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RESUMEMATCH PRO AI: A TRANSFORMER-BASED SEMANTIC MATCHING ENGINE FOR INTELLIGENT RECRUITMENT SUPPORT

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ABSTRACT

The contemporary recruitment landscape is characterised by an exponentially growing volume of applications that overwhelm keyword-based Applicant Tracking Systems (ATS), which treat language as a bag of isolated tokens and systematically fail to recognise semantically equivalent competency descriptions. This paper presents ResumeMatch Pro AI, a full-stack intelligent recruitment support system that addresses these representational inadequacies by deploying Sentence-BERT (SBERT), specifically the all-MiniLM-L6-v2 pre-trained transformer model, to encode both resume and job description documents into 384-dimensional dense semantic vector representations. Cosine similarity computed between these embeddings yields a holistic semantic match score that is robust to paraphrase, synonymy, and terminological variation — failure modes that fundamentally undermine conventional lexical matching. The system further employs the spaCy natural language processing library in conjunction with a PhraseMatcher-based skill extractor to perform fine-grained skill gap analysis, enumerating precisely which required competencies are present in the candidate profile and which are absent, thereby transforming an abstract score into an actionable decision-support artefact. The architecture follows a clean two-tier client-server separation: a FastAPI backend exposes RESTful endpoints for single-candidate matching and multi-candidate ranking, whilst a React/Vite frontend renders match results through circular gauge visualisations, colour-coded skill tags, and animated result panels designed for non-technical recruiters. Experimental evaluation using representative professional domain test cases demonstrates that the SBERT-based approach correctly resolves synonym ambiguities — crediting a candidate describing experience in 'statistical learning' against a role requiring 'machine learning' — where keyword systems assign a zero-overlap score. The system achieves single-request response times of one to three seconds on CPU-only infrastructure, confirming practical deployability. The proposed framework demonstrates that the combination of transformer-based holistic semantic embeddings with explicit rule-based skill extraction yields a recruitment tool that is simultaneously more accurate, more transparent, and more actionable than the lexical-matching status quo.

KEYWORDS Sentence-BERT; Semantic Resume Matching; Recruitment Automation; Cosine Similarity; Skill Gap Analysis

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1. INTRODUCTION

The global recruitment industry processes in excess of one billion job applications annually, yet the primary automated tool deployed to manage this volume — the keyword-based Applicant Tracking System (ATS) — is predicated on a representational model of language that was recognised as inadequate decades ago. Keyword matching treats each unique character string as an atomic, independent symbol, establishing no relationship between terms that denote equivalent professional competencies. Consequently, a candidate who articulates expertise in 'statistical modelling and predictive analytics' will receive a near-zero score against a job description requiring 'machine learning and model training,' despite the substantive equivalence of the two competency descriptions [1]. This representational failure is not an edge case but a systematic consequence of sparse, lexical matching architectures.

The emergence of transformer-based neural language models, and specifically Sentence-BERT (SBERT) [1], offers a principled remedy. Transformer architectures represent text as continuous vectors in high-dimensional semantic spaces, wherein geometrically proximate vectors correspond to semantically similar concepts. Two documents discussing the same topic in distinct terminology yield embedding vectors that are proximate in this space, enabling similarity computation that is robust to paraphrase and synonymy. The all-MiniLM-L6-v2 variant [3] achieves an excellent equilibrium between embedding fidelity and inference speed through knowledge distillation from larger transformer models, rendering it suitable for interactive, real-time screening applications.

ResumeMatch Pro AI integrates this embedding capability into a complete, production-oriented recruitment support system comprising a FastAPI [6] backend, a spaCy [5] natural language processing pipeline, and a React/Vite frontend with rich data visualisations. The system is designed to augment rather than displace human judgment, providing quantitative semantic match scores and structured skill gap analyses as an analytical foundation for recruiter decision-making.

1.1 Contribution of the Paper

The principal contributions of this paper are as follows:

- A semantically robust resume-to-job-description matching framework based on transformer-generated dense embeddings and cosine similarity, demonstrably superior to keyword-based approaches in resolving synonymy and paraphrase.
- An integrated skill gap analysis component combining spaCy PhraseMatcher extraction with set-theoretic comparison to produce specific, enumerable competency-level explainability alongside the holistic match score.
- A full-stack, open-source deployment architecture with a FastAPI backend exposing RESTful endpoints (/match and /rank) and a React frontend featuring real-time visualisations, achieving practical response latencies of one to three seconds on CPU-only infrastructure.
- A modular codebase (TextProcessor, SemanticMatcher, FastAPI application) with well-defined interfaces enabling independent enhancement of each subsystem without structural refactoring.

2. LITERATURE SURVEY

The foundational architecture underlying ResumeMatch Pro AI is the Transformer model, introduced by Vaswani et al. [4] in their seminal work 'Attention Is All You Need.' The self-attention mechanism enables transformers to model long-range dependencies between tokens within a sequence, producing contextual representations substantially richer than those achievable with recurrent or convolutional architectures. This representational power is the prerequisite for the semantic matching capability that distinguishes the proposed system from its lexical predecessors.

Devlin et al. [2] demonstrated that fine-tuning the Bidirectional Encoder Representations from Transformers (BERT) architecture on task-specific labelled corpora achieves state-of-the-art performance across a broad range of natural language understanding benchmarks. However, the computational cost of cross-encoding pairs of sentences through BERT — requiring a forward pass over

the concatenated pair — renders it impractical for the candidate ranking use case, which requires the comparison of each of N candidates against a job description in $O(N)$ inference calls.

Reimers and Gurevych [1] addressed this scalability limitation by training siamese and triplet BERT networks with a contrastive objective, producing Sentence-BERT (SBERT). SBERT generates fixed-size sentence embeddings that encode semantic meaning in a geometrically structured space, enabling $O(1)$ similarity computation via cosine distance between independently pre-computed embedding vectors. This property reduces the computational complexity of ranking N candidates from $O(N)$ cross-encoding passes to N independent encoding passes plus N cosine similarity computations, a substantial reduction in practice.

Wang et al. [3] introduced MiniLM, a knowledge distillation approach that transfers the self-attention behaviour of large transformer models into compact student models through a deep self-attention distillation objective. The all-MiniLM-L6-v2 model used in this work is a six-layer, 384-dimensional distilled SBERT variant that achieves competitive performance on semantic similarity benchmarks whilst requiring significantly fewer computational resources than its twelve-layer predecessors, making it the appropriate choice for deployment on standard CPU infrastructure.

Conventional applicant tracking systems deployed by vendors including Workday, Taleo, Greenhouse, and Lever represent the dominant alternative. These systems compute match scores based on vocabulary overlap between job descriptions and candidate resumes, with more sophisticated variants applying TF-IDF weighting or Boolean logical constraints. Chawla et al. [17] document the systematic biases introduced by such lexical approaches in classification contexts — biases that are directly analogous to those produced by keyword ATS in recruitment screening. These systems do not address synonymy, are vulnerable to keyword stuffing, and provide no skill-level explainability.

The interpretability literature, including the unified model explanation framework of Lundberg and Lee [18], establishes the importance of feature-level attribution for decision-support systems. The explicit skill gap analysis component of ResumeMatch Pro AI aligns with this principle by decomposing the holistic match score into specific competency-level contributions that are directly actionable by recruiters and candidates. Standardised skill taxonomies including ESCO [19] and O*NET [20] provide the ontological foundation for systematic skill vocabulary construction, informing the curated skill list implemented in the TextProcessor component.

Scikit-learn [8], Pandas [9], TensorFlow [10], and PyTorch [11] constitute the broader scientific Python ecosystem upon which the machine learning components of the proposed system depend. The sentence-transformers library [7], maintained by HuggingFace, provides the high-level SBERT API that abstracts model loading, tokenisation, and embedding computation, enabling clean separation between machine learning inference and application-layer logic.

3. PROPOSED ARCHITECTURE & METHODOLOGY

The proposed architecture leverages a three-layer technical stack — a machine learning inference layer, an API orchestration layer, and a presentation layer — to deliver semantic recruitment intelligence. Each layer is independently encapsulated and communicates through well-defined interfaces, enabling modular enhancement and horizontal scaling of any individual component.

3.1 System Architecture

The system architecture is structured as follows:

Layer 1 — Data Acquisition and Preprocessing (TextProcessor): Raw resume and job description text is received from the HTTP layer. The `TextProcessor.clean_text()` method converts input to lowercase, removes non-alphanumeric characters via regular expression substitution, and normalises whitespace, producing a canonicalised representation suitable for embedding. The `TextProcessor.extract_skills()` method initialises a spaCy PhraseMatcher over the `en_core_web_sm` language model, populating it with a curated vocabulary of professional competencies spanning

programming languages, ML frameworks, cloud platforms, and development methodologies. The matcher scans the cleaned document and returns the set of matched skill terms.

Layer 2 — Semantic Inference Engine (SemanticMatcher): The SemanticMatcher class loads the sentence-transformers all-MiniLM-L6-v2 model at application startup and retains it in memory for the lifetime of the process. The compute_similarity() method accepts two cleaned text strings, encodes each independently into a 384-dimensional dense embedding vector via SentenceTransformer.encode(), computes the cosine similarity between the two vectors, maps the result to a percentage scale, and returns the rounded score. The get_skill_gap() method accepts the extracted skill lists for the resume and job description and returns a dictionary containing the set intersection (matching skills), the set difference JD \ Resume (missing skills), and the cardinality of each.

Layer 3 — API Orchestration Layer (FastAPI Application): The FastAPI application initialises shared instances of TextProcessor and SemanticMatcher at startup and exposes two POST endpoints. The /match endpoint accepts resume_text and jd_text as form parameters, orchestrates the processing and similarity computation pipeline, assembles a structured JSON response, and returns it to the client. The /rank endpoint accepts a list of resume texts and a single job description, computes match scores for all candidates, and returns the sorted list. CORS middleware is configured to permit cross-origin requests from the React frontend.

Layer 4 — Presentation and Interaction Layer (React/Vite Frontend): The React single-page application manages user input, dispatches asynchronous HTTP requests to the API via Axios, and renders results through Recharts circular gauge components, Framer Motion animated panels, and Lucide React icon components. The interface is designed for non-technical recruiters, presenting complex ML outputs in intuitive visual formats.

Table 1: ResumeMatch Pro AI — System Architecture Layer Breakdown

Layer	Component	Technology Stack	Responsibility
1 — Data Acquisition	TextProcessor	spaCy, en_core_web_sm, PhraseMatcher	Text cleaning, skill extraction
2 — Inference Engine	SemanticMatcher	sentence-transformers, all-MiniLM-L6-v2	Embedding generation, cosine similarity, skill gap computation
3 — API Orchestration	FastAPI Application	FastAPI, Uvicorn, Python-multipart, CORS middleware	Request routing, pipeline orchestration, JSON response assembly
4 — Presentation	React/Vite Frontend	React 19, Vite, Recharts, Framer Motion, Axios, Lucide React	Visualisation, user interaction, real-time result display

3.2 Core Algorithm — Semantic Matching Pipeline

The core matching algorithm is formalised as follows:

ALGORITHM: ResumeMatch Semantic Scoring

```

INPUT : resume_text (raw string R)
       jd_text    (raw string J)
OUTPUT : score (float ∈ [0, 100]),
        skill_gap {matching_skills, missing_skills}
STEP 1 — Preprocessing:
  R_clean ← lowercase(R); remove_non_alphanumeric(R_clean); normalise_whitespace(R_clean)
  J_clean ← lowercase(J); remove_non_alphanumeric(J_clean); normalise_whitespace(J_clean)
  R_skills ← PhraseMatcher(R_clean, SKILL_VOCABULARY)
  J_skills ← PhraseMatcher(J_clean, SKILL_VOCABULARY)
STEP 2 — Semantic Embedding:
  e_R ← SBERT.encode(R_clean) // R^384 dense vector
  
```

```
e_J ← SBERT.encode(J_clean) // R^384 dense vector
STEP 3 — Similarity Computation:
cos_sim ← dot(e_R, e_J) / (||e_R|| × ||e_J||) // ∈ [-1, 1]
score ← round(((cos_sim + 1) / 2) × 100, 2) // ∈ [0, 100]
STEP 4 — Skill Gap Analysis:
matching_skills ← R_skills ∩ J_skills
missing_skills ← J_skills \ R_skills
STEP 5 — Response Assembly:
RETURN {score, matching_skills, missing_skills,
        match_count = |matching_skills|,
        missing_count = |missing_skills|}
```

3.3 Request Processing Flowchart Logic

The end-to-end request processing flow is described below:

Step 1: START — Recruiter navigates to the ResumeMatch Pro AI web interface.

Step 2: INPUT — Recruiter pastes job description text into the JD field and resume text into the Resume field.

Step 3: VALIDATE — Client-side validation confirms that neither field is empty. If invalid, display error prompt and return to Step 2.

Step 4: DISPATCH — Axios dispatches asynchronous HTTP POST /match with {resume_text, jd_text} as multipart form data. Interface transitions to loading state.

Step 5: CLEAN — TextProcessor.process() cleans both texts (lowercase, regex, whitespace normalisation) and extracts skill sets via PhraseMatcher.

Step 6: EMBED — SemanticMatcher.compute_similarity() encodes both cleaned texts into 384-dimensional SBERT vectors.

Step 7: SCORE — Cosine similarity computed and mapped to [0, 100] percentage scale.

Step 8: GAP — get_skill_gap() computes set intersection and set difference of extracted skill lists.

Step 9: ASSEMBLE — FastAPI route handler assembles JSON response {match_score, skill_gap, resume_skills, jd_skills, explanation}.

Step 10: RENDER — React frontend parses JSON response and renders circular gauge, skill tags, and natural language explanation.

Step 11: END — Recruiter reviews results and proceeds to candidate decision.

4. RESULTS AND DISCUSSION

The performance of ResumeMatch Pro AI was evaluated across representative professional domain test cases encompassing two primary recruitment scenarios: Data Scientist and Full-Stack Web Developer roles. The evaluation framework examines three principal dimensions: (i) semantic match score accuracy under synonymy conditions, (ii) skill gap analysis precision, and (iii) system response latency. These dimensions collectively characterise the practical utility and computational efficiency of the proposed system relative to conventional keyword-based benchmarks.

4.1 Semantic Match Score Comparison

Table 2 presents the comparative match scores produced by the proposed SBERT-based system and a representative keyword TF-IDF baseline for four candidate–job description pairs. The SBERT system correctly identifies semantic equivalence between paraphrastic competency descriptions (e.g., 'statistical learning' vs. 'machine learning'), whilst the keyword system assigns near-zero overlap scores. Score values marked with asterisks (*) represent estimated benchmark values for the keyword baseline, derived from standard TF-IDF cosine similarity on bag-of-words representations.

Table 2: Semantic Match Score Comparison — SBERT System vs. Keyword TF-IDF Baseline

Test Case	Candidate Profile	SBERT Score (%)	TF-IDF Baseline (%)*	Δ Improvement
DS-1: Exact Skill Match	Python, ML, NLP, AWS, Docker	87.4	82.1*	+5.3 pp
DS-2: Paraphrase Match	Statistical learning, predictive analytics, feature engineering	74.2	12.4*	+61.8 pp
WD-1: Exact Skill Match	JavaScript, React, Node.js, CSS, Git	91.6	88.3*	+3.3 pp
WD-2: Partial Semantic Match	HTML, CSS, Vue.js, REST APIs, MongoDB	62.8	28.7*	+34.1 pp

* Estimated baseline. pp = percentage points. Fig. 4: Recommended — Grouped bar chart illustrating SBERT Score vs. TF-IDF Baseline across all four test cases.

The results in Table 2 demonstrate that the SBERT system's most significant advantage manifests in the paraphrase match scenario (DS-2), where it achieves a match score of 74.2% compared to the keyword baseline's 12.4% — an improvement of 61.8 percentage points. This confirms that the principal hypothesis of the proposed approach is validated: transformer-based semantic embeddings successfully resolve the synonym blindness that constitutes the core failure mode of lexical matching systems. For exact-skill-match scenarios (DS-1, WD-1), the SBERT system achieves comparable or marginally superior scores relative to the keyword baseline, indicating that the semantic approach does not sacrifice performance on cases where keyword matching already performs adequately.

4.2 Skill Gap Analysis Accuracy

Table 3: Skill Gap Analysis Results — Data Scientist Test Cases

Test Case	Matching Skills Identified	Missing Skills Identified	Match Score (%)
DS-1	Python, Machine Learning, NLP, AWS, Docker	TensorFlow / PyTorch, Kubernetes	87.4
DS-2	Python, SQL (inferred)	Machine Learning, NLP, TensorFlow, AWS, Azure, GCP, Docker	74.2
WD-1	JavaScript, React, Node.js, CSS, Git	None identified (all JD skills matched)	91.6
WD-2	CSS, MongoDB, REST APIs	JavaScript, React, Node.js / Python backend, Git	62.8

4.3 System Response Latency and Resource Utilisation

Table 4: System Response Latency Profile (CPU-Only Infrastructure)

Processing Stage	Min Latency (ms)	Max Latency (ms)	Dominant Cost (%)
Text Preprocessing (clean + extract)	15	45	~2%
SBERT Embedding (2 documents)	800	1800	~85%
Cosine Similarity Computation	< 1	< 1	< 1%
Skill Gap Analysis	1	5	< 1%
JSON Response Assembly + Network	50	200	~12%
TOTAL (End-to-End)	866	2,051	100%

The latency profile in Table 4 reveals that SBERT embedding computation constitutes approximately 85% of total processing time, confirming that GPU-accelerated inference is the most impactful infrastructure enhancement for high-throughput production deployments. The end-to-end response time range of 866 ms to 2,051 ms on CPU-only hardware is well within acceptable limits for an interactive screening support tool intended for sequential, one-at-a-time candidate review workflows. For bulk candidate ranking use cases requiring sub-second throughput across large candidate pools, GPU-accelerated or batched embedding computation would be recommended.

5. CONCLUSION

This paper has presented ResumeMatch Pro AI, a full-stack intelligent recruitment support system that applies Sentence-BERT semantic embeddings to the problem of resume-to-job-description matching. The system demonstrates, both conceptually and through empirical evaluation, that replacing sparse keyword matching with dense transformer-generated embeddings and cosine similarity computation yields a recruitment tool that is substantially more accurate under synonymy and paraphrase conditions, more resistant to keyword stuffing manipulation, and more actionable through the integration of explicit skill gap analysis.

The all-MiniLM-L6-v2 SBERT model achieves a favourable balance between embedding fidelity and inference speed, enabling practical response latencies of under two seconds on CPU-only infrastructure. The modular architecture — comprising TextProcessor, SemanticMatcher, FastAPI orchestration, and React frontend layers with well-defined interfaces — ensures that each subsystem can be independently enhanced without structural refactoring of the wider system.

The system constitutes a validated proof-of-concept demonstrating that transformer-based semantic intelligence is practically deployable in a recruitment support context using open-source technologies without specialised hardware or proprietary licences. It provides a solid engineering and research foundation for future work.

Future research directions include: (i) integration of direct PDF and DOCX document parsing to eliminate the current text-pasting workflow; (ii) implementation of persistent result storage with a relational database backend to support regulatory audit trail requirements; (iii) fine-tuning the embedding model on domain-adapted recruitment corpora for improved professional vocabulary representation; (iv) application of SHAP-based feature attribution to provide sentence-level explanations of match scores; (v) integration with standardised skill ontologies (ESCO [19], O*NET [20]) for comprehensive, dynamically maintained skill vocabulary management; and (vi) development of a candidate-facing profile improvement portal that translates skill gap analysis into personalised competency development recommendations.

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