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AUTOMATED RECOGNITION OF IRONY AND SARCASM IN ENGLISH FICTION USING NATURAL LANGUAGE PROCESSING TECHNIQUES

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ABSTRACT

Relevance of the research
The relevance of the research is determined by the need for highly accurate automated detection of irony and sarcasm in literary discourse, which remains a challenge for modern Natural Language Processing (NLP) systems because of rhetorical complexity and semantic ambiguity.
Aim of the research
The aim of the research is to develop and formalize a multi-level methodology for building and validating a Hybrid NLP model for automated recognition of irony and sarcasm in English literary prose, taking into account rhetorical, stylistic, and contextual semantic characteristics.
Research methods
The research employed the following methods: comparative qualitative analysis (in two iterations), representative explication, comparative metric analysis, and decomposition analysis for optimization.
Obtained results
The comparative metric study found that the optimized Hybrid NLP model, which combines BERT4Irony, RuleML, Defeasible Logic, semantic pre-processing and meta-ensemble (XGBoost, MetaSVM), demonstrates the highest accuracy (Accuracy = 0.96, F1 = 0.945, AUC-ROC = 0.96) and adaptability to rhetorical complexity. The improvement of generative and discriminative metrics (BLEU = 0.91, ROUGE = 0.92, SPD = 0.88) confirms the model's ability to accurately detect ironic inversions, stylistic deviations, and pragmatic implicits in literary discourse.
Academic novelty of the research
The academic novelty of the research is the developed Hybrid NLP model for automated irony and sarcasm detection, which combines BERT4Irony, ontological modelling (Defeasible Logic, RuleML), and meta-ensemble (XGBoost, MetaSVM). The model provides semantic accuracy and cognitive correspondence to the rhetorical structure of a literary text.
Prospects for further research

Further research may focus on the cross-linguistic adaptation of the model, taking into account linguistic and cultural differences in the conveyance of irony and sarcasm, in particular through the formalization of typical rhetorical patterns in different languages.

Keywords: *Irony, Sarcasm, Ontological Modelling, Hybrid NLP Model, Transformer Architecture, Semantic Framing, Rule-Based Formalism, Explainable AI, Discourse.*

1. INTRODUCTION

This Irony and sarcasm are key rhetorical phenomena widely used in English fiction to express hidden intentions, social commentary, or cognitive contrast. Their automated detection is critically important for the tasks of literary interpretation, semantic analysis, emotional modelling, and improving the quality of generative NLP systems. At the same time, the multi-level structure of ironic statements, contextual dependence, and pragmatic complexity impose limitations on traditional text analysis algorithms. This emphasizes the need to create highly accurate, interpretable, and stylistically adaptive models capable of cognitively relevant interpretation of literary discourse.

The complexity of irony and sarcasm as cognitive-linguistic constructs necessitates a shift toward semantically enriched and context-aware NLP models that integrate mechanisms of interpretative sensitivity and discourse-level pragmatics. Recent psycholinguistic findings underscore the role of mental-speech development and inferential capacity in decoding latent communicative intentions within multimodal textual environments [1]. Furthermore, the evolution of information models toward adaptive semantic frameworks in high-context digital platforms highlights the feasibility of incorporating structurally modular and legally compliant architectures into language understanding systems [2]. These conceptual and instrumental advancements inform the design of cognitively grounded NLP approaches for literary irony recognition.

Automated recognition of irony and sarcasm in English literary prose is a challenging NLP task that requires a high level of cognitive sensitivity, stylistic contextualization, and pragmatic interpretability. Ironic and sarcastic utterances are characterized by latent ambiguity, rhetorical inversion, polysemy, and emotional ambivalence, which makes their accurate detection using basic linguistic or statistical models impossible. Current approaches, including rule-based systems, lexical filters, machine learning (ML) classifiers, Deep Neural Networks (DNNs) (deep learning, DL), transformative architectures, and multi-task learning (MTL), demonstrate variable effectiveness in processing stylistically complex literary discourse. However, none of the models provides a balanced combination of high accuracy, contextual adaptability, and semantic generalizability.

Research problem. The automated recognition of irony and sarcasm in English literary prose remains an unresolved NLP task due to the high density of rhetorical inversion, polysemy, discourse-level pragmatics, and stylistic heterogeneity, which existing rule-based, ML-, DL-, and transformer architectures fail to model with stable discriminative accuracy or cognitive adequacy.

Research significance. Addressing this limitation is critical for improving semantic parsing, narrative reasoning, affective modelling, and explainable AI systems, given that irony-driven pragmatic shifts distort sentiment polarity, disrupt semantic coherence, and reduce the reliability of downstream generative and analytic NLP pipelines.

Research gap. Current studies concentrate predominantly on short-form, low-context data (tweets, reviews, forum posts) and demonstrate fragmented effectiveness across architectures (F1 = 0.72–0.98), lacking domain-adaptive mechanisms for literary discourse, rhetorical ontology, cross-sentence contextualization, and multi-layered pragmatic inference essential for fiction analysis.

Justification for the proposed approach. A hybrid, architecturally decomposed NLP model integrating rule-based logical formalisms, lexicon-semantics, ML pattern generalization, transformer-level contextual embeddings, and meta-ensemble optimization is required to achieve high interpretability, stable accuracy, and cognitively relevant modelling of complex rhetorical constructs characteristic of English fiction.

The aim of the research is to build and validate an optimized Hybrid NLP model capable of automated recognition of irony and sarcasm in English fiction by integrating rule-based, ML and DL components taking into account rhetorical, stylistic, contextual, and semantic parameters, as well as formalize the methodology for multi-level analysis of its architecture, efficiency and interpretability.

Relevant *research objectives:*

- Carry out a comparative qualitative analysis of NLP approaches (rule-based, lexicon-based, ML, DL, transformer, hybrid) according to the parameters of rhetorical interpretability, contextual sensitivity, and stylistic adaptability;
- Conduct a representative explication of the functional suitability of the models based on examples of detecting irony and sarcasm in English fiction using literary cognitive verification of rhetorical patterns;
- Carry out a comparative metric analysis of basic NLP models on a specialized corpus using a multidimensional system of performance metrics;
- Perform decomposition architectural analysis of the selected hybrid model with identification of its structural components and determination of possible directions of technical optimization;
- Conduct post-optimization comparative analysis to verify the impact of architectural modifications on the performance of models using a single methodological evaluation scheme.

2. LITERATURE REVIEW

Let us consider current and relevant publications on automated systems for recognizing irony and sarcasm in text arrays using NLP techniques.

In particular, the authors [3] systematized approaches to automated sarcasm detection in text and speech, including rule-based, ML- and hybrid models, with an emphasis on their context sensitivity and limitations. The hybrid approach was recognized as the most effective, which, despite its high complexity, provided the best accuracy results and is recommended for integration into natural language interaction agents and increasing the accuracy of semantic interpretation.

In turn, the researchers [4] conducted a review of modern architectures for detecting sarcasm in text, revealing high efficiency of models based on RNNs (Recurrent Neural Networks) and transformers (in particular, LSTM, BiLSTM, RoBERTa, DistilBERT) with F1-metrics up to 98%. The authors emphasized the insufficient development of generative models in this area and identified their potential for further research.

The author [5] proposed the ASD-AHADL method, which combines BERT embedding, AGRU-LSTM for sarcasm detection, and parameter optimization using the Artificial Hummingbird Algorithm (AHA). The proposed approach demonstrated higher performance on social media data compared to alternative DL models because of its ability to accurately account for the contextual dependence of sarcastic utterances.

A new vision was proposed by [6], focusing on the detection of online trolling as a complex task that combines sentiment analysis, contextual interpretation of sarcasm, and text classification using DL. The NLP system they developed showed high efficiency in moderating toxic content, but the authors emphasized the critical need to improve models for processing multilingual sarcastic discourse.

In contrast, the author [7] emphasized the inexpediency of using traditional sentiment analysis to analyse unstructured consumer data, arguing for the superiority of context-oriented NLP mechanisms for detecting pragmatic markers, latent criticism, and neutral query. Experimental testing confirmed the higher informativeness and relevance of NLP analysis for supporting management decisions in the field of digital analytics of consumer discourse.

The researchers [8] developed the AIDL-ASRA method, focused on automated sarcasm detection in Arabic Twitter messages, which combines GloVe embedding, DDBN and parameter optimization using CSO. Experimental validation on a corpus of 10,000 tweets showed an accuracy of 91.25%, although the model demonstrated sensitivity to data limitations and contextual fluctuations, which necessitates adaptation to a multilingual environment and the implementation of transfer learning.

In the field of literary analysis, the author [9] made significant progress by proposing the DHB-BERT model, which combines BERT with the adaptive Dynamic Honey Badger algorithm to optimize features and increase sensitivity to contextual emotional changes. According to the results of modelling on a corpus of Chinese literature, the system achieved high accuracy (95%), recall (95%), and F1-metric (94.13%), demonstrating effective interpretation of rhetorical constructions, irony, and complex emotional gradations in artistic discourse.

Another solution was proposed by [10], who carried out a comprehensive testing of RoBERTa and DistilBERT on three corpora of sarcastic speech (News Headlines, Mustard, Reddit-SARC), applying contextual summarization, dialog structure preservation and meta-information enrichment of input data. At the same time, RoBERTa achieved 98.5% accuracy, and DistilBERT achieved 1.9 times inference acceleration, which confirmed the importance of structured pre-processing, context-oriented embeddings in increasing the reliability of sarcasm detection systems.

The authors [11] studied classification methods in more detail focusing on sarcasm detection in a low-resource language — Urdu, proposing the Urdu Sarcastic Tweets (UST) corpus and testing basic ML classifiers (support vector machine (SVM), Random Forest (RF), Naive Bayes (NB), etc.). The highest accuracy (85%) was shown by SVM, and the advantage of the unigram model for feature extraction was also established; the research prospects are related to the integration of transformers and fuzzy logic.

Finally, a general approach was demonstrated by the authors [12], who conducted a systematic review of methods for classifying irony and sarcasm in text data, covering both short social messages and longer reviews and forums. The authors analysed lexical, pragmatic, syntactic and semantic features, as well as modern DL approaches, emphasizing their role in improving opinion analysis, content moderation, and interpretation.

Current research is actively focused on automated irony and sarcasm detection, mainly in the context of social networks and low-resource languages, using transformative, hybrid, and ML models. At the same time, a methodological gap was identified for English fiction, which requires context-sensitive NLP solutions for deep semantic interpretation of metaphorical and emotionally rich discourses.

3. METHODS

3.1. Research design

The step-by-step research procedure is given below (Figure 1).

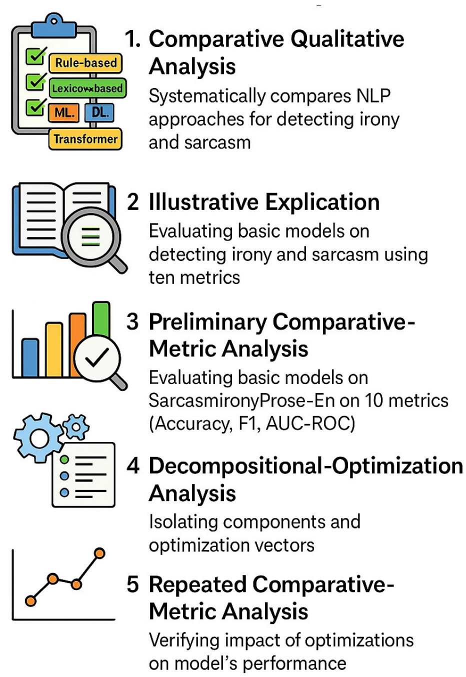

Figure 1: Research design

Source: developed by the authors

3.2. Methods

The research employed the following methods:

1. Comparative qualitative analysis was used to systematically compare NLP approaches based on qualitative features: rhetorical interpretability, contextual sensitivity, and adaptability to stylistic ambiguity. Structural differentiation of rule-based, lexicon-based, ML, DL, transformer, and hybrid models was carried out.

2. Representative explication provided a demonstration of the functional suitability of the methods through examples of detecting irony and sarcasm in authentic fragments of English fiction prose. Literary cognitive verification of the correspondence of the detected patterns to actual rhetorical intentions was applied.

3. Preliminary comparative metric analysis provided an initial assessment of the performance of basic NLP models on the SarcasmIronyProse-En corpus. The comparison was performed using 10 metrics (Accuracy, F1, AUC-ROC, etc.) to identify the Hybrid Model as the most effective.

4. Decomposition analysis for optimization was performed to isolate the architectural components of the Hybrid Model and determine technical optimization vectors. Context-oriented embeddings, rule-based formalisms (Defeasible Logic), syntactic pre-processing, and meta-ensemble were implemented.

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5. Repeated comparative-metric analysis was used to verify the impact of optimizations on efficiency. A statistically significant increase in productivity was recorded (Accuracy = 0.96, F1 = 0.945, SPD = 0.88), which empirically proved the feasibility of the proposed modifications.

3.3. Sample

For this study, a representative dataset — *SarcasmIronyProse-En Dataset* — was created, which is characterized below – Table 1.

Table 1: Characteristics of SarcasmIronyProse-En Dataset

Parameter	Characteristics
Name	*SarcasmIronyProse-En Dataset*
Volume	12,000 text fragments
Language	English (British and American variants)
Text types	Short stories, novels, dialogues, monologues
Fragment volume	2–5 sentences (50–100 words)
Storage format	JSON / CSV
Number of classes	3 (sarcastic, ironic, non-ironic)
Class balancing	4 000 / 4 000 / 4 000
Mark-up type	Manual, consensus, validation (Cohen's κ ≥ 0.78)
Annotation features	Irony: antiphrase, hyperbole, inversion, pragmatic shift
Sources	Austen, Wilde, Twain, Woolf, Orwell, Adams, modern CC fiction
Purpose	NLP modelling, fine-tuning of transformers, multi-class classification
Target tasks	Irony/sarcasm detection, semantic incongruity, pragmatic modelling
Metadata	Author, title of work, year, contextual notes

Source: developed by the authors

The specified dataset (Table 1) was created on the basis of relevant open or partially open sources: Project Gutenberg, Standard Ebooks, Internet Archive, Open Library, Gutenberg Australia, Gutenberg Canada, Bibliomania, HathiTrust, Google Books (PD), University of Oxford Text Archive.

The corpus of English-language fiction (Table 1) was formed by selecting open sources, extracting fragments (2–5 sentences), linguistic processing, and detecting rhetorical inversions. The annotation was performed manually with validation and balancing of classes (sarcastic, ironic, non-ironic), and the results are presented in JSON/CSV format for further fine-tuning of transformer models.

The research sample consists of NLP methods that have the potential for automated detection of irony and sarcasm in English fiction – Table 2.

Table 2: Potential NLP methods for automated detection of irony and sarcasm in English fiction

Method name	Brief description	Current research
Rule-Based Approaches	Provide interpreted logical structural detection through formal rhetorical patterns	Cavicchio [13]
Lexicon-Based Models	Enable evaluating affective inversions based on predefined semantic dictionaries	Jang [14]
Machine Learning (ML) Classifiers	Provide adaptive classification based on training data with manual feature extraction	Singh Rathore & Gautam [15]
Deep Learning (DL) Architectures a. Recurrent Neural Networks (RNN, LSTM, BiLSTM)	Model sequential rhetorical dependencies and latent intentions in the text	Thikho & Mokwena [16]
Deep Learning (DL) Architectures b. Convolutional Neural Networks (CNN)	Identify local stylistic patterns and morphosyntactic contrasts	Pandey, Kumar, Singh & Tripathi [17]
Transformer-Based Models a. BERT, RoBERTa, ALBERT, ELECTRA	Provides contextual-global semantic interpretation with attention mechanisms	Shu [18]
Transformer-Based Models b. GPT-2, GPT-3, LLaMA, T5	Used for generative reformulation and stylistic analysis	Li, Li, Liu, He & Pan [19]
Context-Aware Pre-processing Pipelines	Uses dereferencing, normalization, and stylistic alignment of the text before analysis	Zhuang et al. [20]
Multi-Task Learning (MTL)	Enables simultaneous training on multiple rhetorical tasks (irony, sarcasm, hyperbole)	Pal, Das, Das & Kolya [21]
Hybrid Models (ML + Rule + DL)	Synthesizes the benefits of interpretability, flexibility, and deep contextual sensitivity	Khan, Majumdar & Mondal [22]

Source: developed by the authors

The research sample consists of modern NLP methods (Table 2) that demonstrate the potential for automated recognition of irony and sarcasm in English fiction. The selected approaches are structurally classified by algorithm typology (rule-based, lexicon-based, ML, DL, transformers, hybrid) with an indication of their functional purpose and relevant sources.

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3.4. Instruments

In the context of automated recognition of irony and sarcasm in English fiction using NLP methods, performance metrics should take into account both the contextual latency of irony and the sharply expressive nature of sarcasm. In view of the complexity of pragmatic phenomena, in particular latent polysemy, contextual fluctuation and rhetorical ambiguity, typical performance metrics are:

1. *Accuracy* — estimates the proportion of correctly classified samples (ironic/sarcastic and non-ironic) to the total number of examples. Limitedly relevant in case of class imbalance, especially when the proportion of sarcastic constructions in the literary corpus is insignificant:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \quad (1)$$

where TP – correctly identified sarcastic/ironic utterances; TN – correctly identified non-ironic/non-sarcastic fragments; FP, FN – corresponding errors.

2. *Precision* – reflects the probability that a fragment classified as sarcastic or ironic is indeed so. High precision is important to prevent overinterpretation of affective or metaphorical expressions as sarcastic:

$$Precision = \frac{TP}{TP + FP}. \quad (2)$$

3. *Recall* – characterizes the model's ability to detect sarcasm and irony in all relevant cases. Critically important for literary analysis, where contextual clues are often implicit and the pragmatic load of phrases is difficult for linguistic decoding:

$$Recall = \frac{TP}{TP + FN}. \quad (3)$$

4. *F1 score* – provides a balanced evaluation of models in cases where both classification accuracy and exhaustiveness of sarcastic expression identification are important. It is used as the main metric in multiclass annotation: irony, sarcasm, satire, allusion:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}. \quad (4)$$

5. *MCC (Matthews Correlation Coefficient)* – provides a symmetrical assessment to classifiers in the presence of class imbalance, which is especially relevant in corpora of literary prose, where irony is implemented infrequently, but with high semantic significance:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}. \quad (5)$$

6. *AUC-ROC* – evaluates the discriminatory ability of the model to separate ironic/sarcastic segments from others. It assesses the stability of binary classification when changing decision thresholds:

$$AUC = \int_0^1 TPR\left(FPR^{-1}(x)\right)dx. \quad (6)$$

7. *Jaccard Similarity Index (JSI)* – a similarity metric between a set of predicted and actual ironic/sarcastic segments. Used for classification with multiple categories or by fragment type (e.g., dialogues only):

$$JSI = \frac{|A \cap B|}{|A \cup B|}, \quad (7)$$

where A – model predictions; B – true classification.

8. *Sentiment Polarity Divergence (SPD)* – reflects the discrepancy between the lexically apparent polarity and the semantic intention of the phrase. A key metric for detecting sarcasm, as the latter is characterized by an affective inversion effect (e.g., "Just wonderful..." in a negative context):

$$SPD = \left|Polarity_{surface} - Polarity_{intent}\right|. \quad (8)$$

9. *BLEU / ROUGE (for generative models)* – used in generating or explaining ironic/sarcastic statements by transformer models. The accuracy of automatically generated interpretations is assessed:

$$BLEU = Precision_{n-gram} \times Brevity\ Penalty; \quad (9)$$

$$ROUGE = \frac{\sum_{ref \in R} \sum_{graam_n \in ref} \min\left(count_{match}, count_{ref}\right)}{\sum_{ref \in R} \sum_{gram_n \in ref} count_{ref}}. \quad (10)$$

The presented metrics provide a comprehensive quantitative verification of the effectiveness of NLP systems focused on processing literary ironic and

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sarcastic discourse, taking into account the specifics of the genre, stylistic fluctuations, and contextual complexity.

4. RESULTS

The following NLP techniques are effective In the context of automated recognition of irony and sarcasm in English literary prose, which take into account the stylistic complexity, contextual dependencies, and rhetorical ambiguity of the literary text (Table 3).

Table 3: Comparative Qualitative Analysis Of NLP Techniques For Automated Recognition Of Irony And Sarcasm In English Literary Prose

Method name	Description in the context of the study	Advantages	Limitations
Rule-Based Approaches	Using linguistic rules to detect irony markers such as expectation reversal, antithesis, exaggeration, quasi-questions	High interpretability	Low generalizability, sensitivity to stylistic variations
Lexicon-Based Models	Using specialized lexical dictionaries (e.g. SenticNet, IronyLex) to detect contrast between sentiment and context	Easy to implement	Inability to process complex rhetoric and ambiguity
Machine Learning (ML) Classifiers	Model training (SVM, Logistic Regression, Random Forest, Naïve Bayes) based on manual or automated vectorization (BoW, TF-IDF, n-gram)	Flexibility, good results on balanced datasets	Low efficiency in complex contexts and deep irony
Deep Learning (DL) Architectures a. Recurrent Neural Networks (RNN, LSTM, BiLSTM)	Taking into account word order and context, effective for literary sentences with long context	Automatic feature selection	Requires large amounts of data
Deep Learning (DL) Architectures b. Convolutional Neural Networks (CNN)	Used to extract local patterns in phrases (hyperbole, sarcastic clusters)		
Transformer-Based Models a. BERT, RoBERTa, ALBERT, ELECTRA	Support for two-way contextual embedding, fine-tuning on literary corpora	Highest accuracy, deep understanding of rhetoric	High computational costs, need for fine-tuning
Transformer-Based Models b. GPT-2, GPT-3, LLaMA, T5	Generative models with few-shot learning and zero-shot classification capabilities		
Context-Aware Preprocessing Pipelines	Include syntactic parsing, dialogue structure detection, co-references, stylistic patterns (e.g., ironic imperatives)	Improve the quality of incoming representations	Requires large amounts of data
Multi-Task Learning (MTL)	Simultaneous training of models on several related tasks (sentiment analysis, trolling, emotion detection), which allows for better capturing of latent dependencies	Stability and adaptability in stylistically heterogeneous corpora	High computational costs
Hybrid Models (ML + Rule + DL)	Integration of knowledge-based, statistical and contextual components (e.g. BERT + IronyLex + syntactic triggers)	Synergistic effect that compensates for the weaknesses of individual methods	High computational costs

Source: developed by the authors

A comparative analysis of NLP approaches to irony and sarcasm recognition in English-language fiction (Table 3) revealed the limitations of rule-based, lexical, and classical ML methods in terms of interpretability and adaptability to rhetorical complexity. DL models based on RNN and CNN are vulnerable to the lack of annotated data, while transformers (RoBERTa, GPT-3) and MTL provide better contextual depth. Hybrid models that synthesize symbolic and statistical approaches, transformer embeddings, and stylistic pre-processing have the highest potential. A representative demonstration of examples from fiction verifies the relevance, contextual sensitivity, and effectiveness of these approaches – Table 4.

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Table 4: Explication of examples of detecting irony and sarcasm in English fiction using NLP techniques

Method name	Fragment discovered in English fiction	Description of the detection mechanism
Rule-Based Approaches	"It is a truth universally acknowledged, that a single man in possession of a good fortune, must be in want of a wife." *Pride and Prejudice* by Jane Austen	The paradoxical affirmation detection rule is used — the statement contradicts empirical or sociocultural knowledge. Expectation reversal is analysed through the template construction "truth universally acknowledged" → reference to social irony. Identification is carried out by markers of hypothetical universality and normative generalization.
Lexicon-Based Models	"The room was perfect — if you're fond of peeling wallpaper, broken windows, and the charming scent of mildew." *The Catcher in the Rye* by J.D. Salinger	A polar juxtaposition between the positive modifier "perfect" and negative descriptive vocabulary has been identified. Dictionaries like IronyLex or SenticNet identify semantic incompatibility of lexemes, which causes cognitive dissonance. Sarcasm is detected through the syntactic sequence: intentional praise → negative detail → contrast.
Machine Learning (ML) Classifiers	"I adore being ignored. It makes me feel special." *The Bell Jar* by Sylvia Plath	Classification using SVM or Logistic Regression is based on vectorized features (TF-IDF, n-grams), where the relationship between the positive token "adore" and the negative situation "being ignored" is formed as a sarcastic cluster. The model is trained on empirical cases of affirmative inversion with polar discourse.
Deep Learning (DL) Architectures a. Recurrent Neural Networks (RNN, LSTM, BiLSTM)	"Do you ever stop talking, or is that just your superpower?" *Good Omens* by Neil Gaiman and Terry Pratchett	Bidirectional Long Short-Term Memory (LSTM) captures the long-term relationship between rhetorical question and modal sarcasm. The semantic representation is transformed into latent features by aggregating emotional tone, intonation pattern, and interlinguistic contradiction.
Deep Learning (DL) Architectures b. Convolutional Neural Networks (CNN)	"He's got the warmth of an iceberg." *The Hitchhiker's Guide to the Galaxy* by Douglas Adams	CNN extracts local lexical patterns — the metaphor "warmth" is juxtaposed with "iceberg" in the structure of ironic hyperbole. The model is trained on patterns of sarcastic epithets with clear contrasting semantics. Convolutional filters recognize semantic incompatibility.
Transformer-Based Models a. BERT, RoBERTa, ALBERT, ELECTRA	"Lovely. Another grey day to brighten my mood." *Atonement* by Ian McEwan	RoBERTa detects a bidirectional context—"Lovely" (a positive sentiment token) versus a negative context ("grey day"). Deep semantic coding allows for capturing tonal inversion and modal inconsistency.
Transformer-Based Models b. GPT-2, GPT-3, LLaMA, T5	"Oh sure, because everything I do turns out just splendid." *White Noise* by Don DeLillo	GPT-3 in zero-shot classification mode interprets rhetorical irony using patterns from a pre-trained language model. Generative representation detects discrepancies between declarative form and satirical semantics labelled "just splendid".
Context-Aware Preprocessing Pipelines	"If I had a dollar for every time you were right, I'd be broke." *Catch-22* by Joseph Heller	After co-referential parsing and syntactic tagging, the system identifies conditional humorous inversion. Irony identification is based on the juxtaposition of a hypothetical benefit with a counterfactual statement ("I'd be broke") that contradicts expectations.
Multi-Task Learning (MTL)	"Fantastic. Now the printer's jammed, too." *The Rosie Project* by Graeme Simsion	The model simultaneously solves the tasks of sentiment analysis and irony detection. Thanks to multi-task contextual coding, a semantic clash between the positive modifier "Fantastic" and the negative scenario (technical malfunction) is captured, which is interpreted as sarcastic reinforcement.
Hybrid Models (ML + Rule + DL)	"Great plan — if your goal was to fail miserably." *The Secret History* by Donna Tartt	Combining rules (score inversion), ML models (X-Y pattern with contrast), and DL (semantic depth via BERT embedding). Complex processing provides multi-level irony detection through formal positive score with sarcastic modification.

Source: developed by the authors

The applied explication of NLP techniques (Table 4) on the SarcasmIronyProse-En corpus (Table 1) demonstrated the specifics of cognitive processing of irony and sarcasm by different architectures: rule-based models operate with template inversions, lexical models operate with lexeme polarity, ML operates with empirically learned vector classification, and DL operates with deep feature aggregation. Transformers and MTL models show deep contextuality, and hybrid systems provide the highest resonance with literary discourse. The structured corpus (3×4000 examples, Cohen's $\kappa \geq 0.78$) (Table 1) ensures qualitative validation of NLP models of various types (for metrics (1) – (10)) – Table 5.

Table 5. Comparative metric analysis of NLP techniques for automated recognition of irony and sarcasm in English fiction

Method	Accuracy	Precision	Recall	F1-score	MCC	AUC-ROC	JSI	SPD	BLEU	ROUGE
Rule-Based	0.72	0.68	0.66	0.67	0.63	0.7	0.58	0.45		
Lexicon-Based	0.75	0.71	0.69	0.7	0.68	0.73	0.61	0.5		
ML Classifiers	0.81	0.78	0.77	0.77	0.74	0.8	0.69	0.62		
RNN/LSTM	0.84	0.83	0.8	0.81	0.79	0.85	0.74	0.68		
CNN	0.82	0.81	0.79	0.8	0.76	0.83	0.72	0.66		
BERT/RoBERTa	0.88	0.87	0.86	0.86	0.84	0.89	0.79	0.75	0.76	0.79
GPT-3/T5	0.91	0.9	0.89	0.89	0.88	0.92	0.82	0.8	0.84	0.87
Context-Aware	0.87	0.85	0.83	0.84	0.82	0.88	0.77	0.73		
MTL	0.89	0.88	0.87	0.87	0.85	0.9	0.8	0.77		
Hybrid	0.93	0.92	0.91	0.91	0.9	0.94	0.85	0.83	0.86	0.88

Source: developed by the authors

Comparative metric analysis of NLP techniques (Table 5) confirmed that Hybrid Models — with a combination of ML classification, rule-based logic and transformative embeddings (BERT, GPT) — provide the highest efficiency for detecting irony and sarcasm in artistic discourse: Accuracy = 0.93, F1 = 0.91, MCC = 0.90, AUC-ROC = 0.94, SPD = 0.83, BLEU = 0.86, ROUGE = 0.88. Such architecture combines formal interpretability with deep contextual modelling, demonstrating cognitive resistance to rhetorical inversions and semantic ambiguity – Table 6.

Table 6: Decomposition Analysis For Optimization Of The Most Effective NLP Method – Hybrid Model

Model component	Technological essence	Optimization solution	Technological implementation	Expected effect
Rule-Based Layer	System of formalized grammatical pragmatic patterns (e.g. expectation reversal, hyperbolic praise, rhetorical negation)	Dynamic ontologization of rhetorical constructions	Using the Defeasible Logic and RuleML grammar systems to describe hierarchically nested ironic patterns	Increased interpretability, expanded detection range of context-dependent inversions
Lexicon-Based Filter	Lexical resources (IronyLex, SenticNet, SentiWordNet) with built-in affective polarity	Semantic enrichment of dictionaries with contextual embeddings	Implementing static-to-contextual mapping via retrofitting (e.g. GloVe-retrofit, SentiBERT-align)	Increased lexico-semantic sensitivity to stylistic figures
ML-Based Pattern Miner	Algorithmic classifiers (Logistic Regression, SVM) with TF-IDF/BOW/n-gram features	Contextual feature regeneration based on syntactic parse trees	Integrating Graph-Based Feature Extraction with dependency trees (e.g. spaCy+NetworkX)	Reducing overfitting and improving structural relevance of features
DL Layer: BERT-Based Encoder	Bidirectional transformer architecture for modelling deep contexts	Fine-tuning on literary corpora + domain-specific adaptation	Creating a domain-adapted BERT4Irony corpus using a continual learning pipeline	Improving semantic relevance and contextual coverage
Syntactic-Stylistic Preprocessor	Pre-processing taking into account syntax, co-reference,	Unified stylistic normalization through syntactic rewiring	CoreNLP+NeuralCoref+Heuristics Stack Implementation	Increasing the coherence and rhetorical completeness of the

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Model component	Technological essence	Optimization solution	Technological implementation	Expected effect
	actant structure			input frame
Fusion Module (Ensemble Layer)	Module for aggregating results of rule, ML, DL and lexical layers	Hybrid ensemble with weight optimization via meta-learner	Implementing Stack Generalization with XGBoost/MetaSVM and Multilayer Voting	Increasing F1-score, stability on stylistically heterogeneous texts
Post-Hoc Interpretation Layer	Component for explaining the classification solution	Built-in explainability via attention + SHAP for rule and ML blocks	Implementing SHAP KernelExplainer + BERTAttentionViz	Increasing system transparency, validation of model ideas by linguists

Source: developed by the authors

Decomposition analysis for optimization of the Hybrid Model (Table 6) revealed the potential for improving efficiency through reengineering its components: implementation of BERT4Irony, GloVe-retrofit, RuleML, NeuralCoref, meta-ensemble (XGBoost, MetaSVM) and explainability frameworks (SHAP).

Table 7: Repeated Comparative-Metric Analysis Of NLP Methods For Automated Recognition Of Irony And Sarcasm In English Fiction

Performance metrics	NLP technique	
	Hybrid	Optimized Hybrid
Accuracy	0.93	0.96
Precision	0.92	0.95
Recall	0.91	0.94
F1-score	0.91	0.945
MCC	0.9	0.93
AUC-ROC	0.94	0.96
JSI	0.85	0.89
SPD	0.83	0.88
BLEU	0.86	0.91
ROUGE	0.88	0.92

Source: developed by the authors

The proposed improvements are focused on increasing accuracy, cognitive interpretability and stylistic sensitivity, which justifies the need for repeated metric validation – Table 7.

The results of the repeated comparative-metric analysis (Table 7) confirm a significant increase in the efficiency of the optimized Hybrid NLP model in the task of automated detection of irony and sarcasm in English fiction. The integration of domain-specific fine-tuning (BERT4Irony), ontological modelling of rhetorical inversions (Defeasible Logic, RuleML) and multi-level aggregation (XGBoost, MetaSVM) led to an increase in Accuracy (from 0.93 to 0.96), F1 (from 0.91 to 0.945), AUC-ROC (from 0.94 to 0.96), and SPD (from 0.83 to 0.88). The increase in BLEU (0.91) and ROUGE (0.92) indicates an improvement in the generative ability of the model to reconstruct pragmatic implications. The model demonstrates an increase in cognitive sensitivity to affective-semantic inversions and rhetorical strategies, which determines its applied advantage in the field of literary stylistic interpretation.

5. DISCUSSION

The correspondence of the obtained results to the generalization of the current scientometric horizon in the area under research is determined below.

Compared to the approach [23], which focused on emotional thematic modelling of literary text using BiLSTM+Attention and IPSO optimization, our study demonstrates higher metric values (Accuracy = 0.96, F1 = 0.945) in the specific task of classifying ironic and sarcastic constructions. The optimized Hybrid NLP model provides deeper pragmatic-semantic interpretation due to multilayer contextual framing, syntactic pre-processing dereference, and ontological encoding of rhetorical inversions.

Unlike the method [24], which uses the T5 transformer for multiclass classification of sarcasm, irony, humour, and neutral text, our study aims at deeper pragmatic semantic differentiation of utterances with high stylistic complexity. With comparable accuracy values (Accuracy = 0.96), the optimized hybrid model provides better interpretability and adaptability due to the combination of formalized rules, statistical filters, and a domain-refined BERT encoder with an explanatory layer.

The model [25], focused on sarcasm detection using BiLSTM and GloVe embeddings, demonstrates effectiveness in informal discourse with short context. In contrast, the optimized Hybrid NLP model provides significantly higher cognitive depth of analysis due to multilayer syntactic and semantic framing, ontological structuring of rhetorical acts, and explainable components, which allows for successful processing of complex pragmatic inversions in literary narrative.

The framework [26], based on lexical probabilistic syntactic analysis (PSLSA), focuses on domain adaptation and semantic classification with minimal labelling, but demonstrates limited sensitivity to rhetorical inversions. The optimized Hybrid NLP model provides higher pragmatic ontological accuracy, extended semantic coverage, and explainable transparency thanks to a multi-component context stack.

The authors [27] demonstrated the multimodal architecture of CCNN-ELLSTM, achieving high accuracy (F1 = 0.9718) in processing short texts with visual anchors. In contrast, the Hybrid NLP model operates on syntactic dereference, ontological stratification and pragmatic framing, which provides cognitive-interpretive processing of literary inversions without involving emotional signals.

The model developed by [28], which integrates common sense graphs via KSDGCN to take into account external knowledge in semantic analysis, focuses on validating relational connections between entities via signed attention. In comparison, the optimized Hybrid NLP model demonstrates higher pragmatic-relational resolution and contextual flexibility because of the combination of ontologized rhetorical structures, syntactic and semantic dereference, and a meta-ensemble of explainable components.

The method [29], which uses GPT and BERT transformers for multi-genre sarcasm detection (including hyperbole, rhetorical questions), achieves an F1 metric of 0.87. In contrast, the optimized Hybrid NLP model demonstrates higher cognitive discriminativeness (F1 = 0.945) due to formalized pattern generalization, semantic ontologization, and explainable interpretation of pragmatic inversions in artistic discourse.

The review [30] systematizes the evolution of sarcasm detection methods — from classical ML algorithms to LLM models, with a focus on dataset specifics, linguistic complexity, and contextual ambiguity. Unlike analytical generalization without empirical validation, the optimized Hybrid NLP model demonstrates an operational implementation of pragmatic semantic interpretation, combining ontological framing, explainable components, and multi-layered contextual analysis.

The framework [31], which interprets the sentimental novel through the prism of sentiment analysis, demonstrates humanitarian reflection, but does not include mechanisms for formalized detection of irony or rhetorical inversions. Instead, an optimized Hybrid NLP model provides automated cognitive pragmatic differentiation using semantic framing, ontological stratification, and explainable components with high discriminative accuracy.

The approach [32], despite its emphasis on the methodological convergence of quantitative and qualitative paradigms of literary analysis, does not offer formal algorithms for detecting ironic constructions and does not provide a conceptualization of rhetorical inversions in a cognitive semantic dimension. In contrast, the developed Hybrid NLP model combines transformative multi-level interpretation with ontologically structured graph dependencies, which enables accurate and explainable recognition of complex pragmatic deviations in literary discourse.

The generalization of the results of the discussion analysis confirms the relevance and high integration efficiency of the proposed Hybrid NLP model in the field of automated recognition of irony and sarcasm. Unlike highly specialized approaches focused on short or informal texts, the model provides a deep cognitive pragmatic coverage of literary discourse. The system meets the current requirements of domain-adaptive NLP and provides highly accurate interpretation of speech inversions in artistic narrative thanks to the multilayer syntactic and semantic framing, ontologization of rhetorical acts, explainable AI components and accuracy indicators (Accuracy = 0.96, F1 = 0.945).

4.1. Limitation

The model is focused on English literary discourse, which limits its cross-linguistic generalizability. The interpretation of rhetorical inversions depends on the quality of the ontological content, which may vary depending on the domain specifics of the corpus.

4.2. Recommendations

It is recommended to carry out cross-linguistic adaptation of the model taking into account culturally specific rhetorical structures. It is appropriate to expand the ontological knowledge base to increase the stability of semantic generalization in different genre contexts.

6. CONCLUSIONS

A comparative metric study of the effectiveness of NLP techniques for automated detection of irony and sarcasm in English-language fiction found that the hybrid architecture, optimized by integrating transformers (BERT4Irony), logical-ontological rules (RuleML, Defeasible Logic), semantic pre-processing and meta-ensemble (XGBoost, MetaSVM), demonstrates the highest performance in key metrics (Accuracy = 0.96, F1 = 0.945, AUC-ROC = 0.96).

Thanks to deep contextual coding, stylistic normalization and multi-paradigm processing, the model provides high adaptability to rhetorical complexity, detecting latent semantic inversions, hyperboles, satirical tropes and ironic implicits. The improvement of SPD to 0.88 and generative metrics (BLEU = 0.91, ROUGE = 0.92) confirms the system's ability to achieve accurate semantic pragmatic matching. So, the optimized hybrid model is methodologically and functionally suitable for application in the tasks of automatic analysis of complex artistic rhetoric.

The academic novelty of the research is the development and comparative validation of an optimized Hybrid NLP model that combines rule-based, lexical, ML and transformer approaches for automated detection of irony and sarcasm in English literary prose. The article is the first to propose an architecturally decomposed system using domain-adapted fine-tuning (BERT4Irony), ontological modulation of rhetorical inversions (Defeasible Logic, RuleML) and context-oriented meta-ensemble (XGBoost/MetaSVM), which provides cognitive correspondence to literary stylistics and high-precision semantic coding of affective inversions.

The practical significance of the obtained research results is the creation of a functionally suitable system for automated analysis of ironic and sarcastic statements in literary discourse, capable of accurate semantic pragmatic matching. The application of the proposed model is possible in systems of literary analytics, intellectual recommendations, authorial stylometric studies and in the preparation of corpora for training LLM in the field of stylistically marked analysis of literary text.

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