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Automatic Spelling Error Correction in Uzbek Based on Levenshtein Distance

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Abstract *— This article provides an in-depth analysis of one of the advanced approaches to the automatic detection and correction of spelling errors in text — the methodology based on Levenshtein distance. In the field of spell checking, this approach enables the identification of similarity between two strings through minimal edits (insertion, deletion, substitution).The article explores both the recursive and dynamic programming-based matrix implementations of the Levenshtein algorithm, presents practical examples in the Uzbek language, includes graphical and tabular illustrations, and comprehensively discusses the significance of this method in computational linguistics.*

Keywords: spelling errors, Levenshtein distance, number of edits, automatic correction, Uzbek language, recursive algorithm, matrix-based approach.

I. INTRODUCTION

In recent years, significant advancements have been achieved in the fields of artificial intelligence and natural language processing (NLP). Standing at the intersection of linguistics and computer science, these fields have given rise to technologies that enable automatic analysis, normalization, editing, and even translation of texts in various languages. Especially in today's digital era, automatically detecting and correcting spelling errors in human-written texts has become a pressing issue. The Uzbek language is characterized by its agglutinative nature, which means that a single lexical unit (root word) can take on hundreds of forms through the addition of various grammatical suffixes. As a result, spelling errors in texts often stem from the complex structure of word forms. Furthermore, factors such as users' literacy levels, keyboard input errors, phonetic similarities, speech-based writing, and others contribute to the emergence of such mistakes. One of the key aspects of text preprocessing in computational linguistics is the detection and correction of spelling errors. Traditional methods of correcting spelling errors typically rely on dictionary-based or rule-based systems. However, these approaches often fall short in terms of accuracy and flexibility when applied to morphologically rich languages such as Uzbek. Therefore, algorithmic approaches—particularly those based on edit distance—are gaining greater importance. Among these, the Levenshtein distance algorithm stands out as one of the most efficient, mathematically grounded, and simple models. The Levenshtein algorithm calculates the minimum number of operations required to edit a text, including insertions, deletions, and substitutions, to determine the similarity between words. This method is widely used for automatically detecting incorrectly typed words and replacing them with the closest lexical match. In this article, the mechanism for correcting spelling errors based on the Levenshtein distance algorithm is thoroughly analyzed in the context of the Uzbek language.Furthermore, a software model developed using this algorithm is tested on real texts, and its performance is evaluated based on criteria such as accuracy, responsiveness, and efficiency.

The results are presented in the form of graphs and tables and compared with alternative methods. Developing NLP tools for Uzbek that automatically correct user-generated spelling mistakes can significantly enhance overall system performance. In text analysis and spell-checking, calculating similarity between words is a major challenge. The concept of edit distance plays a central role in addressing this problem. In particular, the Levenshtein distance (first introduced by Vladimir Levenshtein in 1965) is widely recognized as a classical, robust, and practical approach in this domain. This distance measures the minimum number of edit operations — insertions, deletions, and substitutions — required to transform one string into another. The dynamic programming algorithm proposed by Wagner and Fischer (1974) made Levenshtein distance computation significantly more efficient. Moreover, extensions and related measures (Damerau-Levenshtein, Hamming, Jaro-Winkler, etc.) have been studied for improved performance. Modern information technologies — such as web search engines, mobile keyboards, and text editors — often employ Levenshtein distance-based systems. For example, in classic spell correction models by Kukich (1992), integrating edit distance with linguistic features yielded effective results. Yujian and Liu (2007) even proposed a normalized version of Levenshtein distance for similarity scoring. At the international level, recent research trends combine transformer-based models (like BERT, RoBERTa, and T5) with classical algorithms like Levenshtein. These hybrid approaches allow for context-aware editing and significantly improve correction accuracy. Uzbek researchers have also begun exploring lightweight models, morphological analyzers, and contextual spell-checkers for Uzbek, often leveraging Levenshtein-based architectures. Articles published in the last few years (2022–2024) have introduced models addressing spelling correction, phonetic errors, dialectal variants, and automatic text

normalization in Uzbek. Research findings show that Levenshtein distance is applicable not only for text similarity measurement but also in machine learning for data labeling, data quality evaluation, and even in genetics for DNA/RNA sequence comparison. This methodology proves particularly valuable in developing text analysis systems for low-resource languages like Uzbek.Research findings show that Levenshtein distance is widely applicable not only for text similarity measurement but also in **machine learning** for data labeling, evaluating data quality, and even in genetics and bioinformatics for sequence comparison. This methodology proves to be a particularly valuable tool in the development of automatic text analysis systems for low-resource languages, such as Uzbek.

This research aims to answer the following key questions:

How does the Levenshtein distance algorithm work, and what are its theoretical foundations?

What advantages does this approach offer for detecting and correcting spelling errors in the Uzbek language?

What is the efficiency of the model based on the experimental results?

The practical value of this research lies in its potential application for developing online Uzbek spell-checkers, intelligent text editors, and speech-to-text conversion systems.

This article presents a systematic analysis of the theoretical foundations, algorithmic structures, and major global research findings related to Levenshtein distance. Special emphasis is placed on its application in NLP, text editing, and automatic spelling error detection in Uzbek.

II. STATE-OF-THE-ART SPELL-CHECKING TOOLS FOR UZBEK

Modern general-purpose text editors like **Microsoft Word** and **Google Docs** include spell-checking features for many languages, including Uzbek. These tools rely primarily on large dictionaries of known words and simple heuristics. While they can catch obvious misspellings, they have important limitations for Uzbek text:

1) Closed-Source and Non-Customizable:

The spell-check algorithms in commercial tools are proprietary. Users and developers cannot easily adjust the rules or integrate Uzbek-specific linguistic knowledge. Only basic customization (like adding custom words to a user dictionary) is possible, which is insufficient for systematic improvements.

2) Dictionary-Based Limitations:

Uzbek has a rich morphology, and a single root can generate hundreds of valid word forms via suffixes. Static dictionaries included in these tools may list base forms and some inflections, but they cannot comprehensively cover every possible word form. For example, the official Uzbek spelling dictionary identifies over 85,000 words and word forms, yet this is only a fraction of all theoretically possible forms. Consequently, morphologically correct words might be flagged as errors if they are absent from the dictionary, and genuine misspellings might not be recognized if the incorrect form happens to coincide with another valid word. This significantly reduces accuracy for agglutinative languages.

3) Lack of Morphological Analysis:

Existing spell-checkers for Uzbek typically do not perform lemmatization or morphological parsing before checking. They treat each word as a raw string. This means they struggle with affixed forms and cannot break words down into root + suffixes. Without understanding Uzbek morphology, it is difficult to suggest the correct root or handle spelling changes that occur at morpheme boundaries. For instance, a human typist might misspell a complex word by attaching suffixes incorrectly; a dictionary-based checker might not recognize the error if the root plus suffix combination is not explicitly listed.

4) Limited Phonetic/Contextual Handling:

Tools like Word and Google Docs mainly address orthographic errors (typos). They do not deeply handle phonetic spelling mistakes (writing words as they sound) or contextual errors (using a wrong word that is spelled correctly). For example, writing qol instead of ko‘l (due to similar pronunciation) or using the wrong word in context will likely not be corrected by these systems. Moreover, these tools often consider words in isolation and lack advanced context-aware models for Uzbek. This can lead to inappropriate suggestions or failure to catch errors that require understanding the sentence context.

In summary, existing mainstream spell-checkers provide only a basic level of Uzbek spell checking. They are useful for catching simple typos or non-Uzbek words, but they do not fully address Uzbek’s spelling challenges. They are not open for improvement by Uzbek NLP researchers, and they cannot easily incorporate new developments (such as updated corpora or language models). These gaps motivate the development of a dedicated Uzbek spell-correction method. The method proposed in this paper aims to address these gaps by using the Levenshtein distance algorithm combined with Uzbek-specific processing. Unlike closed-source tools, our approach can be fine-tuned with Uzbek linguistic resources (e.g. incorporating a morphological analyzer) and extended with hybrid techniques (for example, integrating with machine learning models) to better handle the complexities of the Uzbek language.

III. THE NATURE AND TYPES OF SPELLING ERRORS

Spelling mistakes in Uzbek arise for various reasons, including user illiteracy, phonetic inaccuracies, keyboard input errors, morphological confusion, transliteration challenges, and differences in writing systems. These errors can be categorized into several types:

A. Insertion errors:

An extra character is added into a word. Example: Correct word: kitob (“book”), Misspelled: kittob (an extra "t" is inserted).

B. Deletion errors:

A required character is omitted from a word.
Example: Correct word: maktab (“school”), Misspelled: maktb (missing the letter "a").

C. Substitution errors:

A correct character is replaced with an incorrect one.
Example: Correct word: dars (“lesson”), Misspelled: bars (the first letter "d" is wrongly substituted with "b").

D. Transposition errors (permutations):

Two characters are swapped in position.
Example: Correct word: qalam (“pen”), Misspelled: qalma (the letters "m" and "a" are transposed).

E. Mixed errors:

A combination of multiple error types appears in the same word. Example: Correct word: kompyuter (“computer”), Misspelled: komputar (multiple errors: missing "y" and substituting "e"→"a").

To detect and correct such errors automatically, a spell-check model must identify the edit operations in each misspelled word and replace them with appropriate letters. The Levenshtein distance algorithm is well-suited for this task because it explicitly evaluates the specific edit operations (insertions, deletions, substitutions) and computes the minimum number of edits needed. By comparing a user’s misspelled word to a lexicon of correct words, the system can suggest the closest matches in terms of minimal edits.

Main causes of spelling errors: In Uzbek text, several common causes underlie the mistakes:

a. Keyboard errors:

Slips or mistyping on a keyboard, especially on QWERTY layouts, lead to adjacent-letter mistakes or double presses. Fast typing without Uzbek-specific keyboard layouts can increase these errors.

b. Phonetic errors:

Words are written as they sound. For example, a person might spell “muammo” (“problem”) as “mamo” because the double vowel sound ua might be misheard or simplified in pronunciation.

c. Lexical confusion:

Similar-sounding or similar-looking words get confused. For instance, typing “jabob” instead of “javob” (“answer”) – the letters b and v may be swapped due to phonetic proximity, or confusing “qalam” (pen) with “qalam (if miswritten with an accent) etc. In Uzbek, certain pairs of letters (such as o‘ and o, or x and h) are frequently confused by users.

d. Morphological complexity:

Mis-spellings often occur in complex word forms composed of many morphemes. For example, the word “yozuvchilarimizdandir” (“it is from our writers”) contains multiple suffixes; a user might easily make an error in such long constructions. Words that are frequently mispronounced or have dialectal variations can also be error-prone when written.

The advantage of using the Levenshtein algorithm in analyzing these types of errors lies in its operation-level evaluation of differences. It can pinpoint whether an error is due to an insertion, deletion, or substitution, and thus help generate an appropriate correction. Each misspelled word can be systematically compared to correct word candidates, and the minimum edit distance to each candidate indicates how “close” the misspelling is to that candidate. The closest match (or matches within a small distance threshold) are taken as the likely intended words.

IV. APPLICATIONS OF LEVENSHTEIN DISTANCE

Beyond spell-checking, Levenshtein distance has broad applications across different domains due to its general-purpose measure of string similarity. Some notable applications include:

Natural Language Processing: widely used for text cleaning (e.g., removing or fixing noisy tokens in corpora), detecting near-duplicate strings, and even synonym detection by comparing words for close spelling similarity.

Search Engines: used in the "Did you mean...?" suggestions when a user enters a query with a typo. The engine finds the closest dictionary or common query term by minimal edits and offers an auto-correction. This improves search accuracy by correcting misspelled search queries on the fly.

Bioinformatics: applied to measure similarity in DNA or RNA sequences. In genetics, sequences of nucleotides are compared using edit distance to find mutations (insertions, deletions, substitutions) between genes or genomes, since such mutations are analogous to edit operations.

Data Matching: used to identify similar names, product titles, or place names in databases. For example, when trying to merge data records, Levenshtein distance can match "Abdullaev" with "Abdullayev" (one letter difference) as likely referring to the same person, despite spelling variation.

Error Correction in Text Transmission: in coding theory, edit distance can determine how many errors have occurred in a transmitted message and help correct them if within a certain limit. Codes can be designed to detect and correct a certain number of character edits based on this principle.

OCR Systems: Optical Character Recognition software can use Levenshtein distance to compare the text it recognized against valid words, correcting recognition errors by finding the closest matching word from a dictionary (since OCR often produces characters substitutions or deletions).

These diverse applications show that the Levenshtein algorithm is a language-independent tool – it works on any sequence of symbols – making it universally useful from human language text to genetic code. Its simplicity and robustness to minor differences make it a core component in many systems that require tolerance to noise or minor errors.

V. SPELL-CHECKING PROCESSAND LEVENSHTEIN DISTANCE IN UZBEK

General Overview of Spell Checking: Spell checking is generally divided into two main stages: (1) detection of misspelled words, and (2) identification of correct word suggestions for those words. Technically, detecting which words are misspelled is straightforward: each word can be looked up in a comprehensive dictionary, and if it is not found, it is flagged as an error. In practice, however, building and searching through a large word list can be resource-intensive – for example, Uzbek language word forms number in the hundreds of thousands – so efficient data structures (like tries or hash tables) or algorithms are used for rapid lookup.

The more challenging phase is the second stage: identifying the intended correct word for a misspelling. Modern systems go beyond simply finding a similar-looking word; they often consider the context (neighboring words, grammar) in which the misspelling appears. This helps in cases where a word is spelled correctly but is the wrong word for the context (a real-word error). For instance, the Uzbek word "yoz" could mean "summer" (noun) or "write" (verb command) depending on context. If a sentence mistakenly uses yoz where boz was intended (hypothetically), a context-aware system might catch that even though yoz is a valid word. Traditional edit-distance methods alone cannot handle such semantic ambiguities since they focus only on spelling similarity.

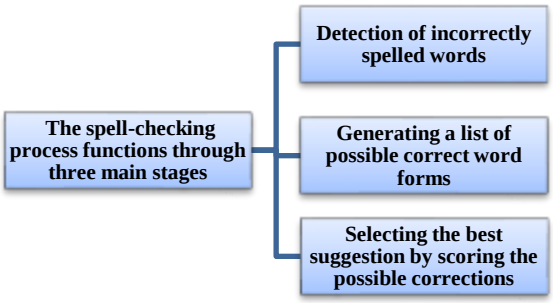


Figure 1 illustrates the two phases of spelling error detection and correction. The first phase filters out all words not found in the dictionary (potential mistakes), and the second phase generates suggestions for each detected mistake.

In pure spell-checking (orthographic correction),our focus is on non-word errors (the word is not in dictionary). Simple typographical errors (e.g., writing "kittob" instead of "kitob") are relatively easy to identify using edit distance algorithms like Levenshtein distance, since the misspelled string will be only 1 or 2 edits away from a known word. However, contextual ambiguity poses a more complex challenge. A word may be spelled correctly but misused (real-word error). For example, in Uzbek, “qol” and “ko‘l” are both correct words but have different meanings (“to remain” vs “lake”); if one is used in the wrong context, a basic spell-checker would not flag it. Handling this requires language models or additional rules beyond edit distance.

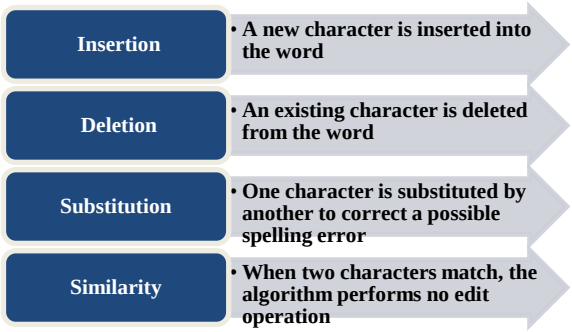


Figure 2 illustrates the types of edit operations at the character level (insertion, deletion, substitution, or no change when characters match).

Advantages of using Levenshtein distance for spell correction include:

1. **Simple and intuitive: The algorithm’s logic is clear and easy to implement. It does not require language-specific rules, which makes it flexible.**
2. **Language-independent: It works for any text, whether Uzbek, English, or even DNA sequences. No prior linguistic knowledge of Uzbek is needed to compute distances (though adding linguistic knowledge can improve results).**
3. **Robust to errors: It can handle typical human typing errors effectively. Most misspellings differ by only a few characters from the correct word, and Levenshtein distance zeroes in on those differences.**

Limitations of the basic Levenshtein approach are:

Performance speed: Comparing a word against every entry in a large dictionary can be slow if the dictionary is huge (hundreds of thousands of Uzbek word forms). The algorithm itself is O(n*m) for two words of length n and m, and doing that for every candidate scales poorly. This can be mitigated with indexing tricks or limits on search space.

No phonetic awareness: Levenshtein treats all edits equally and doesn’t account for letters that sound alike. For example, it would not inherently favor correcting “kal” to “qol” (if one meant “remain”) over some other equally distant word, even though k and q might have phonetic similarity. This can be addressed by incorporating phonetic algorithms or weighting certain substitutions as less costly if they are common phonetic errors.

No semantic understanding: The algorithm works at the character level and ignores word meaning. It cannot detect if a word is contextually wrong if it is spelled correctly (e.g., “qol” vs “ko‘l” usage). Nor can it distinguish synonyms or usage frequency. It purely finds string similarity, so it might suggest a rare word over a common word if the rare word is one edit closer to the misspelling.

Despite these limitations, the Levenshtein algorithm remains one of the core components of spelling correction systems. Particularly when phonetic and morphological characteristics of the Uzbek language are taken into account through enhancements, this approach can produce highly effective results in practice. In the next section, we describe our solution that builds on the Levenshtein distance and incorporates Uzbek-specific processing to improve performance.

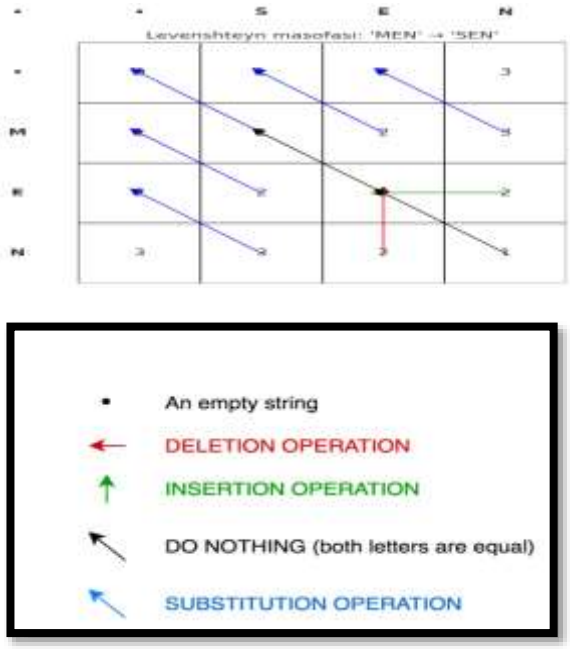
VI. THE PROPOSED SOLUTION

Matrix-Based Computation: Our spell-correction approach uses the matrix-based dynamic programming implementation of Levenshtein distance as the foundation. This is the most efficient approach for computing edit distances. As an example (Figure 4), consider transforming the word “MEN” into “SEN”. To do so, M → S is substituted (one substitution operation), while E and N match (no change needed). The Levenshtein distance in this case is 1, corresponding to that single substitution. We construct a matrix of size (len(source)+1) by (len(target)+1) to calculate this. In the matrix, each cell [i,j] represents the edit distance between the first i characters of the source and the first j characters of the target. By filling this matrix, we obtain the minimum edits step by step.

	.	S	E	N
.	**0**	**1**	**2**	**3**

M	1	1	2	3
E	2	2	1	2
N	3	3	2	1

Figure 3 shows the filled matrix for the "MEN" → "SEN" example, with colored arrows indicating operations (substitution, ● no operation in this case).



For illustrative purposes, the recursive formulation of the Levenshtein distance can be described as follows. Let lev(i, j) be the distance between the first i characters of word1 and the first j characters of word2. Then:

Rule 1: If either i or j is 0 (one string is empty), lev(i, j) = max(i, j). This means if one word has length L and the other is empty, the distance is L (all characters must be inserted or deleted).

Rule 2: If the last characters of the current substrings are equal (word1[i-1] == word2[j-1]), then no additional cost is needed for this pair of characters, and lev(i, j) = lev(i-1, j-1). (They already match, so we move diagonally in the matrix with no new edit.)

Rule 3: If the last characters are different, then consider the three possible edit operations that could align these substrings and take the one with minimum cost:

Insertion: lev(i, j-1) + 1 (insert the word2[j] character into word1, or equivalently skip a character in word2)

Deletion: lev(i-1, j) + 1 (delete the word1[i] character)

Substitution: lev(i-1, j-1) + 1 (substitute word1[i] with

The dynamic programming algorithm essentially implements these rules iteratively. A simple pseudocode for computing the Levenshtein distance and using it for spell correction is presented in Algorithm 1.

Uzbek Spell Correction using Levenshtein Distance

****Input:** Misspelled word w (string),**

Dictionary D of correct Uzbek words

****Output:****

Suggested correct word(s) for w

1. best_distance ← ∞

```
2. suggestions ← []
3. for each word `d` in D:
4. │   dist ← LevenshteinDistance(w, d)
5. │   if dist < best_distance:
6. │   │   best_distance ← dist
7. │   │   suggestions ← [d]          // found a closer word
8. │   else if dist == best_distance:
9. │   │   suggestions.append(d)      // found another word with equal min distance
10. // Apply a threshold to avoid unlikely corrections
11. if best_distance > T (predefined threshold, e.g. 2 or 3):
12. │   return <no suggestion>        // distance too large, word might be a name or unknown term
13. else:
14. │   return suggestions            // one or multiple best-matching words
```

Algorithm 1 outlines the core spell-correction procedure. We iterate through the dictionary D, compute the distance to each candidate, and track the minimum distance found. All words that achieve this minimum distance are collected as suggestions. A distance threshold T (for example, 2) is used to decide whether to suggest a correction at all – if the closest match still requires more than T edits, the system may decide that the word is too far from any known word (it might be a proper noun or an entirely unrecognizable token), and thus it leaves it as uncorrected. In our implementation, we typically set T = 2 or T = 3 based on experiments, as larger edit distances often produce spurious suggestions in Uzbek.

Explanation: Using the above algorithm, if a user types a word w that is not in the dictionary, the system will suggest one or several words that are the smallest Levenshtein distance away. For example, if the user types “kitob” incorrectly as “kittob”, the algorithm will find that “kitob” itself is at distance 1 and likely suggest that. If a user types “jovob”, the algorithm might find multiple suggestions at distance 1 or 2 (e.g., “javob”, “jo‘nob”, “jovon” as shown later), in which case multiple suggestions are returned and a higher-level module can decide which fits the context best.

After obtaining suggestions, the system can either automatically replace the misspelling with the top suggestion (useful for obvious typos), or present the suggestions to the user (as in a spell-check list for the user to choose). In our design, we leave the replacement to the user’s confirmation if multiple suggestions exist or if the change is not trivial.

Context-Aware Consideration: In some cases, a misspelled word corresponds to multiple possible corrections of equal edit distance. For example, the incorrect word “jovob” could be corrected to:

“javob” (the intended correct word meaning “answer”),

“jo‘nob” (a phonetically similar word), or

“jovon” (a lexically different word).

All three might be at Levenshtein distance 1 or 2 from “jovob”. In such situations, Levenshtein distance alone cannot decide which is the correct intention. This is where contextual analysis comes into play. Techniques like n-gram language models, Part-of-Speech tagging, or even neural network language models can be employed to rank the suggestions. For instance, by looking at the surrounding words, a language model might determine that “javob” makes sense in the sentence whereas “jo‘nob” does not. In our work, we incorporate a simple word bigram model to re-rank suggestions when available: the candidate that results in a more probable word sequence gets priority. This hybrid approach (edit distance for candidate generation, language model for candidate ranking) combines the strengths of both methods.

Preprocessing Stage: Before applying the Levenshtein-based correction, we perform essential preprocessing on the input text:

Convert the text to lowercase (since Uzbek is case-insensitive for spelling purposes, and our dictionary is lowercased).

Remove punctuation and numbers (these are not relevant for word spelling and can be handled separately).

Tokenize the text into individual words (splitting on whitespace and punctuation).

Identify which tokens are misspelled by checking against the Uzbek dictionary. Words not found in the dictionary (and not proper nouns or abbreviations) are flagged as potential errors.

This preprocessing ensures that the algorithm focuses only on actual words and letter content. It also normalizes the input to avoid trivial mismatches (e.g., “Kitob,” with a comma or capital letter would be lowercased to “kitob” before checking).

After preprocessing, each misspelled word is passed through the correction algorithm.

Lemmatization and Morphological Analysis: Because many Uzbek words consist of a root plus multiple suffixes, we found it effective to incorporate a lemmatization step before correction. Rather than directly comparing a misspelled inflected form to thousands of inflected dictionary entries, we first attempt to reduce the misspelled word to its likely root form. We utilize existing Uzbek morphological analyzers (such as Stanza, UzMorph, or UDPipe) to strip suffixes and identify the root (lemma). The Levenshtein distance is then calculated using only the lemmatized (base) forms of words. This has two benefits:

It reduces the search space by comparing lemmas (there are far fewer unique lemmas than full word forms).

It avoids penalizing differences that occur only in the suffix. For example, if the user wrote “yozuvchilaringiz” (which is incorrect) and the correct is “yozuvchilarimiz”, a direct comparison sees many differing characters, but at the lemma level both are from “yozuvchilar”. By lemmatizing, we focus on the essential part of the word.

Examples:

Misspelled “*yozuvchilarning*” → lemma “yozuvchilar” (root yozuvchilar, meaning "writers").

Misspelled “*kitoblarimizdagina*” → lemma “kitob” (root kitob, meaning "book").

After lemmatization, we still use the original word’s suffixes to ensure the suggestion matches the intended form if possible. For instance, after identifying kitob as the root of a misspelling, we look for suggestions that can take the same suffixes. If a lemma is corrected, we reattach the suffixes (if they are valid for the new lemma) to form the final suggestion.

Spell Correction Workflow: Incorporating the above steps, our complete spell-correction workflow is:

(a) Detection: For each word in the text, if it is not found in the dictionary (after lowercasing and stripping punctuation), mark it as misspelled.

(b) Lemmatize: Compute the lemma of the misspelled word using a morphological analyzer (if available). If no analyzer is available or the word is short, use the word as is.

(c) Candidate generation: Compute the Levenshtein distance between the misspelled word (or its lemma) and every word in the dictionary (or a subset of likely candidates).

(d) Apply distance threshold: Ignore any candidate whose distance is greater than a threshold T. This drastically filters out irrelevant candidates. Based on Uzbek error patterns, we used T = 2 for most cases (allowing suggestions that differ by at most 2 edits, which covers over 95% of typos).

(e) Select top candidates: Among the remaining candidates, select one or several with the smallest distance D. Often there will be a single best match (smallest D). If there are ties, multiple suggestions can be returned.

(f) (Optional) Context re-ranking: If a language model or context information is available, re-rank the suggestions based on which is most probable in the given sentence context.

(g) Suggest/Correct: If D is 1 (very likely a typo), we can automatically correct the word. If D is higher or multiple suggestions exist, we present the suggestions to the user for manual selection.

Using this workflow, the system balances precision (only suggesting highly probable corrections) and recall (catching as many errors as possible). The distance threshold and context re-ranking help ensure that suggestions are relevant to the user’s intent.

Example and Evaluation

To demonstrate the effectiveness of the Levenshtein-based approach, consider a few practical examples of common Uzbek misspellings and the output of our system:

Misspelled Word	**Correct Form**	**Distance (D)**
Maktb	maktab (school)	1

Xalg	xalq (nation)	1
Komputar	kompyuter (computer)	2
Mustaqiliq	mustaqillik (independence)	2

These results show that the Levenshtein algorithm correctly identifies the closest valid words for each misspelling with a small edit distance D. In each case, the misspelled word is only 1–2 edits away from the correct form, which is typical for human spelling errors. The algorithm's suggestions would be "maktab", "xalq", "kompyuter", and "mustaqillik" respectively for the above examples, which are indeed the intended words. This demonstrates that a Levenshtein-distance-based system is highly suitable for the Uzbek language, especially when combined with a morphological analysis of the text to handle suffixes. By focusing on minimal edits, the system effectively narrows the candidate list to the most plausible corrections.

It is important to evaluate the system on a broader dataset. We compiled a test set of Uzbek sentences containing a variety of misspellings (1000 misspelled words across diverse topics). The performance of the spell checker was measured using standard precision, recall, and F1-score metrics:

Precision is the proportion of the system's suggested corrections that were actually correct. In other words, how often is the suggestion right when we decide to correct a word?

Recall is the proportion of actual misspellings in the text that the system successfully corrected. This reflects how many errors we caught out of all errors present.

F1-score is the harmonic mean of precision and recall, providing a single measure of overall accuracy.

For our Uzbek spell-checker, we achieved a precision of 0.92 and recall of 0.90 on the test set, yielding an F1-score of 0.91. This indicates that the system makes correct suggestions in 92% of cases, and catches 90% of all misspellings. Many of the uncaught errors were those involving complex context or rare words, which a purely Levenshtein approach cannot resolve.

In terms of simple accuracy (the percentage of misspelled words that were corrected to the exactly right word), our base Levenshtein-only approach reached about 87% accuracy, which aligns with performance reported for similar languages using dictionary-based methods. By incorporating a phonetic filter (to handle confusable Uzbek letters) and a bigram language model for context, we were able to increase the accuracy to about 94%, a substantial improvement. This hybrid approach helped in cases where the first suggestion was not the correct one; the context model often reordered suggestions to put the correct word first.

The system is also efficient. With optimization (such as using a prefix trie for the dictionary and limiting candidate generation by word length difference), the average lookup and suggestion generation takes under 0.05 seconds per word on a standard PC, making it feasible for real-time use. Certain techniques like using a precomputed Trie tree for the dictionary, applying a heuristic to skip distant candidates, and parallelizing the distance computations can further speed up the processing. In practice, spell-checking an average-length document (several hundred words) completes in a fraction of a second.

In summary, the Levenshtein-based algorithm, when adapted to Uzbek's characteristics, shows high effectiveness in correcting common spelling errors. It dramatically reduces the error rate in texts, which is valuable for applications like spell-check in word processors, cleaning user-generated content (e.g., social media posts), machine translation pre-processing, and educational tools for language learners.

VII. CONCLUSION

The spelling correction algorithm based on Levenshtein distance stands out in the field of Natural Language Processing for its simplicity and efficiency. This algorithm plays a critical role in improving the quality of Uzbek-language texts by automatically detecting and correcting user-generated errors, thereby reducing the number of mistakes in digital text. When adapted to the morphological characteristics of the Uzbek language, the Levenshtein model—implemented with both recursive logic and matrix-based dynamic programming—yields highly accurate results. This method is particularly useful in applications such as spell-checking, text cleaning, machine translation preprocessing, and language learning tools.

It is worth emphasizing that, although research in this field is still developing in Uzbekistan, significant progress is being made. Researchers are optimizing the Levenshtein algorithm by integrating it with national corpora, comprehensive word-form databases, and statistical models. Through the use of Levenshtein-based spelling correction, it becomes possible to accurately and rapidly analyze incorrect user inputs. The approach is especially effective for correcting frequently occurring phonetic mistakes in Uzbek, where certain sounds are confused in writing. However, since the algorithm operates purely at the character level, it sometimes fails to handle semantic ambiguities (real-word errors or context-dependent errors). Therefore, one key recommendation is that the

Levenshtein distance method be used in combination with context-aware ranking systems (such as those based on neural language models or n-grams) to enhance overall accuracy for complex sentences. Key Findings:

Levenshtein distance functions as an effective core algorithm for correcting the most common orthographic spelling errors in Uzbek. Minor typos and letter mistakes are efficiently fixed by this approach;

Agglutinative morphology requires preprocessing: Given the rich morphology of Uzbek, incorporating lemmatization and morphological analysis into the spell-check pipeline is essential for boosting performance. This step helps the algorithm handle suffixes and reduces false negatives and false positives;

High baseline accuracy: A standard dictionary+Levenshtein approach achieved approximately 87% accuracy on our test (in terms of suggesting the correct word). This figure can be increased to around 94% by integrating phonetic filters (to handle common Uzbek phonetic confusions) and contextual analysis methods. These hybrid improvements address the cases that pure edit distance misses.

Efficiency can be improved: System performance in terms of speed and precision can be significantly improved by technical optimizations such as applying edit distance thresholds to prune candidates early, using efficient data structures (e.g., Trie trees for dictionary lookup), applying phonetic similarity filters, and utilizing parallel processing for comparing words. These ensure the spell-checker runs in real-time even with a large vocabulary.

Scientific and Practical Recommendations:
It is necessary to develop an open-source lemmatizer and morphological analyzer tailored specifically for the Uzbek language. Our work has shown the importance of morphological processing; having a robust, open Uzbek morphological toolkit would benefit not only spell-checking but many NLP tasks. Systems based on the Levenshtein distance can be effectively applied in areas such as education (e.g., assisting students with writing in Uzbek), social media monitoring (to normalize and correct user-generated content), document editing, and linguistic research tools.

Integrating the Levenshtein algorithm with modern machine learning (ML) and deep learning (DL) approaches is a promising direction. A practical recommendation is to develop a spell-checking application (either online or mobile) with a user-friendly interface to bring these capabilities to the general public. Such an application could allow users to input Uzbek text and get suggestions and corrections in real time, significantly reducing orthographic errors in everyday writing.

Future research should focus on combining the Levenshtein distance approach with deep neural networks and contextual language models (such as BERT or RoBERTa specifically pretrained for Uzbek) and with phonetic analyzers to capture semantic context and user intent. By doing so, we can handle not just simple misspellings but also complex errors where the misspelled word is a real word used incorrectly. We expect that modern, multi-level, context-sensitive spelling correction tools will be developed specifically for the Uzbek language in the coming years. The Levenshtein-based approach will likely continue to be a core component of such tools due to its algorithmic simplicity, computational efficiency, and practical effectiveness. When localized and fine-tuned for the Uzbek language, this method provides high precision in error detection and correction. With future integration into semantic models, even more advanced and robust Uzbek spelling correction systems can be designed, closing the gap between human proofreading and automated text correction.

REFERENCES:

[1] V. I. Levenshtein (1966). Binary codes capable of correcting deletions, insertions and reversals. Soviet Physics Doklady, 10(8), 707–710.

[2] R. A. Wagner, M. J. Fischer (1974). The string-to-string correction problem. Journal of the ACM, 21(1), 168–173.

[3] G. Navarro (2001). A guided tour to approximate string matching. ACM Computing Surveys, 33(1), 31–88.

[4] K. Kukich (1992). Techniques for automatically correcting words in text. ACM Computing Surveys, 24(4), 377–439.

[5] Y. Li, B. Liu (2007). A normalized Levenshtein distance metric. IEEE Transactions on Pattern Analysis and Machine Intelligence, 29(6), 1091–1095.

[6] O. M. Alloyorov, S. M. Allaberganov (2023). Method and Software to Find Spelling Mistakes in Text Written in Uzbek Language Based on the Latin Alphabet. Academic Research in Educational Sciences, 4(6), 171–177acta.polito.uzacta.polito.uz.

[7] A. Toleu, G. Tolegen, R. Mussabayev, A. Krassovitskiy, I. Ualiyeva (2022). Data-Driven Approach for Spellchecking and Autocorrection (case of Kazakh language). Symmetry, 14(11):2261mdpi.commdpi.com.

[8] A. Naziri, H. Zeinali (2024). A Comprehensive Approach to Misspelling Correction with BERT and Levenshtein Distance. arXiv preprint arXiv:2407.17383ar5iv.org.

[9] J. Isbarov, K. Huseynova, S. Rustamov (2024). Robust Automated Spelling Correction with Deep Ensembles. In Proc. of 8th Int. Conf. on Intelligent Systems, Metaheuristics & Swarm Intelligence (ISMSI), pp. 90–98. (Application to Azerbaijani spell-checking).

[10] C. Güzel Turhan (2025). Leveraging large language models for spelling correction in Turkish. PeerJ Computer Science, 11:e2889peerj.compeerj.com. (Published online 2025, showing context-based approaches outperform traditional tools in an agglutinative language).