

A Survey on Domain-Specific Auto Spelling Correction using Natural Language Processing

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Abstract -Detecting and correcting spelling errors form an essential part of Natural Language Processing (NLP), as these processes significantly impact the accuracy and reliability of subsequent tasks, such as text classification, information retrieval, and machine translation. This study emphasizes the development of specialized spell-checking and correction systems tailored to specific domains. It examines various techniques ranging from traditional rule-based and hybrid approaches to modern deep learning architectures such as BiLSTM, CNN-LSTM, and Transformer-based models like BERT and BART, as well as large language models (LLMs). The evaluation relies on performance indicators including accuracy, precision, recall, F1-score, BLEU, and robustness. The results indicate that hybrid and deep learning methods deliver superior performance compared to conventional techniques, while LLMs and adversarial training approaches contribute to improved adaptability and stability. Moreover, the research highlights that low-resource languages, such as Tibetan, Wolof, Assamese, and Persian, gain notable advantages from these advanced models. Overall, the study underscores the effectiveness of contextual embeddings, bidirectional correction mechanisms, phonetic-based features, and multilingual zero-shot learning, suggesting that future efforts should focus on developing real-time, multilingual, and domain-adaptive solutions.

Key words: Spell checking, Error correction, NLP, Deep learning, Transformers, LLM, OCR, Low-resource languages

1. INTRODUCTION

A. Spell Checking

Spelling errors are among the most frequent issues in digital and written communication. They can arise from typographical mistakes, phonetic similarities, distractions during typing, or even lack of knowledge of correct spelling. Although they may appear minor, these errors can alter the meaning of sentences, confuse readers, and reduce the overall quality of the text. Spell checking is the process of detecting and correcting such mistakes to ensure that communication remains accurate, professional, and clear. In modern contexts, the importance of spell checking has increased with the widespread use of digital platforms. From mobile keyboards and search engines to academic writing tools, social media, and word processors, spell checking plays an essential role in improving user experience and maintaining reliability in communication. By reducing misunderstandings, increasing confidence, and improving efficiency, spell checkers have become an indispensable part of our everyday technology-driven world.

B. Natural Language Processing (NLP)

Natural Language Processing (NLP) is a branch of artificial intelligence that focuses on enabling computers to process and understand human language. It is a crucial part of many AI applications, and spell checking is one of the earliest

tasks where NLP has been effectively applied. Unlike simple dictionary-based systems that only highlight misspelled words, NLP-powered systems go a step further by considering the surrounding context in which the word appears. For example, words like “peace” and “piece” are spelled correctly but have different meanings; only NLP can identify which word fits best within a sentence. Through techniques such as tokenization, part-of-speech tagging, and semantic analysis, NLP ensures that spell checkers move beyond basic detection and deliver context-aware corrections. Thus, NLP forms the foundation for intelligent and adaptive spelling correction systems that can understand language in a human-like manner.

C. Deep Learning

Deep learning, a subset of machine learning, has transformed the way spelling correction systems are designed. Traditional methods, such as dictionary lookups or statistical n-gram models, are limited in their ability to handle complex or context-dependent errors. Deep learning models, on the other hand, automatically learn patterns from vast datasets and capture both local and global dependencies in text. Neural networks such as Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Transformers are particularly effective for text-based applications. They can understand sequential relationships, recognize long-range dependencies, and even generate corrected text automatically. Unlike rule-based methods that require manual instructions, deep learning adapts continuously as more data becomes available, making it flexible and robust. This ability to learn from examples enables higher accuracy, multilingual adaptability, and stronger generalization in correcting diverse spelling errors.

D. Integration of Spell Checking, NLP, and Deep Learning

The integration of spell checking, NLP, and deep learning has created powerful and intelligent systems capable of not only detecting errors but also suggesting corrections that maintain the intended meaning of the text. Instead of treating words in isolation, these integrated approaches analyze entire sentences to ensure that corrections are both contextually and semantically accurate. This is particularly important in domain-specific applications such as healthcare, education, and law, where even a single incorrect word can have serious consequences. For example, in medical records, a misspelled drug name could lead to misinterpretation and potential risk. By combining the linguistic foundation of NLP with the adaptive learning power of deep learning, modern spell correction systems achieve high precision, adaptability, and efficiency. These integrated systems represent the evolution of traditional spell checkers into advanced tools that are reliable for real-world applications.

E. Large Language Models (LLMs)

Large Language Models (LLMs) such as BERT and GPT represent a significant advancement in the field of NLP. These models are trained on massive corpora of text and are capable of capturing grammar, semantics, and deep contextual meaning. Unlike earlier models that required explicit domain training, LLMs can perform zero-shot and few-shot learning, allowing them to generalize to new tasks with minimal additional training. In spelling correction, LLMs are highly effective because they consider the broader sentence and paragraph-level meaning, not just the immediate word context. This enables them to correct complex errors that may combine spelling, grammar, and semantic mistakes simultaneously. Moreover, LLMs are particularly useful in multilingual and low-resource settings where traditional rule-based systems struggle. Their ability to adapt quickly and provide accurate, context-aware corrections has positioned them as a central component in the latest generation of spell correction systems.

F. Transformers

Transformers are one of the most revolutionary architectures in deep learning and form the backbone of many LLMs. Unlike older models such as RNNs or CNNs, Transformers make use of an attention mechanism that allows them to consider relationships between words across an entire sequence at once. This parallel processing ability makes them extremely efficient and powerful for natural language tasks, including spelling correction. In the context of spell checking, Transformers excel at handling both small character-level mistakes and long-range sentence-level dependencies. They can process large amounts of text rapidly while maintaining accuracy, making them ideal for real-world applications where speed and reliability are important. Today, Transformer-based models are widely recognized as the standard in NLP and continue to drive progress in spelling correction research and applications.

2.LITERATURE SURVEY

A. Language Specific Models

Zemberek, an open-source NLP toolkit designed for Turkish and other Turkic languages, has become a benchmark resource in Turkic NLP research. It provides fast spell checking (75,000 words per second) and morphological parsing (12,000 operations per second) through suffix tree structures and error-tolerant parsing. Its ability to handle agglutinative language features, combined with open-source adaptability, makes it a highly reliable tool for core NLP tasks [1].

Spelling correction has received significant attention since studies reveal that nearly 10–12% of user queries contain errors. Traditional approaches, such as edit distance and noisy channel models, have evolved into hybrid methods that integrate neural networks and web-mined spelling pairs, enabling the correction of multiple error types, including insertions, deletions, and substitutions. Modern approaches such as AraSpell, which applies deep Seq2Seq models, demonstrate the superiority of Transformers, achieving a Character Error Rate of 1.11% and a Word Error Rate of 4.8%, corresponding to an 83% error reduction. Similar advances are observed in TiSpell for Tibetan, Wolof spelling correction with limited data, and Vietnamese systems that combine BERT embeddings with Transformer decoders to achieve strong BLEU scores and context-aware predictions [2],[3], [6], [8], [10].

Language-specific models continue to show promise in low-resource contexts. For instance, PERCORE integrates phonetic features with deep learning to address Persian spelling errors, achieving F1-scores between 0.89 and 0.91, while BiLSTM-based approaches in Assamese leverage bidirectional context for improved accuracy and F1-scores. Alongside these deep learning frameworks, lightweight models such as TextBlob, Levenshtein distance, and POS tagging remain useful for small-scale or classroom applications due to their efficiency, despite having lower accuracy compared to neural methods [11], [13], [18], [19].

B. Deep Learning & Transformer-Based Approaches

Recent work has introduced innovative approaches to generative spell correction. SAGE, for instance, incorporates error emulation pretraining, which enhances robustness by modeling synthetic errors. This strategy allows the model to adapt effectively to unseen and noisy patterns, outperforming standard generative frameworks in both accuracy and generalization [9]. Similarly, embedding models such as BERT have been employed to interpret context-dependent word usage, proving particularly valuable for resolving homophones and grammatical ambiguities. These models ensure greater semantic and syntactic integrity in correction tasks [12].

Large Language Models (LLMs) have also been applied to improve text quality in post-OCR processing, where prompt-based correction substantially reduces character-level and formatting errors, thereby improving the reliability of digitized documents [15]. Adversarial training methods, which introduce perturbed inputs during training, further strengthen system resilience against noisy or unpredictable real-world errors, resulting in improved generalization and accuracy [16]. In addition, hybrid models such as BART and MarianMT combine grammar and spelling correction in a single framework, achieving an overall error reduction of 24.6% and demonstrating the benefits of sentence-level correction across syntax and spelling [17].

Other recent contributions explore noise-based learning strategies and multilingual scalability. The Denoising-to-Correction (D2C) model applies noise to clean data, enabling self-correction without the need for labeled datasets and showing strong effectiveness in Chinese with minimal supervision [20]. Bi-DCSpell extends this idea by employing bidirectional correction, outperforming unidirectional models in both F1-score and accuracy through richer contextual representation [21]. At the multilingual level, Speller100 supports zero-shot spell correction across more than 100 languages, achieving a recall of 50% even for languages not seen during training. This demonstrates its remarkable ability for cross-lingual generalization and broad language coverage [22].

C. Domain-Specific Applications & Educational Tools

NLP-enhanced tools have been widely adopted in educational platforms to provide hybrid correction systems that address spelling, punctuation, and grammar. By offering real-time correction and personalized feedback, these systems improve learner outcomes while reducing the instructional workload for teachers. Studies report measurable gains in spelling accuracy and grammatical correctness among students using such AI-driven tools [4], [23].

Beyond education, recent research has explored domain-specific correction systems tailored to medical records, legal documents, and OCR-generated content. Large Language Models (LLMs) combined with domain-specific datasets have proven especially effective in handling these specialized tasks,

though challenges such as domain adaptation under data scarcity remain [11], [12], [15]. At the same time, several surveys consolidate recent advances in spelling correction, comparing techniques ranging from traditional edit distance and noisy channel models to Seq2Seq, Transformer-based, and self-supervised learning approaches. These reviews highlight best practices and provide valuable insights into evaluation across metrics such as accuracy, recall, BLEU, and F1-score, thereby serving as useful references for benchmarking and future research [24], [25].

Comparative studies also shed light on multilingual and cross-lingual correction. A comprehensive review of error correction in Chinese and English examined rule-based, statistical, and neural approaches, noting key differences in language-specific challenges—such as the character-level emphasis in Chinese versus the syntax-level focus in English. Neural models like BERT and GPT consistently outperformed traditional methods, demonstrating significant improvements in multilingual error handling and setting new benchmarks for accuracy and robustness. These findings underscore the growing role of deep learning in advancing both monolingual and multilingual correction systems [25].

Table 1: Literature Review of Domain-Specific Auto Spelling Correction

S. N O	TITLE OF PAPER	METHODS AND ALGORITHMS USED	KEY FINDINGS	COMPARISON PARAMETER
1	Zemberek: An Open Source NLP Framework for Turkic Languages	- Morphological Parsing -Suffix Tree Structures -Error-tolerant Parser -Spell Checker	-Spell checking speed 75k words/sec -Morphological analysis 12k words/sec	Performance, Multi-language coverage, Basic NLP tasks
2	Query Spelling Correction	Edit Distance, Noisy Channel, N-gram LM, Web-mined pairs, Neural Nets	10-12% queries misspelled; Neural/statistical models improve accuracy	Accuracy, Multiple error handling, Real-time efficiency
3	AraSpell: A Deep Learning Approach for Arabic Spelling Correction	Seq2Seq(RNN, GRU, Transformer), Error injection, 6.9M	Transformer best: CER=1.11%, WER=4.8%; 83% error reduction	RNN vs Transformer; CER, WER, Error reduction rate

	n	sentences		
4	Improving English Writing Skills through NLP-driven Error Detection & Correction	Hybrid NLP+ML Rule-based grammar, Spelling, Grammar, Punctuation	Improves grammar, spelling, punctuation; student writing	Accuracy in grammar/spelling/punctuation; learner improvement
5	A Data-Driven Approach for Spellchecking and Autocorrection	Corpus-based, Edit distance, Frequency ranking, Context-aware correction	Improved accuracy vs dictionary-only; context handles better	Accuracy, Vocabulary coverage, Context sensitivity
6	TiSpell: Tibetan Multilevel Spelling Correction	Semi-masked model + data augmentation	High accuracy for character & syllable correction	Accuracy, Error rate
7	Driving Chinese Spelling Correction: Fine-Grained Evaluation	Error taxonomy + multiple CSC model evaluation	Identifies weaknesses in current CSC models	Precision, Recall
8	BERT + Transformer for Vietnamese Spelling Correction	BERT embeddings + Transformer decoder	High BLEU & accuracy	BLEU, Accuracy
9	Generative Spelling Correction with Error Emulation(SAGE)	Error emulation pretraining + Generative model	Outperformed baseline generative models	Accuracy, Robustness
10	Spell Checking in Low-Resource Languages(Wolof)	Transformer seq-to-seq	Effective correction for Wolof	F1, Accuracy
11	PERCOR E:	Deep learning	F1=0.890-0.905	F1-score, Precision,

	Persian Spelling with Phonetic DL	+ phonetic features		Recall
12	Improving Auto-Correction with Contextual Embeddings	Word embeddings + context	Improving context-aware correction	Accuracy
13	Context-Aware spell Correction using TextBlob	TextBlob + NLP pipeline	Better than edit-distance methods	Accuracy, Edit distance
14	Correcting Spelling in Persian Texts (Hybrid Rule + DL)	Hybrid (rule-based + CNN-LSTM + FastText)	High precision & recall	Precision, Recall, Accuracy
15	OCR Correction using LLMs	LLM prompting for OCR post-processing	Reduced OCR text errors	Error reduction rate
16	Adversarial Training for Chinese Spelling Correction	Adversarial training + data augmentation	More robust CSC models	Robustness, Accuracy
17	Grammatical Error Correction: DL Approaches	BART, MarianMT Transformers	Reduced error=24.6%	Accuracy, Error reduction
18	Assamese Spelling Error Detection	BiLSTM + word embeddings	Higher detection accuracy	Accuracy, F1-score
19	NLP Spell Checking with Python Libraries	TextBlob, Levenshtein distance	Good toolkit performance	Accuracy, Efficiency
20	Chinese Spelling Correction as a Language Learner	Self-supervised (D2C)	Better generalization	Accuracy, Generalization

21	Bi-DCSpell: Bi-directional Detector-Corrector	Bi-directional correction	Outperformed one-way models	Accuracy, F1-score
22	Speller100: Zero-shot Correction for 100+ Languages	Denoising seq-to-seq pretraining	50% recall in unseen languages	Recall, Accuracy
23	AI-powered Language Learning (Grammar & Spelling)	AI grammar + spell checkers	Better student writing accuracy	Accuracy improvement
24	Misspelling in NLP: A Survey	Survey of DL + LLM	Broad summary of methods	Coverage of metrics
25	Research Progress on Chinese & English Error Correction	Rule-based + Statistical + DL review	Comprehensive review	Precision, Recall, Accuracy

3. CONCLUSION

This survey analyzed 25 research works in domain-specific spelling correction using NLP. Deep learning and LLM-based models outperform traditional approaches, especially in handling domain-specific and low-resource languages. However, computational cost and efficiency remain challenges. Overall, NLP-based spell correction is moving toward real-time, multilingual, and domain-adaptive systems that can be applied in education, healthcare, legal, and technical fields. In the future, develop real-time spell checkers for social media and OCR data. Extend support for multilingual and low-resource languages. Build specialized correction systems for the medical and legal fields. Improve efficiency for large-scale applications. Integrate personalized feedback in education tools.

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