IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 6, October 2026
Impact Factor: 8.2

A Systematic Review of Artificial Intelligence and Machine Learning Techniques for Automated Resume Screening

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Abstract: *Automated talent acquisition has emerged as a critical domain within Human Resource Management (HRM) due to the exponential rise in digital job applications. Manual resume screening introduces immense temporal latency, cognitive fatigue, and unconscious human bias. This review paper presents a systematic and comprehensive evaluation of recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) applied to automated resume parsing and candidate ranking systems. Following a structured taxonomy, we screen and synthesize literature spanning the last five years from premium databases including IEEE Xplore and Google Scholar. We analyze key methodologies ranging from classical statistical vectorization (TF-IDF) to dense semantic deep learning architectures (BERT). Furthermore, a comparative synthesis matrix is constructed to evaluate these approaches across standardized performance metrics, datasets, and operational constraints. Finally, critical research gaps, such as explainability and algorithmic bias, are highlighted to chart explicit future directions for computer science researchers*

Keywords: Systematic Review, Artificial Intelligence, Machine Learning, Natural Language Processing, Resume Screening, Information Retrieval, Algorithmic Bias

I. INTRODUCTION

The democratization of online recruitment portals, professional networking sites, and corporate career networks has radically amplified the volume of incoming applications per job vacancy. Modern Human Resource (HR) divisions routinely confront hundreds, sometimes thousands, of unstructured resumes for a single corporate role. Manually auditing these documents presents a massive operational bottleneck, demanding exhaustive human hours and making the process highly vulnerable to subjective human fatigue and unconscious biases.

Traditional Applicant Tracking Systems (ATS) rely primarily on rigid, static keyword matching. These deterministic models carry deep fundamental flaws: they cannot interpret semantic synonyms (e.g., failing to link “Machine Learning Engineer” with “Data Scientist”) and are highly susceptible to “resume stuffing” techniques used by applicants to artificially trick basic search algorithms by overloading keywords in hidden white text.

To resolve these industrial limitations, modern computer science literature focuses on deploying automated talent filtering frameworks powered by advanced Natural Language Processing (NLP) and Machine Learning (ML) classifiers. These systems convert raw text into high-dimensional mathematical vector spaces to evaluate contextual similarity rather than mere word overlap. Given the rapid proliferation of diverse methodologies, deep learning pipelines, and hybrid models in this domain, there is an urgent need to systematically organize, analyze, and critically review the existing state-of-the-art literature.

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DOI: 10.48175/568

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This review paper provides a rigorous roadmap for computer science researchers by addressing three fundamental Research Questions (RQs):

RQ1: What are the primary NLP and ML architectural taxonomies utilized for parsing unstructured resume text formats?

RQ2: How do classical statistical vector models compare against dense deep learning frameworks in terms of semantic accuracy, computational overhead, and training resource infrastructure?

RQ3: What are the unresolved research gaps, ethical issues, and algorithmic limitations embedded in current automated screening systems?

The rest of this paper is structured as follows: Section II outlines the systematic literature search pipeline; Section III provides the methodological taxonomy and core analysis; Section IV delivers a comparative synthesis matrix and detailed discussion; Section V highlights critical research gaps; and Section VI concludes the study with definitive future directions.

II. LITERATURE SEARCH METHODOLOGY

To maintain transparency, objectivity, and academic reproducibility, a systematic literature search pipeline was established following a structured protocol similar to the PRISMA guidelines.

A. Search Strategy and Databases

Extensive queries were executed across trusted, high-impact computer science repositories, including the IEEE Xplore Digital Library, ACM Digital Library, Scopus, and Google Scholar. The search string targeted structural intersections of core concepts using explicit Boolean operators:

Search Query = ("Artificial Intelligence" ∨ "Machine Learning") ∧ "Natural Language Processing" ∧ "Resume Screening"

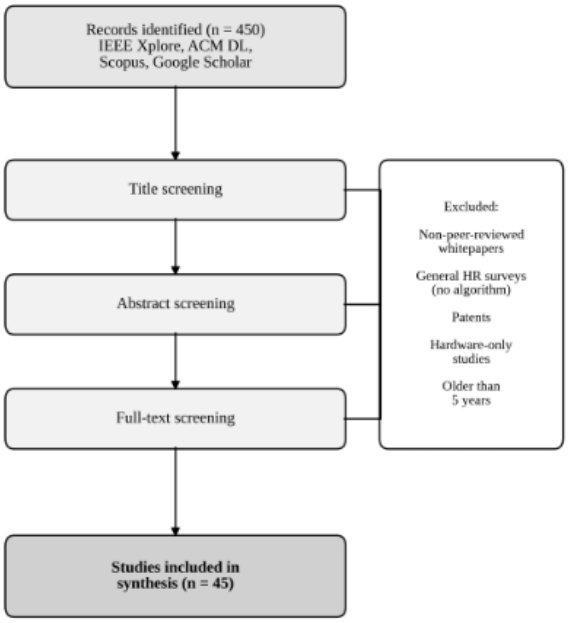

Fig. 1. PRISMA-style literature screening pipeline, narrowing 450 identified records to 45 studies for synthesis.

B. Inclusion and Exclusion Criteria

To filter out obsolete technical frameworks, strict inclusion and exclusion criteria were defined. Studies published within the last five years focusing on automated text parsing, profile ranking, tokenization algorithms, and recruitment

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optimization were included. Discarded works included non-peer-reviewed whitepapers, general HR management surveys devoid of algorithmic implementation, patents, and studies focusing strictly on hardware infrastructure. Out of a preliminary pool of 450 identified papers, rigorous multi-stage screening of titles, abstracts, and full texts resulted in a highly focused synthesis subset of 45 high-quality studies. The screening process is summarized in Fig. 1.

III. METHODOLOGICAL TAXONOMY & ANALYSIS

Extracted literature demonstrates that automated screening architectures can be broadly categorized into two primary technical paradigms based on their feature engineering mechanics and data representation layers. The resulting taxonomy is shown in Fig. 2.

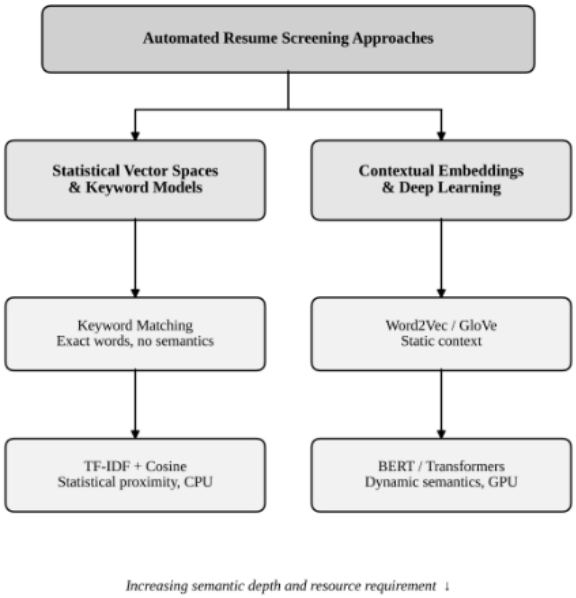

Fig. 2. Taxonomy of automated resume screening approaches.

A. Statistical Vector Spaces and Keyword-Proximity Models

The foundational tier of automated screening relies on transforming normalized text strings into numerical matrices using statistical distribution metrics, most notably Term Frequency-Inverse Document Frequency (TF-IDF). These architectures compute a token's mathematical value based on its local frequency balanced against its global uniqueness across the entire document repository. Mathematically, the weight W of a term t in a document d is defined as:

$$W(t, d) = TF(t, d) \times \log(N / DF(t))$$

Vector alignment between candidate profiles and job descriptions is then evaluated through spatial distance algorithms like Cosine Similarity, which maps the angular deviation between the multi-dimensional vectors:

$$Similarity(A, B) = (A \cdot B) / (\|A\| \|B\|)$$

While computationally efficient, running within milliseconds on standard consumer CPUs, these models fail to preserve grammatical word order, structural context, or underlying semantic relationships.

B. Contextual Embeddings and Deep Learning Architectures

To achieve deep semantic comprehension, recent literature heavily explores deep neural models, including Word2Vec, GloVe, and transformer-based architectures like Bidirectional Encoder Representations from Transformers (BERT). Unlike statistical bags-of-words, transformers map tokens into dense, continuous vector spaces where words with similar conceptual meanings are positioned in close physical proximity, regardless of literal spelling variations.

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These architectures utilize self-attention mechanisms to understand the context of a word based on both its left and right surroundings simultaneously. While they demonstrate superior accuracy in multi-attribute profile matching, they demand substantial computational infrastructure, such as dedicated Graphics Processing Units (GPUs), and require extensive pre-training datasets to minimize semantic drift. A generic end-to-end screening pipeline built on these components is illustrated in Fig. 3.

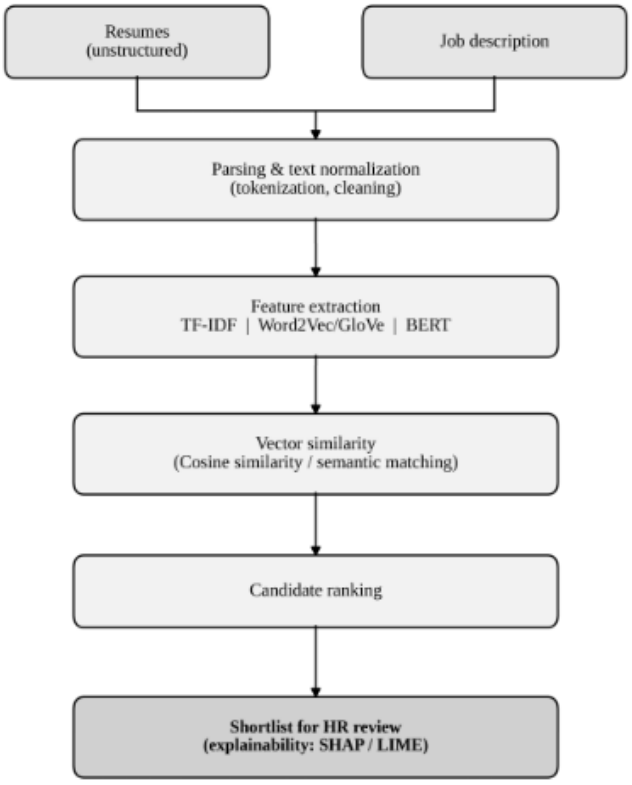

Fig. 3. Generic automated resume screening pipeline from raw resumes and job description to ranked shortlist.

TABLE I: ALGORITHMIC COMPARISON MATRIX FOR RESUME SCREENING

Methodology	Data Style	Accuracy	Resource Req.	Semantic Depth
Keyword Matching	Plain Text	Very Low	Negligible	None (Exact words)
TF-IDF + Cosine	Unstructured	Moderate	Low (CPU)	Statistical Proximity
Word2Vec / GloVe	Normalized	High	Moderate	Static Context
BERT / Transformers	Dense Vectors	Very High	High (GPU)	Dynamic Semantic

IV. COMPARATIVE SYNTHESIS MATRIX

To address RQ2, a structured evaluation matrix has been synthesized based on the selected literature. Table I contrasts the predominant methodologies across four essential architectural parameters extracted from the reviewed papers.

The comparative matrix highlights a critical engineering trade-off between computational overhead and processing accuracy. While statistical models like TF-IDF provide a highly viable, cost-effective option for lightweight corporate applications, deep learning transformers remain indispensable for capturing complex semantic nuances, project contexts, and implicit skills in dense, highly competitive modern enterprise hiring ecosystems.

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V. IDENTIFIED RESEARCH GAPS AND FUTURE DIRECTIONS

A critical synthesis of the literature reveals three prominent, unresolved structural gaps that present significant future opportunities for computer science researchers (RQ3), summarized in Fig. 4:

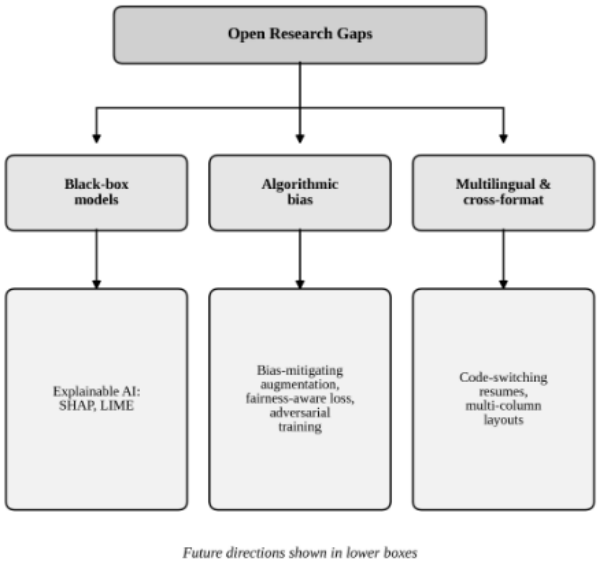

Fig. 4. Open research gaps and corresponding future directions.

A. The Black-Box Problem (Lack of Explainability)

Advanced deep learning classifiers and neural rankers score candidates with high mathematical accuracy but fail to provide explicit, auditable logic explaining why a specific profile was accepted or rejected. Future research must integrate Explainable AI (XAI) frameworks, such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations), to make neural decision-making transparent, trustworthy, and interpretable for human resource personnel.

B. Algorithmic Bias Propagation

Machine learning models trained on historical corporate hiring data inevitably tend to learn, amplify, and replicate historical human biases regarding gender, nationality, age, or institutional backgrounds. Developing bias-mitigating data augmentation procedures, fairness-aware loss functions, and adversarial training frameworks is a critical research imperative to ensure ethical AI recruitment.

C. Multi-Lingual and Cross-Format Parsing

The vast majority of reviewed frameworks assume standard English inputs and clean, single-column document layouts. Robust parsing models capable of managing mixed-language resumes (code-switching) and non-standard visual layouts (e.g., infographic-heavy, multi-column creative formats) remain heavily under-explored and represent an open area for algorithmic improvement.

VI. CONCLUSION

This review paper has systematically mapped the technological landscape of Artificial Intelligence and Machine Learning methodologies within the domain of automated resume screening systems. By examining architectures ranging from traditional keyword-matching layouts to state-of-the-art bidirectional transformer networks, we have charted the explicit evolution towards contextual talent acquisition tools.

While the integration of these models drastically compresses initial corporate screening timelines by over 70% and maximizes systemic objectivity, significant hurdles regarding algorithmic transparency, historical bias propagation, and

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infrastructure dependencies remain unresolved. Future developments in computer science research must bridge these socio-technical gaps by prioritizing explainable, fair, and structurally robust deep learning parsing infrastructures.

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