Enhancing automatic text summarisation by resolving anaphora and identifying abstract and concrete nouns

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Abstract: The primary goal of text summarisation is to distil the most important details and turn them into a brief version that still captures the source material's main points. As the volume of material in a document goes up, it becomes harder to summarize it manually, making automatic summarisation the better alternative. It is essential for email filtering, producing reports, collecting news, following events, and condensing user-generated material. The main goal of this work is to improve how a summary is built by selecting sentences with the greatest share of both concrete and abstract nouns. Emotions and ideas are revealed by using abstract nouns and concrete nouns to express things you can touch or see. We propose that Part of speech (POS) tagging should be performed to highlight and identify noun types and the most informative sentences can be picked by examining their noun density. Each story in the collection is listed in order of the length and only its earliest half is included in the summary. The overall compression ratio for this technique is 54.57%. Precision, recall, and F1-score have been used for evaluation to compare the automatically generated summaries with gold summaries and the results have been found to be 0.0497, 0.4202, and 0.0662. To measure its effectiveness this approach has been compared to recent benchmarks including NarraSum and StorySumm. The research reveals that using noun concreteness can create better and more useful summaries.

Keywords: Sentence Tokenisation, Word Tokenisation, Part of Speech (POS) Tagging, Abstract Nouns, Concrete Nouns.

1. Introduction

The more digital material appears online, the longer it takes and the more effort it requires to find useful information. The process of searching for files requires users to read through a lot of text which can be inefficient. By using automatic text summarisation, important parts of documents are gathered while still maintaining what they originally communicated. It applies to the study of Natural Language Processing (NLP) and is useful for summarizing different types of texts, including books, papers, documents, medical reports, and articles (Sayyed, Pundge & Mahender, 2018; Sayyed & Mahender, 2020; Babu & Badugu, 2023) In the area of narrative texts such as children's stories or stories about morals, summarisation is reasonably complicated. A lot of these storytellers send out emotions, moral messages, or ways of thinking using both concrete things and metaphors. Emotions or concepts are expressed by abstract nouns (honesty, regret, hope), whereas concrete nouns (tree, river, dog) mean tangible things. It is extremely important to include these details to keep the essential message and actions of the story.

This research has been developed to improve the extractive summarisation by using sentences rich in abstract as well as concrete nouns. The assumed idea is that these sentences often capture main events, significant characters, and important feelings needed to tell the story well. However, sometimes it is hard to identify abstract and concrete nouns because the situations may be ambiguous. For instance, in some cases, Light says light (pun intended), but it can also mean enlightenment. So, it concentrates on making extractive summarisation more effective by choosing sentences filled with abstract and concrete nouns. Such sentences are thought to normally include major actions, important people, and emotions crucial for telling the story. However, identifying which nouns are abstract and which are concrete can be tricky since the context may be ambiguous. So, the word light may mean an actual light source or represent enlightenment, depending on how it is used. POS tagging is used along with certain rules to identify nouns and collect sentences with a greater proportion of nouns. The approach tries to preserve the main storyline by grouping some sentences and reducing the summary to only one-half of the length of the original text. In this paper

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Section 2 provides detailed literature review, Section 3 discusses proposed methodology, Section 4 represents experimental result while Section 5 discusses overall view of present work and concluding remarks are provided in Section 6.

2. Literature review

In order to give a synthesized overview of what has been done before, Table 1. Provides in brief important aspects in the text summarization. The table mentions the details about the authors, the year of publication, the methodology, dataset and lacuna of a study, thus providing a comparative outlook on the current body of work.

Table 1. Literature review. *Source: Author's own compilation (2025)*

References	Method	Dataset	Lacuna
(Nallapati et al., 2016)	Attentional Encoder Decoder Recurrent Neural Networks	Gigaword corpus	Does not support larger-scale summarisation. More than one sentence or just a few sentences.
(Suleiman & Awajan, 2019)	Deep learning	DUC dataset and news article dataset	The process discussed must include abstractive methods for better performance evaluation.
(Sinha, A., Yadav & Gahlot, 2018)	Neural Networks	Dataset is not specified	The system has no clear method to combine the extracted elements into clear summaries.
(Lal et al., 2021)	Extractive method	CNN Daily mail dataset and DUC dataset	Repetitious sentences make up the summary which actually lacks the essence of a summary.
(Guadie, Tesfaye & Kebebew, 2021)	TF, IDF	News items posted on social media.	The system should have a lexicon with rules to prevent shortening words and keep the results accurate.
(Keller et al., 2022)	Extractive method	Dataset created from the material science.	The scientific content is often misunderstood, ending up as vague summaries.
(Zhao et al., 2022)	Lead, LexRank, BART, T5, PEGASUS, LED	NarraSum (122K movie/ TV plots with abstractive summaries)	It is too intensive in computing and requires too much resources, which makes it inappropriate to use in small labs or as an educational activity.
(Subbiah et al., 2024)	LLMs.	StorySumm (96 short stories)	Only tests faithfulness but does not provide a procedure to enhance coherence.
(Asmitha et al., 2024)	TF-IDF,Text Rank, LSTM	News, social media and academia textual corpora	Transformer models result in accurate outputs but cost too much to run and use.
(Gaikwad et al., 2024)	Abstractive and Extractive method	CNN/Daily Mail Dataset, Gigaword, PubMed	Abstractive summaries might be misunderstood and make evaluation more difficult.

(Zunke et al., 2024)	TF-IDF,BERT	Research Paper	Important facts are often left out because the algorithm cannot handle all the details.
(Mehta et al., 2024)	Seq 2 seq model	Research paper	Requiring a lot of computing resources limits the wider use of these methods.
(Chen et al., 2024)	Bibliometric analysis method	Research paper	Needs better methods for accuracy and better understanding of the meaning.
(Liu et at., 2024)	Text Rank Algorithm, K Means Clustering	DUC 2004	Needs different methods that can help to achieve better accuracy.

Some of these research pieces (Nallapati et al., 2016; Abdelaleem et al., 2020; Zunke et al., 2024) point out that there is ample repetition in the sentences chosen, the text has little semantic depth, and the approach requires substantial computational effort NarraSum (Zhao et al., 2022) and StorySumm (Subbiah et al., 2024) NarraSum demands powerful computation, and in StorySumm, there is no enhancement toward coherence.

By implementing the present system, the authors aim to solve some of these problems by:

- Processing the data and choosing sentences that have many abstract and concrete nouns of different kinds;
- Filtering sentences to take out any extra information;
- Making sure the story keeps a clear narrative by rearranging sentences;
- Trying to see that even its extractive based system should be low on computation intensive tasks, which makes it more attractive in limited resourses and in educational establishments;
- The approach applied will proactively try to enhance coherence by resolving anaphoras and introducing noun-based salience, thus boosting the achievement by providing consistency and fact grounding.

Unlike many other deep learning methods, the method is simple, easy to understand, and perfect for moral stories, since emotions and real-world aspects are more important in these tales.

3. Proposed method

To summarize stories, this research highlights sentences that have a high count of both abstract and concrete nouns because there are significant signs of informative and emotional parts in the story.

From the web, there have been gathered 100 stories (Butterfly Fields. (n.d.), FirstCry Parenting. (n.d.), Motivation Rich. (n.d.)) that differ in style, length, and the topics they cover. The stories contain as short as 5 sentences or as long as 12. Because of this range, the analysis can cover the model's results on both short and long texts, making the findings more general. For a few sample stories, their complete details are outlined in Table 2 below.

Table 2. Entire summary of the narrative for 10 sample story. *Source: Author's own compilation (2025)*

Narrative nomenclature	Actual length of narrative	Max length of sentence in narrative	Min length of sentence in narrative
ST1	9	26	5
ST2	12	23	6
ST3	5	15	5
ST4	8	26	5
ST5	9	22	6
ST6	11	30	7

ST7	7	24	7
ST8	7	24	7
ST9	7	27	6
ST10	10	29	6

In this section, the process is explained by looking for and selecting sentences with the most abstract and concrete nouns. These six main steps make up the system: sentence Tokenisation, word Tokenisation, POS tagging, noun identification and classification, scoring, and summary generation. The length of the story narrative is the complete number of words in the story mentioned in the Table 2. The maximum sentence length is the number of words in the longest sentence, that is 30 and the minimum sentence length is the number of words in the shortest sentence, that is 5. These measures indicate the general volume of the story, and the length fluctuations of the sentences.

The following steps make up the projected system's workflow, which is depicted in Figure 1:

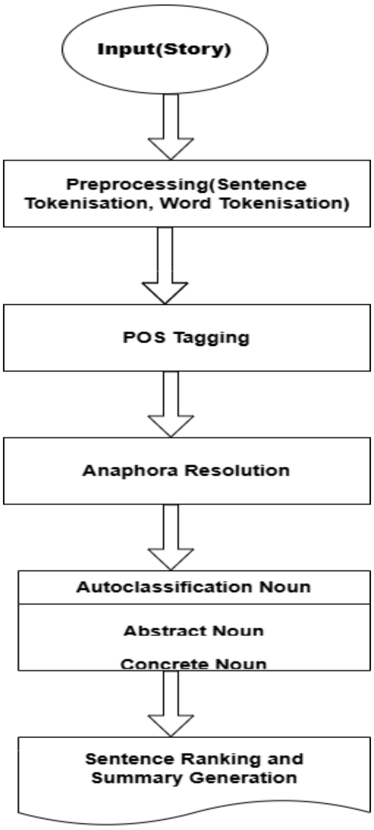

Figure 1. Workflow of the proposed system

3.1. Input collection

100 Narrative stories are gathered from websites on the Internet. These act as data and are the key source for further analysis.

3.2. Sentence tokenisation

All of the text is separated into different sentences by a sentence Tokenisation.

An example of this is provided below, in Figure 2.

```
'Once there was a race going on.',
'A tortoise and a Hare participated when the hare started to run faster.
```

Figure 2. Illustration of sentence tokenisation

3.3. Word tokenisation

After dividing a paragraph into sentences, every sentence is divided into its constituent words using the word Tokenisation. An example of this is shown below:

[('Once',)][('there',)][('was')][('a',)][('race')][('going')][('on')]

3.4. POS tagging

Each word gets a label, or tag, from part-of-speech (POS) tagging to identify it as a noun, verb, or adjective.

An example of this is shown below:

[('race', 'NN'), ('going', 'VBG'), ('on', 'IN')]

3.5. Anaphora resolution

An anaphora resolution has been applied to the story by using the Spanbert model. Identifying the people or objects that pronouns and other referring expressions point to is called anaphora resolution. Instead of referring to someone or something using he, she, it, they, this, or that, it uses specific nouns (such as tortoise, hare), which makes the whole text flow more smoothly and become easier to process.

3.6. Finding and sorting nouns depending on their nature

The POS tags are used to find nouns and then put them into either a concrete or abstract category using semantic rules. Concrete nouns stand for concrete physical items such as ‘tree’ and ‘car’.

Some abstract nouns are used for intangible concepts such as ‘freedom’ or ‘hope’. The purpose of this classification is to rank sentences that hold key parts of the story. Extracted abstract and concrete nouns of a few sample stories are shown in Table 3.

Table 3. Extracted abstract and concrete nouns for ten sample stories.
Source: Author’s own compilation (2025)

Narrative nomenclature	Abstract Noun	Concrete Noun
ST1	speed, surprise, victory, determination, laziness, over-confidence.	tortoise, hare, race, tree, game, point.
ST2	friendship, selfishness, fear, wisdom, loyalty, advice.	bear, jungle, tree, friend, bodies, place, ears.
ST3	greed, patience, desire, loss, disappointment, regret.	farmer, goose, egg, knife, belly, market.
ST4	hospitality, anger, revenge, frustration, cleverness.	fox, stork, house, soup, bowls, vase, neck.
ST5	thirst, determination, resource-fulness, relief	crow, water, pitcher, pebbles, level, surroundings.
ST6	lies, mischief, fear, trust, anger, regret.	boy, wolf, villagers, village.
ST7	honesty, wealth, generosity, loss, relief, gratitude.	woodcutter, axe, river, tree.
ST8	foolishness, greed, desire, loss, disappointment.	dog, meat, stream, shadow, mouth.
ST9	hard work, laziness, respon-sibility, foresight, regret.	ant, grasshopper, food, family, summer, winter.
ST10	fear, hope, courage, resili-ence, community, kindness, solidarity.	girl, lantern, streets, neighbors, village, war, home.

3.7. Summary generation

After the noun density is determined, summaries are formed by choosing those sentences that have the highest number of both abstract and concrete nouns. The sentences are selected as shown according to the order in which the characters first appear. It is suggested to write no more than 50% of the total text in each section to help compress the sentence. The goal is to preserve the key aspects of the story and remove the parts that are not needed. A sample example of a generated summary is shown in Figure3.

```
[1, 1,  'Once there was a race going on.']
[2, 2, 'A tortoise and a Hare participated when the hare started to run faster.']
[3, 2, 'After a while, the hare stopped near a tree and looked back.']
```

Figure 3. Generated summary

The main thoughts of the story are presented by including both abstract and concrete nouns in the summary sentences. It gives an easy-to-follow approach that works better than complicated neural models, and it is easy to understand and linguistically meaningful.

4. Experimental result

In order to assess the effectiveness of the method, 100 narrative stories have been used that have been obtained from different websites. Every story goes through a pipeline where the sentences are tokenized, the nouns are classified, the score of the sentence is determined, and a summary is produced. The idea is to create a precise and significant summary that takes up 50% of the story's length, depending on the number of abstract and concrete nouns. Table 4 gives the compression of a few sample stories measured by the compression ratio.

Table 4. Summarized sentences and compression ratio for sample 10 stories.
Source: Author's own compilation (2025).

Story	Compression Ratio (%)
ST1	55.55
ST 2	50
ST 3	60
ST 4	50
ST 5	55.55
ST 6	54.54
ST 7	57.14
ST 8	57.14
ST 9	57.14
ST 10	50

The following equation 1 has been applied to get the compression ratio of every story.

*Compression Ratio = Summarised sentences / Total sentences of each story*100* (1)

It is proven that the content reductions continued in all the stories, resulting in 50% less content without losing relevance. Analysing 100 stories indicate that 54.57 percent of the original content is maintained on average.

5. Discussions

To evaluate how accurate the summaries are, they have been compared with . The evaluation of the summary is shown in Table 5. Precision calculates the number of selected sentences that are related, whereas Recall measures whether the system found all the relevant sentences. The F1-Score measures both the recall and precision in a balanced way. Precision, Recall, and F1 scores are calculated by using the following equations 2, 3, and 4 respectively. The precision is low at 0.0497, recall is high at 0.4202, and the F1-Score is 0.0662. Still, the fact that the precision is low implies that some of the data collected might not be worthy.

Table 5. Evaluation using precision, recall, F1 score for 100 stories.
Source: Author's own compilation (2025)

	Precision	**Recall**	**F1-score**
Average	0.0497	0.4202	0.0662

5.1. Precision: It gives knowledge of how reliable the predicted positives are.

When the results are very precise, there are fewer mistakes.

$$Precision=TP/(TP+FP) \tag{2}$$

Correctly identified positive outcomes as positive are referred to as TP.

FP stands for a true negative case that is classified as positive.

5.2. Recall: Recall tells us how many of the actual positive cases were counted as correct predictions.

A high recall rate means that there are few times when the test incorrectly shows a situation is negative.

$$Recall=TP/\ (TP+FN) \tag{3}$$

An FN occurs when a real positive case is not identified.

5.3. F1 Score: F1 Score represents the average of the precision and recall rate. It produces just one score that helps, especially for data with unequal class sizes.

Whenever an F1 score is high, you can expect both accurate and comprehensive predictions.

$$F1\ Score=2*(Precision*Recall)\ /\ (Precision+Recall) \tag{4}$$

To assess the extractive summarization methods, they are compared to the two recent benchmarks in the narrative summarization: NarraSum (Zhao et al., 2022) a large-scale benchmark and StorySumm (Subbiah et al., 2024) which is the most relevant to the assumed task of short stories. The comparison of the Proposed Approach with the Existing Benchmarks is shown in Table 6. In comparison to NarraSum that includes ~122K narrative texts and compares extractive (Lead, LexRank) and abstractive (BART, T5, PEGASUS, LED) models, the authors here are working at a smaller scale. NarraSum scores indicate that the abstractive summarization is a very difficult task and the pretraining still achieved only small improvements (e.g., Rouge-1: 32.56 → 32.88). StorySumm, although smaller (96 stories), assesses the faithfulness of the LLM summaries. Despite advanced models like GPT-4 with FABLES, the precision, recall, and balanced accuracy are quite low: precision - 0.78, recall - 0.66, and balanced accuracy - 67% (approximately), whereas in humans, it is close to 85. The present approach, though less competitive in terms of raw scores, actually enhances the referential consistency by including the anaphora resolution and salience-based extraction. Conclusively, this solution is simple and provides a small-scale adaptation of the story summarization but it has limitations of scale, compared to the systems trained by NarraSum. The extractive formulation will deal with certain faithfulness issues identified in StorySumm. The anaphora resolution minimizes the referential errors and incoherence, and the noun based salience makes sure that the corresponding sentences are to remain in the source text. This decreases the amount of hallucinations and keeps the event fidelity in the minimal form. These design decisions are linked to a better factual consistency as compared to the abstractive models, but the current level of precision is not enough, so the future work should combine the linguistic strategies with a large-scale abstractive training.

Table 6. Comparison of the proposed approach with the existing benchmarks.
Source: Author's own compilation (2025)

System	Dataset and method	Result	Strength	Lacuna
The present work	Custom dataset (100 stories from web), Extractive Method	Precision: 0.0497, Recall: 0.4202, F1 score: 0.0662. Comprehension ratio: 54.57%.	Lightweight, easy to interpret, has coherence promoted through anaphora, near-optimal compression (50 per cent)	Low precision.
(Subbiah etal., 2024)	StorySumm (96 stories), LLMs.	Precision: 0.78, Recall: 0.66, balanced accuracy: 67%	Offers high resolution faithfulness detection (hallucinations/mistakes)	Small dataset
(Zhao et al., 2022)	NarraSum, Lead, LexRank, BART, T5, PEGASUS, LED	ROUGE-1 ≈ 32–33	The large-scale benchmark dataset that has a cross-domain generalization potential.	The very large, abstractive models exhibit some impressive generative ability.

6. Conclusions

A noun-based extractive summarisation method for short stories is presented in this paper. The experiments demonstrate that the linguistic features can be successfully used (namely abstract/concrete noun salience and anaphora resolution) in short story extractive summarization. The system demonstrated good recall with high compression and proved its applications in computationally constrained environments. But the lesser accuracy brings forward the issue of more sophisticated selection mechanisms. Relative to benchmarks, this approach is less wordy and more coherence-seeking than NarraSum, and also confronts the referential faithfulness issues that were raised in StorySumm. In the future work, this framework would be applied to bigger benchmark datasets and combine linguistic strategies with abstractive models based on the transformer architecture to find a better balance between faithfulness, scalability and performance.

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