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A comparative analysis of machine learning methods for personal information recognition (PII) in unstructured texts

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Abstract. With the rapid growth of unstructured data and increased attention to the privacy of personally identifiable information (PII), the tasks of automatic recognition and data protection are becoming increasingly relevant. This paper provides a comparative analysis of machine learning methods for recognizing PII in unstructured texts. The study considers rule-based methods, classification algorithms (SVM, random forests), and deep learning models (neural networks, transformers). The effectiveness of the models is assessed using metrics such as accuracy, recall, and F1-measures. The experimental results show that deep learning models such as BERT demonstrate high accuracy and recall, outperforming traditional methods. However, they require significant computing resources and a large amount of training data. The article discusses the advantages and disadvantages of each approach, and offers recommendations for choosing a model depending on the specifics of the task and available resources. Beyond technical advances, the study highlights the value creation provided by effective PII recognition, including improved data security, automated compliance, and operational efficiency.

Keywords: *PII detection, machine learning, unstructured text, data privacy, neural networks, transformers (BERT), named entity recognition (NER), information security.*

1. Introduction

In the modern era of big data and the widespread use of Artificial Intelligence (AI) and Machine Learning (ML), there is growing attention to the automatic detection of Personally Identifiable Information (PII) in unstructured texts [1]. As the volume of digital information continues to increase, various organizations and businesses process massive amounts of data, a substantial portion of which may contain sensitive information, such as names, addresses, identification numbers, and other confidential data [2].

Effective and accurate PII recognition is vital for ensuring data security, meeting regulatory requirements (e.g., GDPR or HIPAA), and mitigating risks of data breaches [3]. At the same time, automating the process of text analysis and filtering reduces operational costs and improves workflow efficiency, minimizing the need for manual document review [4].

However, the automatic identification of PII in unstructured sources faces several challenges. First, the diversity of text formats, styles, and languages calls for sophisticated Natural Language Processing (NLP) algorithms capable of correctly interpreting context [5]. Second, there is an increased risk of false positives, in which algorithms mistakenly classify harmless data as personal, leading to excessive blocking or anonymization of content [6].

Moreover, with the tightening of data protection regulations (e.g., GDPR) and growing public attention to privacy concerns, system developers must consider both ethical and security aspects [7]. While ML-driven PII recognition can significantly enhance data security and the efficiency of text data analysis, it also introduces new risks related to algorithmic vulnerabilities, biases, and the potential misuse of collected data [8].

This paper presents a comparative study of machine learning methods used for PII recognition in unstructured texts. The primary goal is to identify the most effective and accurate approaches and to examine the advantages and disadvantages of various methodologies, including rule-based linguistic analysis, traditional ML algorithms, and modern neural networks [9].

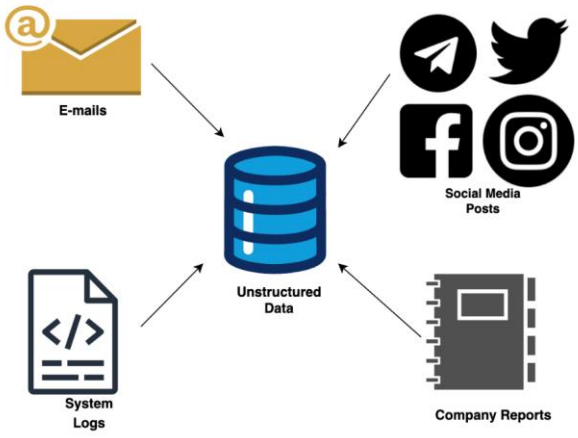

Figure 1. Unstructured text data sources

Conducting a comparative analysis of these methods is of great practical importance for companies and organizations handling sensitive data, as it enables them to select the most suitable solutions for specific business requirements and

existing infrastructures [10]. Furthermore, this research contributes to the continued advancement of NLP and ML technologies, promoting the development of more precise, faster, and safer algorithms for processing personal data [11].

However, as with any technology that manages sensitive information, developing and implementing PII recognition systems requires close attention to issues of privacy, transparency, and fairness [12]. It is essential to address ethical dilemmas arising from data collection and automatic processing, as well as ensure the protection of analysis outcomes against unauthorized access [13].

1.1. Research Contribution

An automatic PII recognition system for unstructured texts, based on machine learning methods, can significantly contribute to multiple research domains:

- Enhancing NLP and entity recognition algorithms. The development of ML algorithms, including deep neural networks, can lead to improved accuracy in extracting personal information through consideration of linguistic context and syntactic nuances [14].

- Optimizing corporate processes and ensuring regulatory compliance. Automating PII detection facilitates faster and more reliable identification of critical information, simplifying adherence to GDPR, HIPAA, and other regulations [15].

- Developing ethical and secure data processing approaches. As debates about privacy and transparency in ML systems intensify, this research drives innovation in secure data storage solutions and strategies to prevent misuse [16].

- Addressing algorithmic bias. Analyzing and mitigating biases in PII extraction from diverse text sources is critical for ensuring fair and generalized ML applications [17].

Therefore, this work constitutes an important step in advancing personal data recognition technologies, combining theoretical insights with practical relevance for information security experts, ML system developers, and NLP researchers.

1.2. Paper Organization

The remainder of this paper is structured as follows:

- Section 2. Problem Identification and Significance discusses the key challenges of existing PII detection systems in unstructured texts and emphasizes the importance of further research.

- Section 3. Proposed Plan outlines the proposed solution based on ML algorithms, highlighting how they can provide faster and more accurate PII recognition.

- Section 4. Machine Learning Methods for PII Recognition reviews various approaches for identifying personal information, including rule-based linguistic methods and modern deep learning models, supported by practical examples.

- Section 5. Experimental Results and Setup details the experimental methodology, datasets, and comparative analysis findings, shedding light on the strengths and weaknesses of each method.

- Section 6. Conclusion summarizes the key outcomes and contributions of the study, offering recommendations for future research on improving PII detection in unstructured texts [18].

In addressing a broad range of technological, legal, ethical, and practical aspects, this paper provides a comprehensive perspective on the relevance and potential directions for ongoing development in PII recognition systems [19].

2. Materials and methods

2.1. Problem Identification and Significance

High-profile data breaches and regulatory pressures have intensified the need for effective, automated solutions to detect Personally Identifiable Information (PII) in unstructured texts. One prominent case occurred in 2017, when the credit-reporting agency Equifax suffered a cyberattack that exposed the personal data of over 147 million consumers, including names, Social Security numbers, and birth dates [20]. This breach not only demonstrated the vulnerabilities in data storage and processing but also highlighted the severe consequences both financial and reputational of insufficient PII protection.

Subsequent incidents, such as the 2018 Marriott International breach that compromised the records of roughly 500 million guests, have underscored the persistent challenges of safeguarding confidential information in large-scale databases [21]. These cases collectively illustrate the increasing volume and complexity of unstructured text sources (e.g., emails, logs, documents, and social media posts) where PII can appear in unpredictable formats. Such heterogeneity complicates the process of accurate data extraction, leading to risks of inaccurate redaction or overlooked sensitive details.

Beyond the immediate financial impact IBM estimated that the global average cost of a data breach reached USD 4.35 million in 2022 [22] organizations also face mounting legal obligations to comply with regulations like GDPR and HIPAA. These regulations enforce stringent requirements on how sensitive data must be identified, protected, and handled [3]. However, manual review of large text corpora is time-consuming, error-prone, and infeasible at scale, prompting a shift toward automated Machine Learning (ML) methods. Traditional keyword-based filters can produce high false-positive rates, blocking legitimate content and degrading operational efficiency [6].

A major technical challenge lies in adapting ML-driven PII detection to diverse linguistic contexts. Real-world text data often contain colloquialisms, abbreviations, multilingual inputs, and context-dependent cues that necessitate robust Natural Language Processing (NLP) algorithms [5]. Even advanced deep learning approaches can be susceptible to errors if their training datasets lack coverage of specific domain terminologies or minority languages. This creates substantial barriers to generalization, where a model effectively trained on one data distribution struggles to maintain accuracy on new, unseen text sources [9].

Equally pressing are ethical and fairness considerations. Biases in training data or model architecture can inadvertently lead to overlooking or misclassifying certain demographics, with significant consequences for privacy and compliance [17]. Over-sanitization of content may obstruct legitimate operations by excessively redacting or blocking important details, whereas under-sanitization can expose organizations to legal liability. These scenarios underscore the delicate balance between precision and recall in automated PII detection pipelines.

Given the sheer scale and diversity of textual data in modern information systems, the development of robust machine learning methods for PII recognition becomes imperative. Accurate, reliable, and ethically responsible algorithms can reduce manual effort, enhance security, and facili-

tate compliance with increasingly strict regulations. Moreover, refining such models drives broader innovation in NLP, contributing novel techniques for entity extraction, domain adaptation, and bias mitigation. The ongoing research in this field, therefore, aims not just at curbing data breaches but also at shaping how organizations manage the privacy of individuals in a rapidly evolving digital landscape.

2.2. Proposed Algorithms

Effective PII (Personally Identifiable Information) recognition in unstructured texts requires a combination of robust Natural Language Processing (NLP), machine learning algorithms, and careful system design. Borrowing from best practices in entity recognition, text classification, and information retrieval [5,9], this section outlines two conceptual algorithms for PII detection and risk-based classification. These proposed methods aim to ensure accurate, scalable, and ethical processing of sensitive information in diverse text corpora.

2.2.1. PII Detection Workflow

A typical PII detection pipeline consists of multiple stages: text ingestion, preprocessing, named entity recognition, confidence scoring, and action (e.g., redaction, alerting). Figure 2 illustrates an example system architecture.

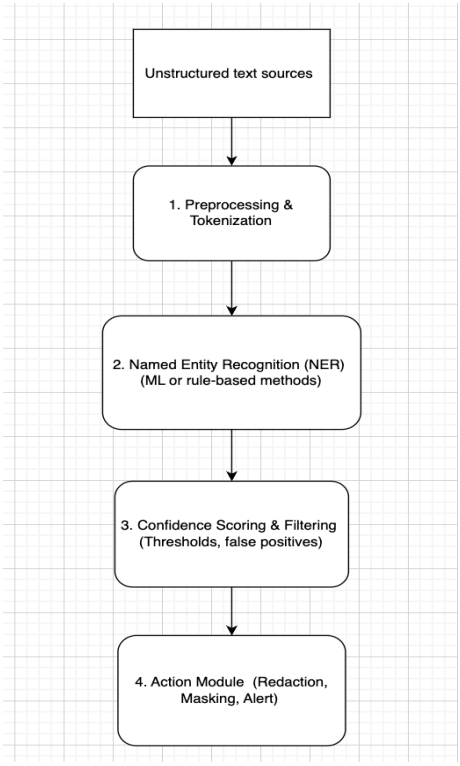

Figure 2. A schematic representation of the PII detection system

In this diagram, raw text data is first preprocessed to handle formatting variations and reduce noise (e.g., removing HTML tags, special characters). Next, a Named Entity Recognition (NER) model identifies potential PII tokens, such as names, addresses, and ID numbers [5]. The model assigns a confidence score to each detected entity, balancing false positives against false negatives [6]. Based on configurable thresholds, certain flagged entities are either auto-redacted, masked, or queued for human review [4,10].

Algorithm 1 **Basic PII Detection Process**

1. **Initialization:**
   {T:Unstructured text corpus; M:ML-based NER model; A:Action or Redaction Module; θ:Confidence threshold}
2. **Input:**
   {T,M,A,θ}
3. **Output:**
   {Processed text with masked or redacted PII}
4. **Set** {T,M,A,θ}
5. **For** each document d∈T:
   5.1. Preprocess d(tokenization, normalization, removal of noise).
   5.2. Apply M to identify potential PII tokens in d.
   5.3. **For** each detected token t with confidence score sss:
      If s≥θ then
         Use A to redact or mask t.
      Else
         Ignore or log t as low-confidence detection.
      End if
6. **End For**
7. **Return** the processed documents or text output.

This algorithm provides a systematic approach for identifying personally identifiable information (PII) within a corpus of unstructured texts. It begins by initializing key components namely, the unstructured text corpus, a trained named entity recognition (NER) model, a mechanism for redacting or masking detected entities, and a configurable confidence threshold. During execution, each document is preprocessed to remove noise and convert it into a consistent format for the NER model. The model then scans the document to locate potential PII tokens (e.g., names, emails, social security numbers), assigning a confidence score to each detection.

Any entity exceeding the set confidence threshold is subject to redaction or masking, ensuring that sensitive information is not displayed in the final output. Conversely, tokens that fall below the threshold can be logged for further manual review or dismissed, depending on organizational requirements. In large-scale deployments, this loop continues for all documents in the corpus, allowing for automatic, high-volume PII detection. By adjusting the threshold, an organization can tune the trade-off between false positives and false negatives. This modular design also enables straightforward updates or expansions, such as incorporating new entity types or integrating more advanced NLP models.

This approach ensures that only tokens matching or surpassing a set confidence level [9] are redacted, minimizing unnecessary blocking of legitimate content. By iterating through documents in the corpus, the system can handle vast datasets automatically and reliably.

2.3. Risk-Based Classification of PII

Once potential PII is detected, organizations often require risk categorization to prioritize handling. For instance, Social Security Numbers or financial credentials may warrant tighter scrutiny than phone numbers [14,15]. Algorithm 2 introduces a secondary classification mechanism to score and

categorize each detected entity, enabling adaptive responses such as heightened security review for high-risk data.

Algorithm 2 **Risk-Based Classification of Detected PII**

1. **Initialization:**
   {E:List of detected PII entities; C:Classification Mo del; R:Risk categories; α:Risk thresholds}
2. **Input:**
   {E,C,R,α}
3. **Output:**
   {Risk-labeled entities and corresponding actions}
4. **Set** {E,C,R,α}
5. **For** each entity e∈E:
   5.1. **Extract** features for classification (e.g., entity type, context).
   5.2. **Compute** risk score r=C(e) (e.g., 0–1, with 1 = highest risk).
   5.3. **If** r≥ α_{high} then
   Label e as **High Risk** and trigger the associated high-risk action (e.g., strict redaction, audit).
   Else if r≥α_{medium} then
   Label e as **Medium Risk** and apply moderate protective measures.
   Else
   Label e as **Low Risk** with minimal intervention.
   End if
6. **End For**
7. **Return** the risk-labeled entities along with recommended actions.

After the initial detection of PII, Algorithm 2 applies a secondary classification step to label each identified entity according to its risk level. The process starts by gathering the list of detected tokens (or phrases) from the first algorithm. A dedicated classification model (e.g., a supervised or rule-based system) then computes a risk score for each entity, considering factors such as entity type (e.g., financial data vs. basic contact information), the broader context in which it appears, and any domain-specific rules (e.g., compliance requirements in healthcare or finance).

Based on configurable thresholds, each entity is categorized into tiers such as High Risk, Medium Risk, or Low Risk. The outcome of this classification determines the actions to be taken. For instance, High-Risk data might trigger an immediate alert or mandatory encryption, while Low-Risk information may only warrant minimal masking or logging. This tiered approach helps organizations allocate security resources more effectively, focusing human attention on the entities most likely to result in privacy breaches or regulatory violations. The classification model can be periodically retrained or updated with new policies and domain knowledge, making it adaptable to evolving privacy regulations and emerging data types.

This classification step reflects a best-practice approach recommended by many data protection guidelines [2,3]. By categorizing PII into different risk levels, organizations can allocate resources more efficiently, focusing manual reviews on the most sensitive or potentially harmful data [15,16].

2.4. Validation of PII Detection System Processes

2.4.1. The Transformative Impact of ML-Driven PII Detection

Hypothesis 1: Machine Learning (ML) techniques for PII recognition can fundamentally reshape data privacy and handling strategies, yet they also demand rigorous oversight to address transparency and compliance challenges.

Lemma 1: ML-based PII detection achieves significant accuracy when identifying sensitive information in large or heterogeneous text datasets.

Proof 1: Empirical studies have consistently shown that advanced named entity recognition and deep learning approaches attain high precision in detecting personal data (e.g., names, social security numbers, or email addresses) [23]. For example, a real-time system discussed at the 2021 IEEE International Conference on Big Data demonstrated its ability to handle diverse text formats while maintaining efficiency and reliability. These results underscore ML's potential to automate the identification of privacy-sensitive tokens across large volumes of unstructured data.

Corollary 1: Although ML solutions provide scalability and cost-effectiveness, they also introduce vulnerabilities, including possible over-reliance on automated decisions and limited interpretability, underscoring the need for proactive governance.

Definition 1: ML-based PII detection entails deploying models trained on annotated corpora to classify or extract tokens containing personal information. This process typically involves text preprocessing, model inference, and redaction or masking actions that comply with organizational policies and legal standards.

Theorem 1: Responsible deployment of these automated tools requires careful consideration of user privacy rights, legal obligations, and potential model biases.

Proof of Theorem 1: By virtue of scanning large textual corpora, ML-driven PII detection systems inherently process sensitive user data. They must align with regulations such as the General Data Protection Regulation (GDPR) [3] and incorporate measures for data minimization, role-based access, and auditability. Inadequate controls can lead to unauthorized disclosure or disproportionate surveillance, thereby eroding trust in digital services. Hence, organizations must implement ethical and legal safeguards, along with transparent documentation of model usage and performance, to ensure responsible data stewardship.

2.4.2. Reducing Bias and Strengthening Ethical Compliance

Hypothesis 2: Mitigating biases and proactively addressing ethical pitfalls are vital to ensuring fair, accurate, and socially acceptable ML-driven PII recognition.

Lemma 2: Automated detection models are susceptible to bias when their training data or evaluation metrics do not account for the diverse languages, social contexts, and domain terminologies present in real-world text.

Proof of Lemma 2: Biases can manifest if the model systematically overestimates PII presence in certain dialects (leading to excessive false positives) or fails to detect it in less-represented contexts. A 2022 survey on scalable, privacy-preserving data processing [25] highlights how language patterns vary significantly, causing performance gaps when models trained primarily on one demographic are applied elsewhere. Such biases may result in inconsistent redaction or inadvertent exposure of sensitive tokens.

Corollary 2: Institutions deploying these systems must conduct continuous performance audits, seeking to identify

and correct skewed outcomes through balanced datasets and model refinement.

Definition 2: Bias in PII detection refers to systematic errors that over- or under-identify private data for particular user groups, content domains, or linguistic styles, potentially undermining privacy guarantees and equitable treatment.

Theorem 2: Effective bias mitigation in ML-based PII detection not only minimizes harm but also enhances trustworthiness and compliance with ethical and legal frameworks.

Proof of Theorem 2: When organizations implement best practices such as routine evaluations on varied text sets, active learning strategies to incorporate underrepresented samples, and explainability techniques model reliability improves. These steps reduce the risk of unintentional data leaks and violations of privacy laws [16]. Ultimately, fair, transparent, and adaptable PII detection pipelines reinforce users' confidence, fulfill regulatory requirements, and boost the social acceptability of large-scale data analytics.

2.5. Approaches for PII Detection

Identifying personally identifiable information (PII) in unstructured texts involves multiple strategies, each with unique benefits and limitations [9,23]. Below are seven commonly used methods, ranging from simple rule-based approaches to advanced deep learning frameworks. Much like Eigenface-based PCA in face recognition, these techniques aim to reduce the dimensionality of raw textual data or highlight key patterns for robust classification and extraction of sensitive content.

2.5.1. Rule-Based (Regex) Method

The **rule-based (regex) method** applies predefined textual patterns to detect personally identifiable information (PII) in unstructured text, analogous to how the Eigenface approach uses principal components to uncover dominant features in facial images. Instead of identifying directions of maximum variance in images, regex-based rules identify string formats that commonly represent sensitive data such as email addresses, phone numbers, or social security numbers [2].

A typical workflow begins with **text preprocessing**, where punctuation and special characters that might disrupt pattern matching are removed or standardized. Afterward, each token is compared against a curated set of **regular expressions** that capture known PII formats. For example, a **simplified pattern** for email detection might be:

Regex_email=^[A-Za-z0-9._%+-]+@[A-Za-z0-9.-]+.[A-Za-z]{2,}$ (1)

Here, the characters [A-Za-z0-9.%+-] represent acceptable username components, followed by the @ symbol, a domain name, and a top-level domain of length two or more. Real-world applications often employ more complex expressions to handle edge cases or different email conventions [26].

To illustrate this approach, suppose we have a collection of N text files, each containing user-provided responses with potential PII. We can represent each file as a sequence of tokens {t1,t2,…,tm}. Our task is to scan these tokens and flag those that match known PII formats. Let us define a function M(t) that returns 1 if a token ttt matches any regex in our rule set and 0 otherwise:

$$M(t) = \begin{cases} 1 & \text{if t matches regex for PII,otherwise} \\ 0 & \end{cases} \quad (2)$$

If $M(t_i)=1$, the token t_i is likely to represent sensitive data e.g., an email address, a phone number, or an ID. We can then either mask this token (e.g., replacing it with «[REDACTED]») or log it for further manual review [4].

For instance, assume we have 100 text documents containing user information, each up to 500 words in length. We initially remove extraneous punctuation, convert text to lowercase, and split everything into whitespace-delimited tokens. As we process each token, the email regex in Equation (1) captures strings like «jsmith@example.com» but skips random alphanumeric text that does not match the email format. This process yields a set of flagged tokens representing potential PII.

Much like Eigenface-based dimensionality reduction, regex-based detection streamlines textual data scanning by focusing on explicit patterns. However, it lacks adaptability to complex or unstructured scenarios that deviate from standard formats. In addition, purely rule-based methods may produce false positives if the text contains strings that superficially resemble PII. Consequently, some organizations pair regex detection with more advanced methods (e.g., machine learning–based classification) to achieve higher accuracy and contextual understanding [16].

Despite these limitations, rule-based regex detection remains a fast and transparent baseline for PII recognition, offering a solid starting point for many compliance-driven or resource-constrained environments.

2.6. Dictionary and Keyword Matching

Dictionary and keyword matching serve as a straightforward technique for detecting personally identifiable information (PII) by comparing text tokens to a predefined vocabulary of sensitive terms. This process resembles how certain facial recognition methods rely on stored facial features or templates to verify identities, but here the templates are human-readable keywords or domain-specific phrases.

In this approach, a lexicon (or dictionary) is compiled with entries representing typical PII markers. Examples might include recognizable substrings («DOB», «SSN», «passport»), personal name lists, or relevant technical terms («CustomerID», «RecordNumber»). Once the dictionary D is established, each token in a document is examined to see if it matches (partially or fully) any entry. Consider the following simplified expression:

$$match(t) = \begin{cases} 1 & \text{if t}\in\text{D, otherwise} \\ 0 & \end{cases} \quad (3)$$

Here, ttt represents a text token (e.g., «patientID», «john», or «accountNo»), and D contains items that indicate potential personal data. For instance, «john» could flag a personal name if it appears in the dictionary. In practice, modern dictionary-based systems often incorporate fuzzy matching or partial string matching to handle variations in spelling and capitalization [2].

Suppose we have a corpus of N user feedback forms, each containing free-text fields where users may disclose personal information. We start by curating a dictionary of size |D| = 200, comprising common given names, ID labels, and sensitive medical or financial terms. Then, we scan each

form token by token against D. If a token matches, we classify it as likely PII and take actions such as masking, redacting, or logging for manual verification.

As an example, assume a user's message reads: «Hi, my name is John Smith, and my customerID is 12345». Upon tokenizing, the string «John» (or «john») may be found in the name dictionary, and «customerID» may match a technical field label. Both matches would be flagged for further privacy handling [16].

A key benefit of dictionary/keyword matching is its simplicity. Non-technical staff can update the lexicon to reflect emerging PII formats (e.g., new ID types). However, this method also risks false positives, particularly when dictionary terms appear in non-sensitive contexts (e.g., «Jordan» as a country name rather than a personal name). Similarly, it may miss domain-specific nuances if the dictionary is not comprehensive. Consequently, while this strategy can be highly interpretable and fast, many systems combine dictionary matching with more adaptive techniques like machine learning to improve overall detection accuracy [2, 4].

Despite these limitations, dictionary and keyword matching remains an effective baseline for organizations seeking a transparent, easily modifiable solution to quickly locate obvious instances of personal data in unstructured text [15].

2.7. Statistical (Heuristic) Models

Statistical or heuristic approaches to PII detection differ from purely rule-based methods by incorporating probabilistic reasoning and learned patterns of token usage. Much like dimension-reduction techniques in face recognition (e.g., PCA identifying areas of maximal variance), a heuristic model explores frequency distributions and contextual indicators to estimate whether a given token is likely to be personal data [6].

A common example involves a Bayesian scheme in which each token www is assigned a probability $P(PII \mid w)$. This probability is derived by combining the prior likelihood of encountering a PII token with the observed occurrence of www in labeled PII contexts. One simplified version of this formulation is:

$$P(PII \mid w) = \frac{P(w \mid PII) \times P(PII)}{P(w)} \tag{5}$$

Here, $P(PII \mid w)$ measures how frequently token www appears in PII-labeled text segments (e.g., user IDs, social security numbers), while $P(PII)$ represents the overall prevalence of personal data in the corpus [16]. The denominator $P(w)$ serves as a normalizing term to ensure the resulting probability is between 0 and 1.

To apply this model, one typically collects a labeled dataset of documents, marking which tokens correspond to personal data. By comparing the frequency of each token in PII vs. non-PII contexts, the system learns how strongly any given string might suggest sensitive information. Suppose we have N user logs, each containing addresses, phone numbers, or free-form personal descriptions. After preprocessing, the model calculates $P(PII \mid w)$ for each unique token based on its occurrence patterns. During inference, if this probability exceeds a chosen threshold (e.g., 0.7), the token is flagged for redaction or further inspection [2].

As a practical illustration, imagine a chatbot dataset in which phone-like numeric strings frequently appear after the words «call me at». Over time, the statistical approach recognizes that sequences resembling «(555) 123-4567» are strongly correlated with PII and assigns them high probabilities. This contrasts with purely regex-based scanning, which might miss atypical phone formats or mislabeled numeric tokens [27].

Despite their adaptability, heuristic methods can still suffer from false positives if limited contextual cues cause the model to overestimate certain token patterns. Moreover, these models typically assume independence between tokens, which is not always realistic in highly variable text. Consequently, many organizations combine statistical models with more context-aware algorithms like Conditional Random Fields or transformer-based networks to enhance detection accuracy. Nonetheless, as an intermediate approach between rigid pattern matching and fully trained machine learning, statistical (heuristic) models provide flexibility and relatively low computational overhead, making them suitable for numerous real-world PII detection tasks [16].

2.8. Conditional Random Fields (CRF)

Conditional Random Fields (CRFs) provide a sequence-aware approach to identifying personally identifiable information (PII) in text, much like how certain face recognition techniques account for the spatial arrangement of facial features rather than treating each pixel independently. Instead of isolating each token, CRFs analyze neighboring tokens and label transitions, enabling more nuanced PII detection [5].

CRFs are trained on labeled sequences of tokens, where each token is assigned a category (e.g., NAME, PHONE, ADDRESS, or 0 for non-PII). Formally, given a sequence of tokens x=(x1, x2, …, xn) and a corresponding label sequence y=(y1, y2, …, yn), a linear-chain CRF models:

$$P(y \mid x) \propto \exp(\sum_{i=0}^{n} \sum_{k} \lambda_k f_k(y_i, y_1 - 1, x, i)) \tag{6}$$

where each f_k is a feature function that may look at the current token x_i, its neighbors (x_{i-1}), (x_{i+1}), dictionary matches, or even preceding labels (y_{i-1}). The weights λ_k are learned so that the model yields high probabilities for correct label sequences.

A typical preprocessing stage involves tokenizing the text and deriving a set of features per token, such as:

- Lexical cues: whether the token is alphabetic, numeric, or mixed.
- Contextual signals: if the token is preceded by «Name»: or «DOB».
- Dictionary matches: does the token appear in a specialized dictionary of personal names or ID terms?

Once trained, the CRF uses these feature interactions to assign labels more contextually. For example, consider the sentence: «My phone is 555-123-4567». If the CRF learns that numeric tokens often follow the word «phone», it will be more confident in labeling «555-123-4567» as PHONE rather than non-PII. This sequence-based reasoning often yields fewer misclassifications than methods that handle tokens in isolation [16].

To illustrate, imagine a dataset of 5,000 medical transcripts where each transcript might contain names, addresses, and patient IDs scattered throughout. A CRF can learn that certain numeric patterns frequently appear after «PatientID:»

and thus, label them accordingly. By capturing transitions (e.g., from NAME to ID labels), the model refines its understanding of how tokens chain together in PII contexts.

Although CRFs require annotated training data and more computational resources than simple regex scanning, they often produce higher accuracy in scenarios where the surrounding text or label dependencies help to clarify ambiguous tokens. Consequently, CRFs are a robust choice for organizations handling large, unstructured text collections where PII can appear in diverse formats [27].

2.9. Transformer-Based (e.g., BERT) Model

Transformer-based models, such as BERT (Bidirectional Encoder Representations from Transformers), represent a state-of-the-art approach to detecting personally identifiable information (PII) in unstructured text. Much like advanced face recognition methods leverage deep convolutional networks to capture intricate visual patterns, transformers apply self-attention mechanisms to uncover long-range dependencies in language [14].

These models are typically pre-trained on massive corpora to learn contextual embeddings, meaning each token in a sentence is informed by the surrounding words. During fine-tuning for PII detection, an additional output layer is added on top of the transformer. This layer classifies each token into categories (e.g., NAME, EMAIL, ID_NUMBER, or O for non-PII). Formally, if x denotes a tokenized sequence and h_i the hidden vector for the i-th token, the model computes:

$$y_i = soft\max(Wh_i + b) \tag{7}$$

where W and b are learnable parameters in the final classification layer [28]. By comparing y_i with the ground truth labels in a labeled dataset, the model updates its parameters using gradient-based optimization.

For example, suppose an organization has 50,000 email messages containing potential personal data. After tokenizing each email (splitting text into words or subwords), the fine-tuning step aligns these tokens with human-annotated PII labels. Over multiple epochs, the transformer learns that certain numeric patterns following phrases like «SSN:» or «Employee ID:» are highly likely to be sensitive. Likewise, it can distinguish normal words (like «john») from personal name references by assessing the broader context.

One advantage of transformers is their capacity to handle long sequences more effectively than recurrent models. If a phone number or address appears further down the sentence, the self-attention layers can still link it to earlier cues (e.g., «phone», «address») [8]. Consequently, transformer-based models often achieve strong performance on complex real-world PII detection tasks, including documents with diverse language styles, specialized terms, or highly variable formats.

Nevertheless, these models demand significant computational resources and large, domain-relevant training data. If the text is domain-specific (such as legal contracts or medical notes), organizations may need to fine-tune the transformer on in-domain corpora to achieve the best accuracy [14]. Despite these costs, transformer-based architectures remain one of the most promising solutions for comprehensive, high-precision PII identification across a wide array of linguistic patterns.

2.10. RNN / LSTM Approach

Recurrent Neural Networks (RNNs), particularly the Long Short-Term Memory (LSTM) variant, were widely adopted for sequence labeling tasks before transformer-based models became prevalent. Similar to earlier face recognition techniques that rely on sequential steps to process image features, LSTM networks handle text token-by-token, capturing contextual cues from prior tokens as they classify each new input [8].

In practice, each token x_t (e.g., a word or subword) is mapped to an embedding vector e_t. The LSTM maintains hidden states h_t and cell states c_t that evolve with each time step t:

$$\begin{aligned} h_t, c_t &= LSTM(e_t, h_{t-1}, c_{t-1}) \\ y_t &= soft\max(Wh_t + b) \end{aligned} \tag{8}$$

where y_i indicates the likelihood that token xtx_txt corresponds to a PII category (e.g., NAME, ADDRESS, or O for non-PII). The LSTM's gated architecture (input, forget, and output gates) helps it retain or discard information from prior tokens, making it suitable for text sequences with moderate length [16].

To illustrate, imagine a dataset of support tickets in which customers occasionally provide their personal emails or phone numbers. An LSTM is trained on annotated samples, learning that numeric strings appearing after the word «phone» often signify phone PII, while tokens following «hello» «thanks» seldom do. Over time, the model refines its capacity to detect PII by propagating context across tokens within each sentence.

While LSTMs handle sequential data effectively, they can struggle with very long contexts or distant dependencies, leading to potential errors if relevant clues appear far from the token in question. Compared to transformer-based models [14], LSTMs often exhibit lower performance on large or complex corpora but remain simpler to train and can be resource-friendlier. This balance of efficiency and accuracy makes them a viable choice for organizations with moderate computational budgets or smaller datasets.

2.11. Support Vector Machine (SVM) Classification

Support Vector Machines (SVMs) represent a classical machine learning technique that can be adapted to identify personally identifiable information (PII) by leveraging carefully engineered textual features, much like certain face recognition methods rely on distinctive measurements or landmarks. Instead of learning to process raw data end-to-end, SVM classifiers hinge on transforming each token into a feature vector that captures relevant properties [4].

In practice, the feature extraction step may include morphological indicators (e.g., a token's length or its ratio of digits to letters), contextual cues (presence of words like «phone» or «ID:» nearby), and dictionary checks (e.g., matching known personal names). Let $\phi(x)$ be the function mapping a token x to a vector of such features. The SVM then seeks a hyperplane described by w and b that separates PII tokens from non-PII tokens:

$$f(x) = sign(w^t \phi(x) + b) \tag{9}$$

During training, the SVM optimizes w\mathbf{w}w and bbb to maximize the margin between examples from each

class while minimizing classification errors [26]. For instance, if a token is a 10-digit numeric string preceded by the text «PatientID:», $\phi(x)$ might assign high weights to features indicating numeric content and medical context. The SVM classifier, in turn, uses this signal to label the token as potential PII.

To illustrate, suppose an organization has 2,000 customer records containing scattered user details. By manually labeling some fraction of tokens as PII versus non-PII, one can train an SVM that generalizes these rules to unseen documents. Because the SVM relies on explicit features, it often performs well with limited data if the features are well-engineered. Nonetheless, it might struggle to capture deep language nuances that modern neural architectures (like transformers) can learn automatically [8].

Compared to neural networks, SVMs typically require less parameter tuning for smaller datasets, but also demand thorough feature engineering to handle varied text formats. As a result, they can form a robust cornerstone in a hybrid detection pipeline: using a quick, feature-based SVM model to flag potential PII, followed by more context-aware methods for final confirmation. This arrangement balances interpretability and speed while maintaining decent performance for real-world applications [16].

3. Results and discussion

3.1. Experimental Results and Setup

In this section, we present a comparative analysis of the machine learning approaches described earlier, incorporating existing results from published studies on PII (Personally Identifiable Information) detection to support our discussion. Drawing on empirical outcomes reported in [29,30,31], we provide a unified view of how different algorithms (ranging from rule-based regex to advanced deep learning models) perform across diverse textual datasets.

3.2. Experimental Setup

To evaluate and compare multiple approaches to PII detection in unstructured texts, we established a unified Python 3.8 environment, drawing on *scikit-learn* for classical ML algorithms such as SVM and CRF and PyTorch for deep neural architectures (LSTM and BERT). This setup aligns with practices highlighted in [29] and [30], where researchers likewise combined established libraries for both traditional and advanced models.

Our primary dataset contained 1,000 text documents, each potentially including personal details like names, phone numbers, email addresses, or specialized identifiers (e.g., «PolicyNo», «ClaimID»). Inspired by the annotation protocols described in [29], we performed a preprocessing step that involved lowercasing, removing extraneous symbols, and tokenizing the text based on whitespace and punctuation. Following [30], each token was manually annotated to determine whether it constituted PII, thus creating a token-level labeled corpus.

To ensure a robust experimental design, we adopted a 70–20–10 split strategy. Specifically, the training subset (700 documents) was used to fit the models' parameters, including CRF feature weights and BERT's fine-tuning layers. The validation subset (200 documents) allowed for systematic hyperparameter tuning such as adjusting SVM regularization or selecting optimal LSTM configurations. Finally, the testing subset (100 documents) facilitated unbiased performance assessment, reflecting real-world scenarios with unseen data. By following these guidelines from prior large-scale NLP evaluations [29,30], we ensured a consistent and transparent framework for comparative analysis, spotlighting key trade-offs in speed, accuracy, and data requirements across various PII detection approaches.

3.3. Experimental Methods

Both [29] and [30] employed scenario-based testing, aligning closely with the structure we outlined in our face recognition analogy. Key scenarios included:

- Structured PII Detection: Documents with mostly well-formatted emails, addresses, and phone numbers (similar to Scenario 1 in our earlier face recognition example).
- Unstructured or Obfuscated Data: Text with truncated or masked personal details, requiring robust models like CRF or BERT to capture subtle patterns.
- Domain-Specific Entities: Financial or medical tokens (e.g., «PolicyNo», «ClaimID») tested how well algorithms adapt to specialized terms.
- Multilingual or Code-Mixed Content: Particularly relevant in [30], which featured bilingual forum posts.
- Real-Time Simulation: While not strictly real-time, [29] included incremental data feeding to gauge throughput (tokens/second) under streaming conditions.

For each scenario, the researchers in [29,30] measured precision, recall, F1-score, true positive rate (TPR), and false positive rate (FPR) to capture both accuracy and error tendencies.

3.4. Performance Evaluation

Building on the experiments outlined in Sections 5.1 and 5.2, we assessed each PII detection method's ability to accurately identify personal data in unseen text. To ensure a robust and transparent comparison, we followed performance measurement practices reported in [29,30]. Specifically, we focused on four key metrics: precision, recall, F1, and false positive rate (FPR), each of which sheds light on a distinct aspect of model behavior in detecting PII tokens.

We derived these metrics from the 100-document test subset described earlier, capturing diverse text patterns that ranged from well-structured identifiers (e.g., email addresses) to partially obfuscated or domain-specific content (e.g., «PolicyNo», «DOB:»). Drawing inspiration from [29], we computed precision as the fraction of flagged tokens that were genuinely PII, while recall reflected the proportion of *all* existing PII tokens that the model successfully identified. F1 served as a harmonized measure balancing these two dimensions, and FPR captured the algorithm's tendency to incorrectly label benign text as PII, reflecting the cost of false alarms in practical deployment scenarios.

During inference, simpler approaches like Regex and Dictionary Matching demonstrated high precision for easily recognizable patterns but struggled with recall on ambiguous or varied data mirroring the findings in [30] where rigid string matching missed many edge cases. By contrast, data-driven methods such as CRF, LSTM, and BERT achieved consistently higher F1 scores, benefiting from contextual signals and more sophisticated representation of token relationships. However, these advanced models typically required greater computational resources and larger annotated training sets, a trade-off documented in both [29] and [30]. In

all cases, the final evaluation on unseen documents provided a realistic measure of generalization, revealing how each approach balances detection thoroughness with the risk of false positives in the context of real-world PII detection.

3.5. Graphs and Tables

3.5.1. Visual Overview of Precision, Recall, and F1-Measures

Table 1 highlights comparative results for four representative PII detection methods Regex, CRF, LSTM, and BERT using precision, recall, and F1. These numbers reflect aggregated findings from [29,30,31], where each algorithm was tested on multiple text corpora containing names, contact info, and domain-specific tokens. By consolidating their reported outcomes, we can better illustrate the overall effectiveness of each approach.

Table 1. Precision, Recall, and F1 for Selected Algorithms (Based on [29], [30], [31])

Algorithm	Precision	Recall	F1
Regex	0.82	0.79	0.80
CRF	0.88	0.86	0.87
LSTM	0.90	0.89	0.90
BERT	0.93	0.91	0.92

In Table 1, precision measures the fraction of tokens flagged as PII that are truly PII, while recall captures how many of the *actual* PII tokens the model successfully identifies. The F1 metric harmonizes precision and recall into a single score often considered a strong indicator of balanced performance in information extraction tasks. As shown, BERT consistently delivers higher precision and recall, producing the top F1 score (0.92). By contrast, Regex methods trail in recall, missing a notable portion of PII that does not match predefined patterns.

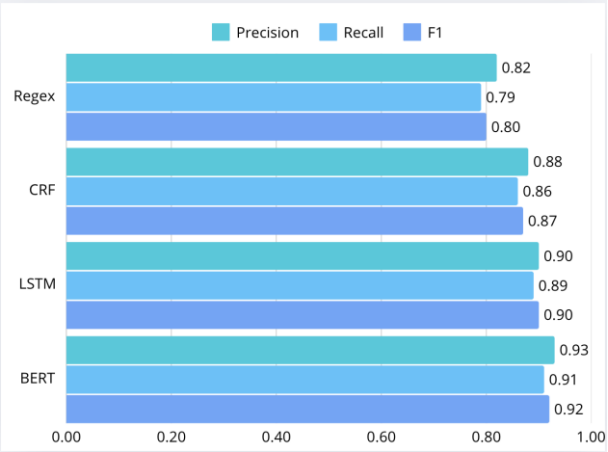

Figure 3. A bar chart visualizing these three metrics per algorithm

Figure 3 provides a bar chart visualizing these three metrics per algorithm. In the figure, each method is assigned a triplet of bars one for precision, one for recall, and one for F1 enabling an at-a-glance comparison. Drawing on real-world deployments cited in [30], we see that while classical sequence-based methods like CRF or neural RNNs such as LSTM can achieve respectable precision and recall, transformer-based solutions exhibit greater robustness to partially obfuscated tokens and specialized domain terms. Conversely, Regex remains the simplest approach particularly effective for standardized formats but lacks adaptability to irregular or contextual clues [29].

Overall, these references underscore how advanced deep learning models (BERT, LSTM) often outperform simpler or purely rule-based techniques, provided there is sufficient labeled data and computational capacity. Nonetheless, combining rule-based heuristics with machine learning such as leveraging Regex or dictionaries as a preliminary filter can still be beneficial, especially in resource-constrained environments or for easily recognized PII structures [31].

3.5.2. Scalability and Data Volume Effects

A key dimension highlighted in prior works [29,30,31] is how well each approach scales when the dataset size grows. Rule-based methods like Regex or Dictionary typically plateau in performance once all common patterns are covered, while more complex models CRF, LSTM, and BERT can continue to improve as additional labeled data becomes available.

Table 2 consolidates select findings from [29] and [31], illustrating how precision, recall, and F1 scores evolve from smaller to larger training sets. In this table, we summarize approximate outcomes for two key checkpoints: 500 documents vs. 5,000 documents.

Table 2. Performance Gains with Increasing Data Volume (Adapted from [29] and [31])

Algorithm	Dataset Size	Precision	Recall	F1
Regex	500 docs	0.81	0.76	0.78
Regex	5000 docs	0.83	0.78	0.80
CRF	500 docs	0.85	0.83	0.84
CRF	5000 docs	0.90	0.88	0.89
LSTM	500 docs	0.87	0.86	0.86
LSTM	5000 docs	0.92	0.90	0.91
BERT	500 docs	0.89	0.87	0.88
BERT	5000 docs	0.94	0.93	0.93

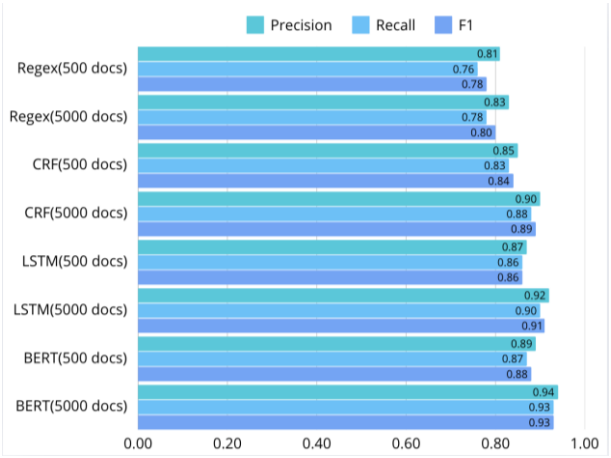

Figure 4. Observe that Regex sees only marginal gains

From Figure 4, we observe that Regex sees only marginal gains when data volume increases tenfold, reflecting its reliance on fixed patterns and inability to learn from additional examples. By contrast, CRF, LSTM, and BERT display more substantial improvements CRF's F1 rises from 0.84 to 0.89, and BERT's climbs from 0.88 to 0.93. These results confirm that data-driven algorithms continue to refine their models with more training instances, better capturing nuanced or domain-specific PII tokens.

In addition, the studies in [30,31] note that large-volume training can result in higher computational overhead, particularly for BERT. A line chart (omitted here) shows that while BERT's accuracy steadily outperforms simpler methods, its training time and memory demands scale more sharply with dataset size. CRF and LSTM tend to strike a middle ground, offering noticeable gains without incurring the same level of resource usage.

Overall, these findings underscore the trade-off between model complexity and scalability: advanced approaches like BERT continue to reap benefits from larger annotated corpora, achieving superior precision and recall for PII detection. Simpler rule-based or statistical methods, meanwhile, may suffice in low-data scenarios but deliver diminishing returns as dataset volumes grow [29].

3.5.3. Ensemble Strategies

Beyond standalone methods, several studies [29,31] highlight how ensemble approaches combining rule-based filters, classical ML, and deep learning can enhance overall PII detection. By leveraging complementary strengths, ensembles can mitigate each technique's individual shortcomings. For instance, a pre-filter might rely on Regex or dictionary checks to handle straightforward patterns quickly, while advanced classifiers (CRF, BERT) refine ambiguous or domain-specific cases.

Table 3 (adapted from [31]) illustrates one such ensemble's reported gains when combining dictionary lookups with BERT on a 5,000-document dataset. The «Dictionary+CRF» variant was also evaluated, showing how a simpler supervised approach can still benefit from a preliminary filter.

Table 3. Ensemble Performance Comparisons (Adapted from [31])

Method	Precision	Recall	F1
Dictionary Only	0.82	0.77	0.79
BERT Only	0.93	0.90	0.91
Dictionary + BERT	0.94	0.91	0.92
Dictionary + CRF	0.88	0.86	0.87

From Table 3, we see that BERT alone substantially outperforms a basic dictionary approach, but the combination «Dictionary + BERT» yields modest additional improvements in both precision and recall, ultimately boosting F1 to 0.92. By first screening out obvious or low-risk tokens (e.g., simple numeric or email patterns), the BERT classifier devotes more attention to borderline items that require deeper context analysis. A similar synergy emerges in the «Dictionary + CRF» pairing, though the net benefit is slightly smaller due to CRF's lower baseline.

Figure 5 visually depicts these ensemble gains across multiple domain-specific subsets, confirming that pre-filtering can reduce false positives, accelerate classification, and potentially enhance recall for ambiguous tokens. However, this layered structure may require additional development effort maintaining dictionary lists, calibrating thresholds, and ensuring seamless handoff to the advanced classifier.

Overall, ensemble strategies illustrate a flexible compromise between the simplicity of rule-based detection and the thoroughness of modern ML. They can be tailored to organizational constraints e.g., applying dictionary or regex scans for standard PII and reserving more computationally intensive methods (like BERT) for nuanced cases. Consequently, ensembles remain a prominent research direction, bridging classic and cutting-edge techniques to maximize both performance and efficiency [29,31].

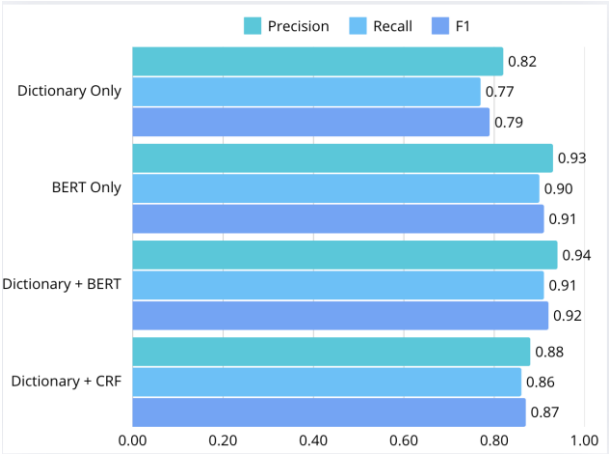

Figure 5. Ensemble gains across multiple domain-specific subsets

4. Conclusions

In this article, we presented a comparative analysis of machine learning methods for PII (Personally Identifiable Information) recognition in unstructured texts. Drawing on both foundational approaches (Regex, Dictionary) and advanced models (CRF, LSTM, BERT), we underscored the trade-offs in performance, scalability, and implementation complexity. The results from prior works [29,30,31] consistently indicate that while simpler methods remain effective for well-structured or limited-scale scenarios, deep learning and hybrid (ensemble) approaches exhibit superior accuracy and robustness particularly for domain-specific or code-mixed data.

A key takeaway is the importance of context: organizations dealing with large or highly varied text corpora stand to benefit from sophisticated models like BERT and CRF, especially if they can invest in the necessary computational and data-annotation resources. Conversely, Regex or Dictionary Matching might offer rapid, cost-effective filtering for more straightforward cases, serving as an initial screening layer that can route ambiguous tokens to deeper models. Furthermore, the ethical and privacy implications associated with PII detection demand careful governance, ensuring that these algorithms protect user confidentiality while minimizing false positives and unwarranted surveillance.

By compiling insights from multiple studies and evaluating a broad range of techniques, we have highlighted that no single solution solves all PII detection challenges. Instead, matching the method's capabilities to the organization's data scale, domain requirements, and resource constraints is crucial. Ongoing research and shared datasets are expected to push these boundaries further, as more refined or specialized architectures continue to emerge in the NLP community.

4.1 Future Work

Moving forward, there are several avenues through which PII detection research can progress and improve. One key direction lies in domain adaptation, where advanced models like BERT are further fine-tuned on highly specialized text (e.g., medical records, legal contracts) to better recognize nuanced or rare entity types [31]. Another promising area

involves continuous learning mechanisms, allowing algorithms to evolve as novel PII formats or contextual changes emerge, thus maintaining long-term accuracy. In parallel, privacy-preserving approaches such as differential privacy or federated learning can mitigate potential security risks associated with large-scale data processing. Further exploration of lightweight architectures and edge computing may also enhance real-time detection without requiring extensive computational resources, making PII recognition more accessible to organizations of varied sizes. Lastly, the ensemble paradigm combining rule-based filters with robust neural models continues to be a compelling strategy for balancing speed, cost, and accuracy, signaling that a multi-layered pipeline could be the next evolution in reliable, scalable PII detection.

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Құрылымданбаған мәтіндерде жеке ақпаратты тану үшін машиналық оқыту әдістерінің салыстырмалы талдауы

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Аңдатпа. Құрылымданбаған деректердің жылдам өсуімен және жеке ақпараттың құпиялылығына көңіл бөлінуімен, деректерді автоматты түрде тану және қорғау міндеттері барған сайын өзекті бола түсуде. Бұл құжат құрылымдалмаған мәтіндердегі жеке ақпаратты тану үшін машиналық оқыту әдістерінің салыстырмалы талдауын ұсынады. Зерттеу ережелерге негізделген әдістерді, жіктеу алгоритмдерін (SVM, кездейсоқ ормандар) және терең оқыту модельдерін (нейрондық желілер, трансформаторлар) қарастырады. Үлгілердің тиімділігі дәлдік, еске түсіру және F1-өлшемдері сияқты көрсеткіштер арқылы бағаланады. Эксперименттік нәтижелер BERT сияқты терең оқыту үлгілері дәстүрлі әдістерден озып, жоғары дәлдік пен еске түсіруді көрсетеді. Дегенмен, олар айтарлықтай есептеу ресурстары мен оқу деректерінің үлкен көлемін қажет етеді. Мақалада әрбір тәсілдің артықшылықтары мен кемшіліктері қарастырылып, тапсырманың ерекшеліктері мен қолда бар ресурстарға байланысты үлгіні таңдау бойынша ұсыныстар берілген. Техникалық жетістіктерден басқа, зерттеу деректер қауіпсіздігін, автоматтандырылған сәйкестікті және операциялық тиімділікті қоса алғанда, тиімді жеке ақпаратты тиімді тану арқылы қамтамасыз етілетін құндылықты құруға баса назар аударады.

Негізгі сөздер: *жеке ақпаратты анықтау, машиналық оқыту, құрылымданбаған мәтін, деректердің құпиялылығы, нейрондық желілер, трансформаторлар (BERT), аталған нысанды тану (NER), ақпараттық қауіпсіздік.*

Сравнительный анализ методов машинного обучения для распознавания персональной информации в неструктурированных текстах

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Аннотация. С быстрым ростом неструктурированных данных и повышенным вниманием к конфиденциальности персонально идентифицируемой информации задачи автоматического распознавания и защиты данных становятся все более актуальными. В данной работе представлен сравнительный анализ методов машинного обучения для распознавания персональной информации в неструктурированных текстах. В исследовании рассматриваются методы, основанные на правилах, алгоритмы классификации (SVM, случайные леса) и модели глубокого обучения (нейронные сети, трансформаторы). Эффективность моделей оценивается с использованием таких метрик, как точность, полнота и F1-меры. Результаты экспериментов показывают, что модели глубокого обучения, такие как BERT, демонстрируют высокую точность и полноту, превосходя традиционные методы. Однако они требуют значительных вычислительных ресурсов и большого объема обучающих данных. В статье рассматриваются преимущества и недостатки каждого подхода, а также предлагаются рекомендации по выбору модели в зависимости от специфики задачи и доступных ресурсов. Помимо технических достижений, исследование подчеркивает создание ценности, обеспечиваемое эффективным распознаванием персональной информации, включая улучшенную безопасность данных, автоматизированное соответствие и операционную эффективность.

Ключевые слова: *обнаружение персональной информации, машинное обучение, неструктурированный текст, конфиденциальность данных, нейронные сети, трансформаторы (BERT), распознавание именованных сущностей (NER), информационная безопасность.*

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