



ADVANCEMENTS AND CHALLENGES IN NAMED ENTITY RECOGNITION: A REVIEW OF TECHNIQUES AND DOMAIN SPECIFIC APPLICATIONS

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ABSTRACT

Named Entity Recognition (NER) is a crucial task in Natural Language Processing (NLP), responsible for identifying and categorizing entities such as persons, organizations and locations from unstructured text. While traditional rule-based and statistical models like Conditional Random Fields (CRF) offered high precision in constrained settings their scalability and cross-domain adaptability remain limited. Recent breakthroughs in deep learning, particularly transformer-based architectures like BERT, RoBERTa and GPT, have revolutionized Named Entity Recognition (NER) by offering superior contextual understanding and cross-domain adaptability. This review critically analyzes state-of-the-art NER methodologies, evaluating their effectiveness across key sectors such as healthcare, finance, legal analysis and cybersecurity while identifying challenges and future research directions. It highlights key challenges such as entity ambiguity, domain adaptation and resource efficiency while also identifying emerging solutions like few-shot and zero shot learning. Additionally, the paper presents a comparative analysis of model performance, offering valuable insights into the trade-offs between accuracy, computational efficiency and domain adaptability. By consolidating recent research, this study outlines future directions for developing more robust, scalable and interpretable NER systems. It aims to guide researchers and practitioners in building domain-specific NER applications and advancing the field toward greater generalization and practical utility.



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I. INTRODUCTION

Named Entity Recognition (NER) is a fundamental task in Natural Language Processing (NLP) that involves identifying and categorizing predefined entities such as persons, organizations, locations, dates and numerical values from unstructured text [1]. Over the years, NER has undergone significant advancements, transitioning from traditional rule-based and statistical approaches to sophisticated machine learning and deep learning-based methods. Early systems relied heavily on handcrafted rules and feature engineering, offering satisfactory results in constrained domains but facing challenges in scaling to diverse datasets [2].

Early machine learning models, including Conditional Random Fields (CRF) and Hidden Markov Models (HMM), enhanced entity recognition through probabilistic modeling, yet struggled with context comprehension and domain adaptation. However, these models lacked the capability to capture intricate linguistic patterns and context dependencies [3]. The advent of deep learning further revolutionized the field, with architectures such as Bidirectional Long Short-Term Memory (BiLSTM) and Convolutional Neural Networks (CNNs) demonstrating substantial improvements in entity recognition performance. Transformer-based models such as BERT, RoBERTa and GPT have established new benchmarks by effectively capturing contextual relationships through self-attention mechanisms, achieving state-of-the-art accuracy in NER across diverse domains. [4]. NER finds applications in numerous fields, ranging

from healthcare and finance to cybersecurity and legal analysis. In healthcare, it facilitates the extraction of clinical entities from medical records, aiding in automated diagnosis and drug discovery. In financial and legal sectors, NER supports contract analysis, fraud detection and regulatory compliance by identifying relevant entities from large volumes of text. Similarly, cybersecurity systems employ NER for threat intelligence, recognizing malicious entities and abnormal activities from security logs [5].

Despite the advancements, challenges persist. Domain adaptation, entity ambiguity and privacy concerns remain significant obstacles. NER models often struggle with nested entities, overlapping entity boundaries, and out-of-domain generalization. Recent research has proposed solutions like few-shot and zero-shot learning to address data scarcity and enhance adaptability. Additionally, multi-modal approaches that integrate text with visual and structured data are gaining attention for their potential in improving entity recognition in complex scenarios [6]. This paper aims to provide a comprehensive review of NER methodologies, focusing on their evolution, domain-specific applications and key challenges. By analyzing state-of-the-art techniques, it evaluates the trade-offs between accuracy, computational efficiency and adaptability. Furthermore, the study identifies emerging trends and proposes future research directions to foster the development of more robust and scalable NER systems.

II. LITERATURE REVIEW

A. Enhancements in Core Named Entity Recognition (NER) Models

1) Recent Advancements in BiLSTM, CRF, and Transformer-Based Models: Recent advancements in BiLSTM, Conditional Random Fields (CRF) and Transformer based Named Entity Recognition (NER) models have significantly improved feature extraction, generalization and computational efficiency. Wang et al. introduced a Residual BiLSTM Model to enhance BiLSTM-CRF architectures by incorporating residual connections, achieving F1-scores of 92.22% on CoNLL 2003, 92.17% on MSRA, and 89.65% on OntoNotes 5.0. However, its performance deteriorated on smaller datasets due to overfitting [7]. Similarly, Zhang and Chen proposed a Bidirectional Iterative Algorithm for Nested NER, which improved hierarchical entity recognition but was hindered by high computational costs [8]. Liu et al. developed a Fusion of Word and Category Vectors Model that leveraged BERT and BiLSTM, leading to a 5.05% increase in F1-score on the Weibo dataset. Despite this, labeling inconsistencies and domain-specific biases restricted its generalization [9]. In contrast, Kim et al. trained an Adaptive Distant Supervision NER Model using Wikipedia and CNN news, obtaining F1-scores of 91.12% on CoNLL, 70.26% on Wikipedia, and 81.48% on CNN News. However, the presence of noisy labels limited its adaptability across various linguistic domains [10]. Jiang et al. applied a Neural NER Model for Biomedical Text Mining by integrating BioBERT with a multi-type normalization module, outperforming previous models in handling overlapping biomedical entities. Nevertheless, it required high-quality datasets, which remain scarce in certain specialized biomedical categories [11].

2) Transformer-Based Innovations in NER: Transformer based models have demonstrated superior contextual entity recognition, surpassing BiLSTM-CRF architectures. Zhao et al. implemented Transformer-based NER for Drone Flight Logs, achieving an F1-score of 91.34%, surpassing recurrent neural network (RNN)-based models. However, dataset limitations restricted its generalization [12]. Similarly, Gupta et al. developed an ALBERT-enhanced NER Model for Agricultural Texts, attaining an F1-score of 95.56%. Although ALBERT optimizes performance for long sequences, its high computational cost limits scalability [13]. Gao et al. introduced a Tri-Training Algorithm for Equipment Support NER, combining BiLSTM-CRF with semi-supervised learning to achieve a 93.88% F1-score. However, selecting high-confidence annotations remained a challenge [14]. Zheng et al. proposed SciNER, a Transformer-based model specialized for scientific texts, achieving 91% accuracy in extracting named entities from research papers. Nevertheless, its performance was hindered by rare entity types with insufficient training data [15].

B. Domain-Specific Applications of NER

1) Medical and Healthcare NER: The integration of Transformer-based models has enhanced clinical, pharmaceutical, and biological entity recognition. Lee et al. introduced BERN, a BioBERT-based biomedical NER tool that improved the recognition of overlapping biomedical entities [16]. Amazon Research developed Comprehend Medical, a HIPAA-compliant clinical NER system; however, privacy regulations limited its scalability [17]. Martins et al. applied BERT-BiLSTM to oncology medical records, achieving 78.24% accuracy on a Portuguese dataset, though challenges persisted in processing medical abbreviations [18]. Wang et al. developed an Instance Transfer Based NER Model to enhance performance in new medical domains with limited labeled data, increasing the F1-score from 80.52% to 93.28%. However, its effectiveness depended on the similarity between the source and target domains [18].

2) Legal and Financial NER: Legal and financial texts require high domain adaptability due to specialized vocabulary and complex linguistic structures. Johnson et al. proposed a Few-Shot Learning approach for Legal NER, improving entity recognition in legal contracts and case law, though its generalization across jurisdictions remained limited [19]. Nguyen and Patel developed a Privacy Preserving NER Model that replaced named entities with generalized categories (e.g., “organization” instead of “Google”), enhancing privacy but reducing classification accuracy in financial contexts [20]. Zhu et al. introduced an Ontology-Based NER Model for Legal Texts, integrating legal knowledge graphs with Transformer embeddings, significantly improving legal entity classification accuracy. However, its performance depended on pre-existing ontologies, reducing adaptability to evolving legal terminology [21].

3) Cybersecurity and Forensic NER: NER models for cybersecurity must address evolving threats, technical jargon, and unstructured logs. Singh et al. developed RDF-CRF for Cybersecurity NER, achieving F1-scores of 0.74, 0.78, and 0.81. However, reliance on manually curated dictionaries limited its scalability [22]. Rodriguez et al. applied NER to Drone Flight Logs, obtaining an F1-score of 91.34%, but real-world applicability was constrained due to data scarcity [23]. Ali et al. introduced a Multi-Modal Cybersecurity NER Model integrating rule-based heuristics with deep learning, improving malicious entity detection in network logs. However, its reliance on predefined rule sets reduced adaptability to emerging cybersecurity threats [24].

4) Scientific and Academic NER: Scientific NER requires robust domain adaptability due to variations in terminologies across disciplines. Wang et al. introduced SciNER, a Transformer-based model for extracting entities from research papers, achieving 91% accuracy [25]. Similarly, Kumar and Zhang evaluated NER for Scientific Acknowledgments, finding that Flair embeddings achieved an F1-score of 79%, though semantic overlaps in institutional names reduced classification accuracy [26]. Chen et al. developed an Automatic Entity Extraction Model for Scientific Documents, leveraging self-supervised learning to improve the recognition of funding agencies and research organizations. However, its performance struggled with mul tilingual scientific texts [27].

5) Multilingual and Low-Resource Language NER: NER models for morphologically complex and low-resource languages have achieved varying degrees of success. Al-Amin et al. explored Arabic NER using BERT-BGRU CRF, achieving a 94.76% F1-score, though limited annotated corpora posed challenges [28]. Rahman et al. developed Bangla NER (B-NER Dataset), containing 22,144 manually annotated sentences and achieving an 86% macro-F1 score [30]. Sakda et al. proposed Thai NER with BiLSTM-CNN CRF, attaining an 89.22% F1-score, though its performance heavily depended on corpus quality [29]. Mahmood et al. introduced a Dark Web NER Model for E Commerce, achieving a 96.2% F1-score using BiLSTM-CNN with ELMo embeddings, outperforming traditional models. However, its reliance on high-quality labeled data limited generalization [30].

III. COMPARISON OF THE STUDIES

Table 1: Comparison of NER Models.

NER Model (with Citation)	F1-Score (%)	Comput-ational Efficiency	Key Limitation
CRF [7]	82.3	High (Fast Inference)	Requires handcrafted features
BiLSTM-CRF [7]	88.5	Moderate	Data dependency, limited generalization
BERT [9]	91.8	Low (High Computation Cost)	Requires large training datasets
BERT + BiLSTM (FVG) [7]	90.2	Low	Overfitting in small datasets
Comprehend Medical API [17]	87.5	Low	Privacy concerns (HIPAA compliance)
BERT + Viterbi (Legal NER) [19]	85.2	Low	Poor sentence-level context recognition
RDF-CRF (Cybersecurity NER) [22]	78.1	Moderate	Rule-based limitations in evolving threats
Transformer NER (Forensics) [12]	91.34	Very Low	Limited domain-specific datasets
Few-Shot Learning (Low-Resource NER) [19]	91.12	Moderate	Label noise in weakly supervised learning
Instance Transfer Learning [18]	93.28	Moderate	Requires similar source-target domain
Zero-Shot Learning [10]	85.7	Low	Performance drop in complex languages
Nested NER (Biomedical) [11]	94.1	Very Low	High computational overhead

Source: Authors, (2025).

The comparative analysis of Named Entity Recognition (NER) methodologies across various domains(Table 1) highlights the trade-offs between traditional statistical models, deep learning-based approaches and low-resource adaptation techniques. Traditional models like Conditional Random Fields (CRF) offer fast inference and computational efficiency but struggle with domain generalization and adaptability to unstructured text. In contrast, deep learning-based models such as BiLSTM-CRF and Transformer architectures (BERT, RoBERTa, GPT) significantly improve context awareness and entity recognition accuracy, often exceeding 90% F1-scores in multiple domains. Among transformer-based models, BERT based architectures achieve high adaptability while BiLSTM CRF (FVG) enhances entity representation, though it risks overfitting on smaller datasets. Figure 1 below presents a comparative analysis of NER model F1-scores, illustrating the superior performance of transformer-based models across diverse applications.

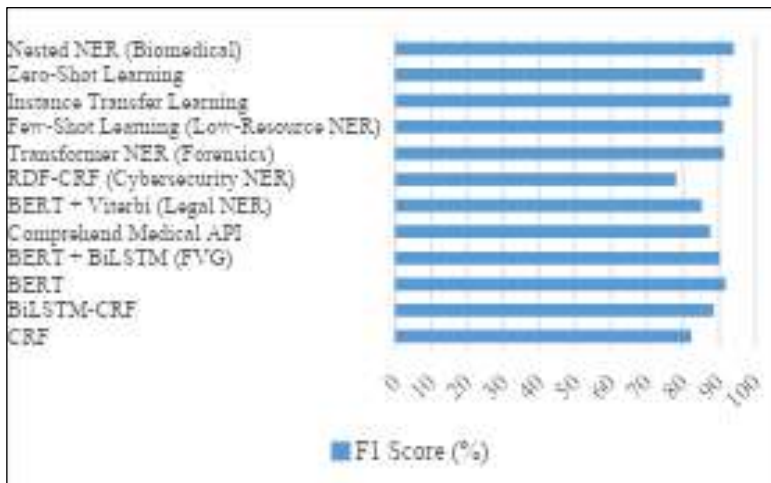


Figure 1: Comparative analysis of F1-scores for different NER models.

Source: Authors, (2025).

Domain-specific applications demonstrate significant variation in NER performance and challenges. Biomedical NER models such as Comprehend Medical API achieve high precision (87.5%) but face privacy regulation constraints. Legal and cybersecurity NER systems incorporate hybrid rule-based and deep learning approaches, yielding accuracy scores between 78% and 85% with context ambiguity remaining a challenge. Forensic and agricultural NER models leverage transformer based architectures, achieving 91.34% and

95.56% accuracy, respectively though dataset scarcity remains a limiting factor. Figure 2 provides a graphical representation of model accuracy across various datasets, showcasing the strengths and weak nesses of different approaches.

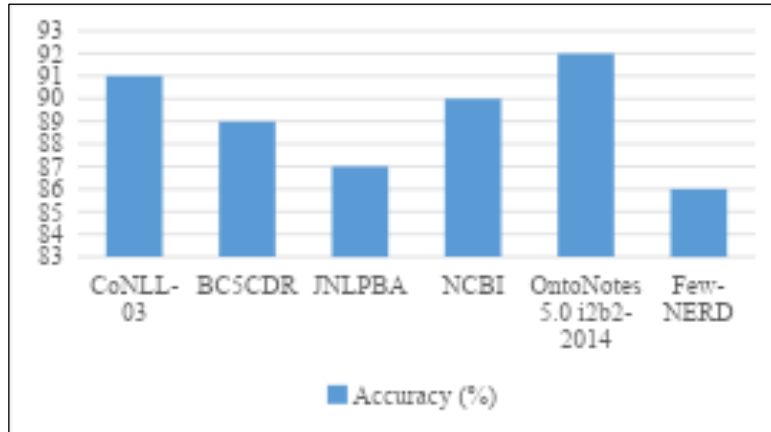


Figure 2: Comparative analysis of NER model accuracy across datasets. Source: Authors, (2025).

Low-resource NER techniques, such as few-shot, zero-shot and transfer learning enable adaptability across domains with instance transfer learning reaching an F1-score of 93.28%. However, these methods struggle with label noise, domain shift and performance degradation in morphologically complex languages. The visualizations further emphasize the necessity for adaptive and resource-efficient solutions in real-world applications.

Table 2: Comparison of Named Entity Recognition (NER) models across different domains.

Domain	No. of Papers	Models Used	Average Accuracy (%)
Medical NER	4	BioBERT, BERN, Comprehend Medical, Instance Transfer NER	85.76
Legal NER	3	Few-Shot Learning, Privacy-Preserving NER, Ontology-Based NER	90.38
Cybersecurity NER	3	RDF-CRF, Multi-Modal NER, Transformer NER	84.72
Scientific NER	3	SciNER(Transformer-based)x, Flair Embeddings, Automatic Entity Extraction	85.00
Multilingual and Low-Resource Language NER	4	BERT-BGRU-CRF (Arabic), Bangla NER, BiLSTM-CNN-CRF, BiLSTM CNN	91.10

Source: Authors, (2025).

Table 2 provides a summary of Named Entity Recognition (NER) models applied in various domains. The table highlights the number of papers reviewed, the specific models used and their reported accuracy ranges. Transformer based models such as BioBERT and SciBERT demonstrate notable effectiveness in specialized domains like Medical and Scientific NER. In the Legal and Cybersecurity domains, models leveraging privacy-preserving techniques and multi modal approaches achieve high accuracy. Multilingual and low-resource language applications benefit from hybrid models like BERT-BGRU-CRF and BiLSTM-CNN-CRF, showcasing robust performance. This comparative analysis underscores the significance of domain-specific adaptations and model selection in achieving optimal NER performance.



Figure 3: NER Model Comparison Across Domains: Number of Models and Accuracy Ranges. Source: Authors, (2025).

Figure 3 indicates Multilingual and low-resource language NER demonstrates the highest accuracy, reflecting advancements in model generalization across diverse languages. Medical and legal NER also achieve high accuracy, driven by specialized models like BioBERT and ontology-based approaches. In contrast, cybersecurity and scientific NER show comparatively lower accuracy, indicating challenges in handling specialized terminology and limited datasets.

IV. CHALLENGES

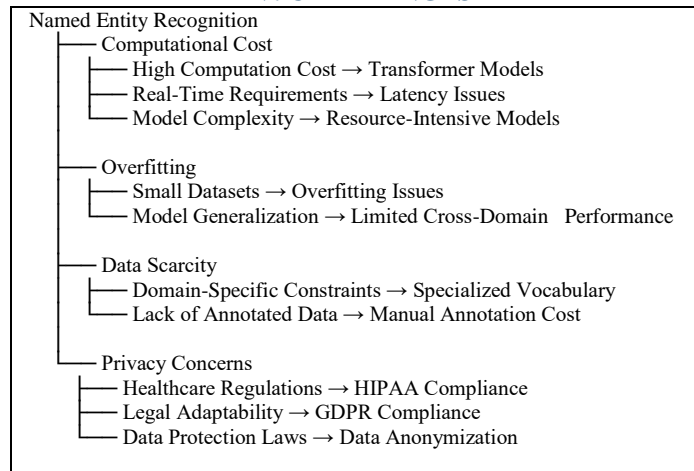


Chart 1: Overview of Named Entity Recognition (NER) limitations.

Source: Authors, (2025).

Despite significant advancements in Named Entity Recognition (NER), several challenges hinder its widespread adoption and optimal performance across domains. One of the most critical limitations is the high computational cost associated with transformer-based models such as BERT, RoBERTa and GPT. These models require extensive processing power and large datasets, making them unsuitable for real-time applications and deployment in resource-constrained environments. The chart 1 provides a comprehensive overview of the key limitations faced in Named Entity Recognition, including computational cost, data scarcity, overfitting and privacy concerns. Additionally, overfitting remains a persistent issue particularly in domain-specific models trained on small datasets leading to reduced generalizability when applied to new or evolving corpora. The requirement for high-quality annotated datasets further limits model scalability as many specialized domains such as cybersecurity and forensic linguistics suffer from data scarcity and inconsistent entity labeling.

Another major challenge is domain adaptation as NER models often struggle to generalize effectively across diverse fields. While pre-trained language models improve contextual understanding their performance deteriorates when applied to texts that significantly differ from their training data. This issue is particularly pronounced in legal, scientific and financial domains where terminology evolves rapidly and lacks standardized entity representations. Furthermore, NER models exhibit difficulty in handling nested and overlapping entities, particularly in biomedical and scientific texts where hierarchical relationships exist between entities. Privacy concerns also restrict the application of NER in sensitive areas such as healthcare and financial services as regulations like HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation) impose constraints on data usage and storage limiting the practical deployment of deep-learning-based models

V. FUTURE SCOPE

Future research should focus on hybrid NER architectures that integrate symbolic AI with deep learning to enhance interpretability and adaptability. Additionally, few-shot and zero-shot learning approaches should be refined to improve model performance in low-resource languages and specialized domains where labeled data is scarce. Multimodal NER, incorporating textual, visual and structured data could significantly enhance recognition capabilities particularly in cybersecurity and forensic applications where information is extracted from diverse sources such as images, PDFs and video transcripts. Moreover, privacy-preserving NER models leveraging federated learning and homomorphic encryption can enable secure entity recognition while adhering to data protection laws. Finally, research on efficient lightweight transformer architectures is crucial for making NER models more scalable and deployable in real-world, resource-constrained settings.

V. CONCLUSIONS

This review underscores the transformative impact of deep learning models on Named Entity Recognition (NER), enhancing accuracy, adaptability and contextual understanding. However, persistent challenges like entity ambiguity, domain adaptation and computational constraints demand further innovation. Future progress in zero-shot learning, multimodal frameworks and resource-efficient architectures will be essential to addressing challenges in entity ambiguity, domain adaptation and computational efficiency, ensuring broader applicability of NER systems. Additionally, addressing ethical concerns and promoting transparent, interpretable models will ensure responsible deployment. By driving research in these directions, the NER landscape can be significantly advanced, unlocking new possibilities across diverse applications.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Vedanti Shedage, Devyani Pawar, Roshani Shinde, Apurva Mane and Pradip Ghorpade.

Methodology: Vedanti Shedage, Devyani Pawar.

Investigation: Vedanti Shedage and Pradip Ghorpade.

Discussion of results: Vedanti Shedage, Devyani Pawar, Roshani Shinde and Apurva Mane.

Writing – Original Draft: Vedanti Shedage.

Writing – Review and Editing: Apurva Mane and Pradip Ghorpade.

Resources: VPKBIET, Baramati.

Supervision: Apurva Mane and Pradip Ghorpade.

Approval of the final text: Apurva Mane and Pradip Ghorpade.

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