have been significantly advanced for classification and sequence labeling tasks, such as natural language inference (Bowman et al., 2015), named-entity recognition, SQuAD question answering, etc. However, little attention has been paid to pretraining for seq2seq text generation. A typical seq2seq network consists of a bidirectional encoder, a unidirectional decoder, and attention between the encoder and decoder. Previous works considered either an encoder or decoder for the pre-training stage. Ramachandran et al. (2016) propose to train two independent language models for the encoder and decoder respectively. All of the aforementioned methods are only able to partially pre-train the seq2seq networks and therefore are unable to unleash the full potential of transfer learning for text generation.

Deep learning technologies are capable of generating realistic artifacts similar to genuine human-generated artifacts. Neural language models are inundated for realistic text generation. To this end, adversaries could capitalize on these technologies to generate realistic artifacts to trick naive users into fraudulent activities in case of machine-generated chatbot conversation in a phishing scam or deepfake-based disinformation campaign. The need to distinguish machine-generated texts from human-written ones naturally arises in what is known as the Turing Test. (Uchendu & Shu, n.d.) noted that a more critical solution may be identified NLG method among many candidates has generated a given text in question; that is, the Authorship Attribution (AA) problem.

Advances in Text Generation Tasks

The count of publications spread over the period starting from 2009 to 2022 revealed slow progress in long text generation research outputs, especially between 2009 – 2015. However, the research focus increased since 2016 with the highest trend observed in 2021 because of the advent of high-performance NLP approaches to simplify automatic text generation tasks. However, there is a sluggish pace in the area of correct and generative speech generations for political functions, which could be the most interesting area of research post 2022 periods. The graphical representation of the various research outputs from 2009 – 2022 is depicted in Figure 2.

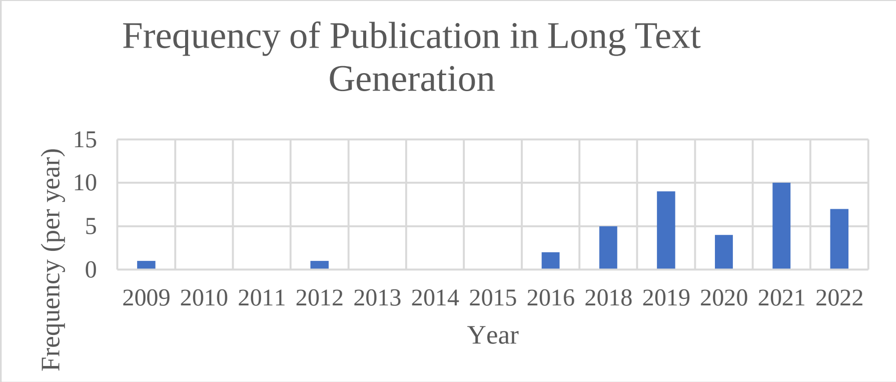

Figure 2. The counts of research outputs from 2009 – 2022.

Taxonomy of the text generation research

This paper created a taxonomy that summarises the key components of the various research endeavors from 2009 – 2022. At the root of the hierarchy is NLP which branched out into text generation and text detection. The hierarchy is further at the branch of text generation to automatic responses and fact-checking, long texts, and short text generations. While, the text generation branch breaks down into hate speech detection, sentiment analysis, and combating extreme political polarization. A further breakdown of the entire taxonomy construction is shown in Figure 3.

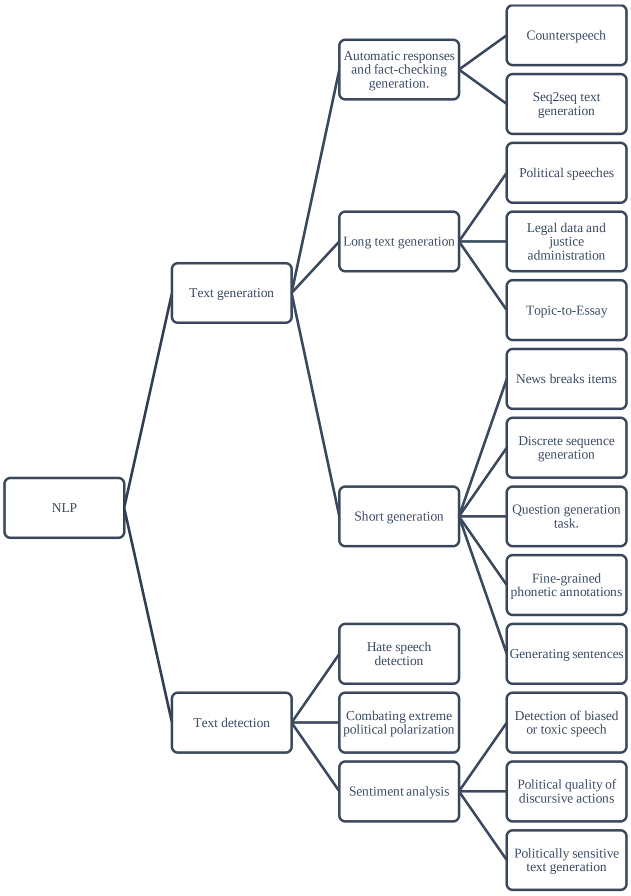

Figure 3. The taxonomy of research endeavours since 2009 – 2022.

Textual and Speech Datasets

The paper highlights the most commonly utilized datasets for different text generation tasks and automatic text detection problems reported in studies as presented in Table 1.

Table 1. Textual and Speech Datasets

S/No.	Author(s)	Name of Dataset
1.	Kassarnig (2016)	Covote
2.	Jonsson (2018)	Swedish Riksdag
3.	Navali, Kolachalam & Vala (2019)	Tweets
4.	Song & Shmatikov (2019)	Online services.
5.	Vo & Lee (2019)	The online social system
6.	Chan & Fan (2019)	SQuAD
7.	Brown (2019)	Corpus
8.	Beliaev, Rebryk & Ginsburg (2020)	LJSpeech
9.	Zhu & Bhat (2021)	Counterspeech
10.	Uchimoto, Sekine & Isahara (2021)	Monolingual corpus
11.	Ren et al. (2021)	News report dataset
12.	He & Rao (2022)	ZhiHu
13.	Zhang et al. (2022)	Data argumentation
14.	Khan et al. (2022)	Twitter DS1 and DS2
15.	Garcia-diaz et al. (2022)	PoliCorpus-2020

Methods and Strengths of Texts Generation Problems

The summary of key methods of text generation problems and matching strengths are presented in Table 2.

Table 2. The text generation methods and strengths.

S/N	Author(s)	Methodology	Strengths
1.	Dethlefs & Cuayahuitl (2009)	Hierarchical reinforcement learning	Learned generation policy with interdependencies.
2.	Konstas & Lapata (2012)	Probabilistic context-free grammar.	Identify deviations and rerank discriminations in local and global features.
3.	Kassarnig (2016)	n-grams, Justeson & Katz POS tag filter, RNN, and latent Dirichlet allocation.	High-quality grammatical correctness and sentence transitions
4.	Semeniuta, Severyn & Barth (2016)	Fully feed-forward convolutional and deconvolutional components with a recurrent language model.	Better handling of long sequences.
5.	Wang, Qui & Wan (2018)	RNN and VAE.	Learn the data distribution and emits the dissimilar data.
6.	Whitehead et al. (2018)	knowledge-aware video description network.	The generation procedure is guided by the event and entity types.
7.	Guo et al. (2018)	LeakGAN	Highly effective in long and short text generation and performance
8.	Kulgod, Patel & Ram (2018)	GANs variant with a CNN discriminator and RNN generator.	Effective for political speeches and Chinese poems generation.
9.	Jonsson (2018)	Cooperative training and adversarial training.	Quality and diversity of generated texts.
10.	Garten et al. (2019)	LSTM	Text meaning-based annotations tasks effectiveness.
11.	Li et al. (2019)	GANs	Effective over synthetic and real-world datasets.
12.	Bullock & Luengo-Oroz (2019)		Automated text generation for peace and political stability.
13.	Navali, Kolachalam & Vala (2019)	Context Free Grammars and Hidden Markov Models	83% precision was achieved.
14.	Song & Shmatikov (2019)	Black-box auditing.	Effectively detected particular users' texts were used.
15.	Vo & Lee (2019)	FCRGD model.	Combating fake news writers with formal and persuasive language.
16.	Wang et al. (2019)	Transformer and pointer-generator networks for PoDA.	Significantly speed up convergence.
17.	Chan & Fan (2019)	Pre-trained BERT language model.	BLUE 4 score obtained at 22.17 from 16.85.
18.	Brown (2019)	SynthNotes	Greater realism and variability in the generated notes.
19	Wu et al. (2020)	TransSent	High discourse transfer effectiveness for free text, and dialogue generation.
20.	Prabhumoye (2020)	Style transfer.	Sentence ordering of effective learning of structures.
21.	Pan et al. (2020)	Transfer learning is known as PoDA.	Abstractive summarization and low error.

22.	Beliaev, Rebryk & Ginsburg (2020)	TalkNet.	Work skipping and repetition reduced.
23.	Wu et al. (2021)	Knowledge dataset and network architectures.	Highly applicable for text generation applications.
24.	Uchendu et al. (2021)	GPT2, GROVER, and FAIR methods.	Generate high-quality human-mimicking texts.
25.	Zhu & Bhat (2021)	A three-module pipeline: Generate, Prune, Select for Counterspeech generation.	Highly effective in producing diverse and relevant counterspeech.
26.	Nguyen (2021)	Deep reinforcement learning algorithm.	Effective for reward functions.
27.	Zhang (2021)	Text generation technology in the legal field.	
28.	Liu, Jia & Vosoughi (2021)	GAN network.	3-10% improvements in flipping neutralizing rate.
29.	Uchimoto, Sekine & Isahara (2021)	Dependency trees.	Dependency information among words.
30.	Ren et al. (2021)	hybrid deep generative neural model (Revised VAE).	SOTA performance was obtained against both baseline models.
31.	Ji et al. (2021)	Hierarchical encoding–decoding mechanism.	Effective for generating a set of consecutive words.
32.	Re Rosa & Papa (2021)	Generative Adversarial Networks	GAN is best for continuous information (image) instead of discrete data (text),
33.	Yergaliyeva et al. (2022)	Statistical methods-based contextual materials.	Linguistic personological and linguocultural viewpoints.
34.	He & Rao (2022)	Transformer-based Hierarchical Topic-to-Essay Generation Model.	Captured long dependencies in texts and information relevance.
35.	Sridhar & Yang (2022)	Knowledge-informed encoder-decoder framework.	High-quality stereotypes in toxic speech generations.
36.	Zhang et al. (2022)	machine translation-based sequence paraphrasing model (L2-GEN).	Highly effective for unseen words and new learner population by 3.9%.
37.	Martin (2022)	Hermeneutic and rhetoric analysis of public speech.	- Interpretative force with calculative context and incalculable future. - Predictive of future scenarios.
38.	Khan et al. (2022)	HCovBi-Caps.	The deep learning approach performed at an accuracy of 93.00% to 90.00%. during training and validation.
39.	Garcia-diaz et al. (2022)	CNN, RNN trained with linguistic features and statistical features. Lexical, morphosyntactic, and stylometric features.	Political speeches can be profiled based on the lexical and personal traits of speakers' speeches.

Research Gaps

The paper outlines the different research gaps and subsequent research directions in the field of text generation and speech generation as shown in Table 3.

Table 3. Research gaps and future focus.

S/No.	Author(s)	Research Gaps
1.	Dethlefs & Cuayahuitl (2009)	Low availability of real datasets.
2.	Konstas & Lapata (2012)	Discourse-level documents uncovered.
3.	Kassarnig (2016)	Low accuracy of texts generated.
4.	Semeniuta, Severyn & Barth (2016)	Sentiment and writing style generation are inaccurate.
5.	Wang, Qui & Wan (2018)	Improve data generation accuracy.
6.	Whitehead et al. (2018)	Smaller dataset sizes.
7.	Guo et al. (2018)	Complex sentence structures unsupportive.
8.	Kulgod, Patel & Ram (2018)	More concrete sentence creation: food, places, and topics
9.	Jonsson (2018)	Only English political speeches were covered.
10.	Garten et al. (2019)	RNN-based text encoders are valuable.
11.	Li et al. (2019)	Extended for seq2seq applications.
12.	Bullock & Luengo-Oroz (2019)	Lack of appropriate policy and low adoption.
13.	Navali, Kolachalam & Vala (2019)	Low accuracy can be improved with deep learning approaches.
14.	Song & Shmatikov (2019)	Relationship between internal representation and prediction.
15.	Vo & Lee (2019)	To be extended for speech generation tasks.
16.	Wang et al. (2019)	Cross-lingual tasks.
17.	Chan & Fan (2019)	Long text generation or political speeches.
18.	Brown (2019)	Limited to the medical domain.
19	Wu et al. (2020)	Unsupportive of long text generation.

20.	Prabhumoye (2020)	Uncontrollable text generation tasks.
21.	Pan et al. (2020)	Unsupervised models and multi-lingual tasks were not considered.
22.	Beliaev, Rebryk & Ginsburg (2020)	Text speech tasks not covered.
23.	Wu et al. (2021)	Lack of empirical results to show the effectiveness of auto-text generation tasks.
24.	Uchendu et al. (2021)	Low linguistic features were generated.
25.	Zhu & Bhat (2021)	Limited to safe and commonplace responses.
26.	Nguyen (2021)	Lack of diversity in grammar construction.
27.	Zhang (2021)	Report generations uncovered.
28.	Liu, Jia & Vosoughi (2021)	Polarity labels for large annotation.
29.	Uchimoto, Sekine & Isahara (2021)	Synonyms of words and keywords uncovered.
30.	Ren et al. (2021)	Accuracy can be improved.
31.	Ji et al. (2021)	Low outcomes effectiveness.
32.	Re Rosa & Papa (2021)	More models can be experimented with.
33.	Yergaliyeva et al. (2022)	Political comments modeling and generation were considered.
34.	He & Rao (2022)	Newer and high-performance models were not considered for speech generation tasks.
35.	Sridhar & Yang (2022)	Ensemble and mixture models could be investigated.
36.	Zhang et al. (2022)	Not adopted for long speech text generation.
37.	Martin (2022)	- Time and unpredictive understanding of future events. - Inappropriate description of thoughts.
38.	Khan et al. (2022)	Not applied to speech generation performance.
39.	Garcia-diaz et al. (2022)	Not applied to the curation of political parties' speeches.

Conclusion

This paper undertakes a survey of recent advances in automatic texts and speech generation from the years 2009 – 2022. The paper outlines the trends in the research focus during the period of study with staggered progress with most in the last years. The common datasets, methods, and matching strengths were discussed. Also, some research gaps were provided from the different studies to motivate future research engagements in the subject areas especially for long text generation.

The concept of NLP has gained the attention of researchers for 2006-2022 with gradual advancements in short text generation to long text generation tasks. The main problems identified in the low accuracy, incoherence, and insensible sentences at the outcomes of various auto-generated models. The use of machine learning and deep learning algorithms in the encoding and decoding phases of text seq2seq generation is commonplace. However, speech generation tasks had fewer works directly related to political speeches, which served as motivation for this study. There is seemingly a lack of real datasets for speech generation transcripts for carrying out automatic approaches (Dethlefs & Cuayahuitl, 2009). In other cases, the datasets available in English are relatively small for modeling purposes due to complex sentence structures (Whitehead et al., 2018; Guo et al., 2018; Jonsson, 2018). There are no curated long text generation transcripts for political speeches as Medical Corpus (Brown, 2019); Chan & Fan, 2019).

There is a need to consider grammatically diverse and linguistic personological text transcripts in modeling NLP research (Yergaliyeva et al., 2022). The generation of long speech texts is relatively new and evolving as in the case of political speech transcription generation tasks that require better accuracy, appropriate description of thoughts, and effective political speech curation (Ji et al., 2021; Ren et al., 2021; Zhang et al., 2022). There are largely ineffective inaccuracies in models and approaches for generating appropriate speech transcripts generation. There are proposals for new models such as the ensemble approach, GAN, Deep Learning, RNN-LSTM, and seq2seq (Kassarnig, 2016; Wang, Qui & Wan, 2018; Garten et al., 2019).

Future works are expected to focus on the long text generations, dialogues, and generative and discourse text generations. The main applications of text generation are political speech transcripts generation, examination questions setting and grading, robotics, and events reportage.

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