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Revolutionizing the Hiring Process with Automated Evaluation and Behavioral Analysis – IntelliHire

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***Abstract* - IntelliHire introduces an advanced automated system to revolutionize candidate evaluation, addressing the limitations of traditional techniques such as biased interviews and manual resume screening. By leveraging cutting-edge technology, IntelliHire provides an impartial assessment of candidates' knowledge, positive mindset, resume content, facial expressions, ethical benchmarks, and language proficiency. This comprehensive method employs diverse components, including contextual resume parsing, facial expressions and personality evaluation, and robust assessments using deep learning models and Machine Learning algorithms. The benefits include reduced bias, enhanced efficiency, cost savings, and refined candidate selection. This research contributes to the evolution of human resources and recruitment strategies, with potential for further development and enhancement of IntelliHire's capabilities.**

Keywords: automated evaluation, behavioral analysis, Machine Learning, deep learning, candidate evaluation, non-verbal cues, resume screening, facial expressions, personality evaluation, language fluency, knowledge evaluation, positive mindset evaluation, holistic assessment, unbiased assessment, automated hiring evaluation.

I. INTRODUCTION

Candidate evaluation is a pivotal aspect of the recruitment process, with in-person interviews and resume checks traditionally holding prominence [1]. The landscape has changed due to global factors like the Covid-19 pandemic and remote work, propelling the adoption of video interviews [2]. Statistics reveal that nearly 60% of hiring managers now use video interviews, marking a 49% increase since 2011 [3]. Automation and AI advancements are disrupting recruitment, offering potential transformative effects. Virtual interviews offer time and cost savings for employers and candidates alike [5]. However, human-resource-dependent video interview evaluations are resource-intensive. Employing automation, particularly in initial video interview stages, can streamline processes and optimize resource allocation [6]. Employing advanced technologies—Machine Learning (ML) algorithms, Deep Learning (DL) models, Natural Language Processing (NLP), and computer vision—can enable data-driven hiring decisions [7].Several crucial factors contribute to a comprehensive candidate assessment. Facial expressions provide insights into confidence levels [8]. Precise responses demonstrate expertise and problem-solving skills [9]. Mindset and attitude assessments align candidates with company culture. Personality attributes, alongside skills, are vital [8]. English proficiency, often crucial, adds to evaluation factors [9].The study's objective is to develop a sophisticated automated evaluation and behavioral analysis system for video interviews, revolutionizing recruitment [8]. This system integrates advanced elements—candidate knowledge, positivity assessment, contextual resume analysis, micro expression and facial expression scrutiny, behavioral cues, ethical standards, and language proficiency evaluation [8]. The system empowers firms to make informed hiring decisions, enhancing efficiency, reducing biases, and elevating the candidate selection process [9].This research paper reviews literature, outlines the methodology for each system component, presents findings, and discusses implications and future directions. It contributes substantially to human resources and recruitment, showcasing AI's potential in enhancing hiring processes. The research equips firms with cutting-edge tools, insights, and objective evaluation criteria, enabling efficient and fair recruitment practices in the digital age.

II. LITERATURE REVIEW

A key component of talent acquisition for firms is the process of hiring, and conventional approaches to candidate evaluation frequently fall short in terms of efficacy and efficiency. The goal of this study of the literature is to examine the recent developments and research in the areas of automated assessment and behavioral analysis, which serve as the IntelliHire system's cornerstones.

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A) Candidate Knowledge and Positive Mindset Evaluation

Video interviews have gained popularity for their convenience and cost-effectiveness [10]. However, assessing numerous candidates manually can be resource-intensive [10]. The Long Answer Analyzer, an automated system employing advanced technology, addresses this challenge [10]. Leveraging NLP, it extracts valuable information from spoken responses [12]. Incorporating sentiment analysis models enhances emotional tone recognition [13]. Datasets like the North Texas University Examination dataset and Dyna Sent Data Set aid training [11]. NLP techniques, including tokenization, part-of-speech tagging, and Named Entity Recognition (NER), enhance spoken response analysis. NLP libraries like Natural Language Toolkit (NLTK), Spacy, and BERT improve understanding [12]. Sentiment analysis models, such as "cardiffnlp/twitter-roberta-base-sentiment," gauge optimism in responses [13]. IntelliHire automates candidate knowledge and positivity assessment, enabling rapid evaluation and informed selections. The Long Answer Analyzer optimizes candidate evaluation, providing unbiased, data-driven insights. IntelliHire transforms hiring by integrating these innovations [10].

B) Resume Screening

Manual resume screening in hiring is known for being time-consuming and prone to errors and bias. Automated resume parser systems with contextual understanding have made significant advancements. Sinha and Akhtar highlighted ML's potential for accurate screening [14]. Deepak and Santhanavijayan used PDFMiner, PyPDF2, Apache Tika, and Apache POI to extract data from various formats [15]. Channabasamma, Suresh, and Reddy used NLP methods like part-of-speech tagging and NER for contextual resume analysis [16]. Tallapragada, Raj, and colleagues employed ML methods, including Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), for contextual comprehension [17]. Automated systems like these, including Tripathi's ontological technique and NLP approaches [18], revolutionize resume screening by extracting data, comprehending context, and minimizing biases, resulting in more efficient and effective hiring.

C) Behaviour analysis

Non-verbal cues like facial expressions and gestures are pivotal in evaluating candidates during job interviews. Such cues provide insights into emotional state, communication skills, and suitability for a role. A system that accurately assesses facial expressions and behavioral patterns is crucial. Research, including Das, Pandey, and Rautaray's work, has advanced facial expression and personality evaluation using ML models. These models categorize emotions exhibited by candidates, enhancing interviewer insights. CNN models analyze hand motions, improving nonverbal behavior understanding. OpenCV aids face detection for precise facial expression analysis. Data visualization from classified facial expression and gesture analysis generates insightful reports for informed hiring decisions [19].Additional research explores personality-facial expression links. Majumder and Behera employ DL for facial expression identification [21]. Krumhuber and Manstead highlight non-verbal cues' role in evaluations [22]. Hemamou predicts job success via facial expression analysis [23]. Real-time facial expression analysis methods offer feedback [24]. Integration of facial expression analysis with personality tests is explored by Hickman and Bosch [25]. The relationship between facial expressions and personality traits is examined by Argyle [26]. Fox and Spector study the impact of facial expression evaluation on perceptions and outcomes. Technology augments interviews, providing deeper insights into candidates through non-verbal cues [27]. This approach enhances assessment accuracy, equipping hiring managers with comprehensive insights for informed decisions.

D) Ethical Benchmarks and Language Fluency Evaluation

Automated evaluation of ethical standards and language proficiency enhances candidate assessment. Hanavi and F. Hidayat detect prohibited objects in video interviews, upholding ethical conduct [28]. Russell and Sparks link moral behavior to job performance and organizational success [29]. Kodiyan examines ethical implications of automated candidate evaluation [30]. Lee and Kim develop a system to identify ethical behavior markers [31]. Williams and Davis stress the importance of language proficiency in hiring [32]. Cahill and Evanini create an automated method for evaluating language fluency [33]. Harzing highlights the role of language proficiency in intercultural dialogue [34]. Tao and Evanini focus on automated speech recognition for language proficiency assessment. IntelliHire leverages diverse research, employing advanced technologies—React JS, Python, Node JS, NLTK, BERT, Apache Tika, CNN, Azure Cosmos DB, and more—for comprehensive candidate evaluation [35]. By reducing manual screening time, minimizing biases, and offering deeper insights, IntelliHire enhances efficiency and effectiveness in candidate selection, revolutionizing the hiring process.

III. METHODOLOGY

A) Knowledge and Positive Mindset Evaluation

The Long Answer Analyzer employs the North Texas University Examination dataset for software engineering knowledge assessment and the DynaSent Dataset for positive mindset evaluation [36][37]. Techniques like synonym

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substitution and sentiment amplification enhance dataset diversity. Such techniques strengthen the model's ability to generalize by providing various training examples, mitigating overfitting risks. Imputation methods handle missing values, ensuring fair assessment. Standardization maintains score consistency. Text cleaning removes noise, improving later NLP tasks. The datasets are split into training, validation, and testing sets, enabling fair model evaluation. Preprocessing processes yield uniform datasets for training models, ensuring reliable predictions. The architecture, depicted in Figure 1, involves the Long Answer Analyzer and the positive mindset evaluation component. NLP techniques extract structured data from text responses. Sentiment analysis models evaluate candidates' emotional tone.

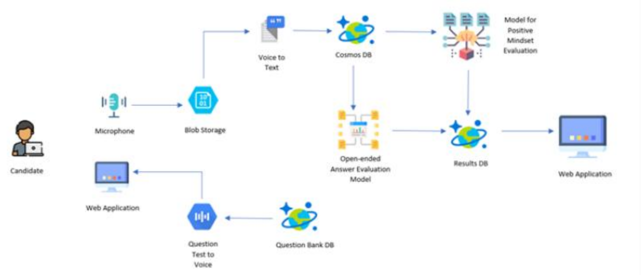

Figure 1: Candidate Knowledge, Positive Mindset Architecture

Frameworks like Tensor Flow facilitate component integration and data flow. This architecture guarantees thorough evaluation of candidate knowledge and positive mindset. Models are trained using preprocessed data, optimizing parameters and hyperparameters. Robust resources ensure effective learning and convergence [36].

B) Resume Screening

A diverse dataset of resumes is collected, covering various industries, roles, and experience levels. Resumes are preprocessed using programs like PDFMiner, Apache Tika, etc., extracting text and removing formatting irregularities.

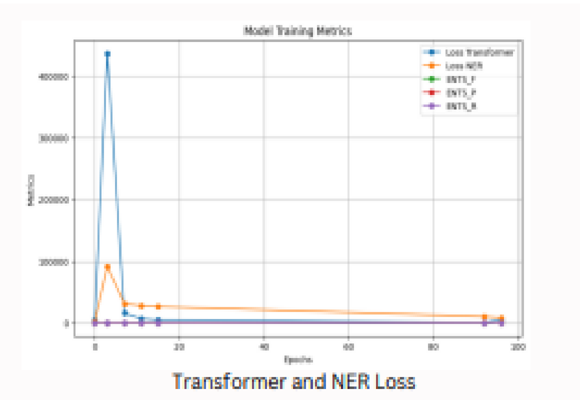

Figure 2: Model Training Metrics

NLP algorithms analyze resume contextual information. Tokenization separates text, part-of-speech tagging identifies word roles, and NER identifies entities. Libraries like NLTK, Spacy, and BERT apply these techniques, enhancing contextual understanding. ML models (e.g., SVM, Random Forests, CNN) decode resume content and context. Trained with preprocessed data, they extract relevant information, considering correlations between CV sections and job qualifications. The NER loss and accuracy of the trained model have graphed in the Figure 2, Figure 3 respectively.

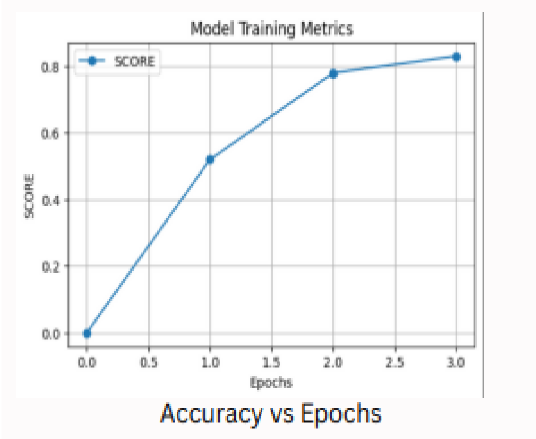

Figure 3: Accuracy vs Epoches Plot Diagram

Assessed resume data is structured in JSON format for easy processing. Candidate ranking utilizes text classification and word embedding, considering contextual resume analysis, and extracted data (skills, experience). The parser assigns scores based on job-match, aiding recruiters in focusing on promising candidates. Keywords are extracted to gather candidate skills using methods like TF-IDF analysis. Extracted keywords provide valuable insights for quick evaluation and comparison.

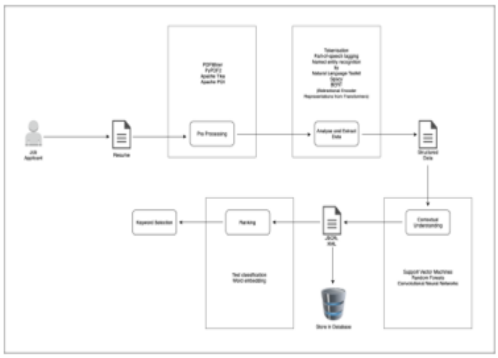

Figure 4: System Diagram Resume Parser with Contextual Understanding

As the Figure4 the methodology for the Resume Parser with Contextual Understanding encompasses ML model development, structured data representation, ranking, keyword extraction, and appropriate technology use [38].

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C) Behaviour Analysis

The Facial Expressions and Personality Evaluation component uses two datasets. The FER 2023 dataset contains video recordings of real job interviews, capturing facial expressions and behaviors. The Positive Mindset Evaluation dataset includes positive and negative expressions and behaviors, helping analyze candidates' nonverbal cues. These datasets create a foundation for training and evaluating the component, enhancing accuracy, and providing insights into nonverbal indications. As the Figure 5 the system architecture efficiently evaluates candidates' nonverbal cues and personality traits.

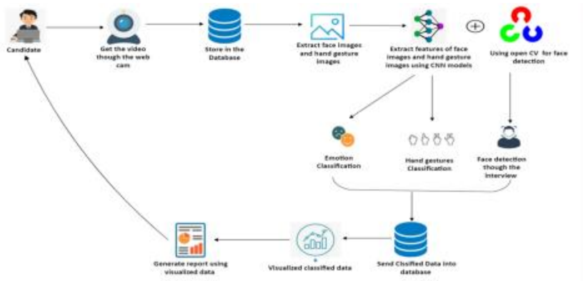

Figure 5: System Architecture of Facial Expressions and Personality Evaluation

Candidates are filmed during interviews, and OpenCV extracts key facial and hand gesture images. CNN models identify features for emotion and gesture classification, categorizing facial expressions and hand movements. Data, including labels and metadata, are stored and analyzed, generating comprehensive reports. These reports aid recruiters in evaluating candidates' nonverbal cues, enhancing the selection process. Besides facial expressions, confidence is evaluated using voice tone, speaking patterns, and body language. Sentiment analysis, pitch analysis, and body posture analysis gauge confidence, providing deeper insights into candidates' suitability. The methodology encompasses dataset acquisition, system architecture design, feature extraction and classification, confidence evaluation, and addressing research questions related to nonverbal cues. By considering nonverbal cues and psychological attributes alongside technical skills, this approach enhances the hiring process [38].

D) Ethical Benchmarks and Language Fluency Evaluation

The Ethical Benchmarks and Language Fluency Evaluation component utilizes two datasets: OIDv4 for Unauthorized Object Detection and language transcriptions for Language Proficiency. OIDv4 dataset helps YOLOv5 algorithm detect prohibited objects. Language proficiency is assessed using transcribed audio, checked for grammar errors using the language_tool_python package. Refer to the Figure 6 the Ethical Benchmarks and Language Fluency Evaluation component follows a structured process to analyze candidate videos [38].

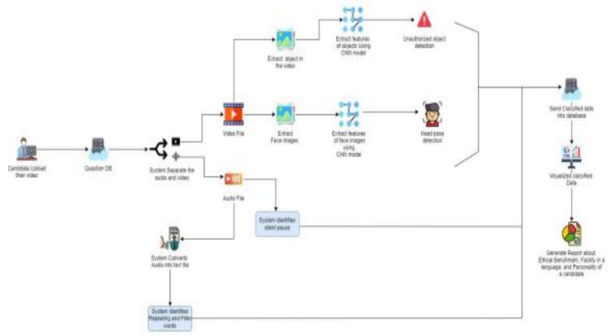

Figure 6: System Diagram of Facial Expressions and Personality Evaluation

Questions from a database guide the evaluation process. The candidate's video is separated into audio and video components for independent analysis. Object extraction algorithms identify and categorize items, while a CNN model analyzes facial expressions. Automated speech recognition transforms audio to text, identifying language proficiency and removing extraneous details. Classified data is stored and analyzed, generating detailed reports for recruiters. This approach ensures ethical compliance and language skills are evaluated accurately, enhancing the hiring process [40].

IV. RESULTS AND DISCUSSION

The Positive Mindset Evaluation component embedded in the IntelliHire system has yielded noteworthy outcomes, demonstrating its significant impact on the delicate process of candidate selection. The results obtained in all essential evaluation criteria serve as evidence of the component's consistent strength and unmatched effectiveness. Within the vast realm of Answer Evaluation, the IntelliHire system has displayed its remarkable prowess by producing a Coisine Similarity Score that is flawless, attaining a perfect 1.0. The score indicates a clear and definitive agreement between the candidates' responses. Figure 7 - the result highlights the exceptional accuracy of the system in understanding the complex subtleties and semantic complexities of candidate responses, enabling a seamless alignment that establishes an exceptional standard in the evaluation procedure. The remarkable achievement in the Positive Mindset Evaluation component illustrates the significant impact that automated methods such as IntelliHire have on the forefront. The integration of state-of-the-art technologies and sophisticated methodology has resulted in an assessment framework that exceeds traditional approaches, establishing IntelliHire as a leader in contemporary recruitment strategies. The extraordinary performance of the component, demonstrated by its persistent ability to produce outstanding outcomes,

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highlights its crucial significance in redefining the identification and assessment of positive mindsets throughout the process of candidate selection.

```
# Call the function with 'model' and 'tokenizer'
score = inference_answer_evaluation(answer01, answer02)
print("Cosine similarity score:", score)

Cosine similarity score: 1.0
```

Figure 7: Output of Similarity Score - Answer Evaluation

This Figure 8 exemplifies the system's precision in assessing the semantic similarity of answers. Furthermore, upon deeper examination of the intricacies inherent in the Positive Mindset Evaluation component, a comprehensive view of exemplary achievement emerges. The aspect of the IntelliHire system has demonstrated an impressive capacity to identify and interpret favorable emotions with a high degree of precision, which serves as evidence of its advanced design and implementation. The results collected provide strong evidence of the system's ability to accurately identify, analyze, and understand the subtle indications of positive present in the candidates' interview answers. This talent might be likened to a keen lens that has the capacity to capture even the most delicate undercurrents of optimism, showcasing a remarkable aptitude for deciphering the complex interaction between language and emotion. The findings of this study not only highlight the impressive technological capabilities of the component, but also indicate a significant shift in the fundamental nature of evaluation. The capabilities of IntelliHire extend beyond conventional assessment methods, as it incorporates emotion analysis to reveal the underlying positivity that is frequently concealed inside language expressions. These accomplishments contribute to a comprehensive and perceptive method of assessing candidates, reinforcing the significant impact of IntelliHire in transforming contemporary hiring methodologies.

```
inference_positivity_text('Every day is a new opportunity for growth and happiness.')
                                                                                Python
'positive'
```

Figure 8: Output - Positive Mindset Evaluation

Shifting attention to the complex realm of Confidence Evaluation, a captivating insight arises from the system's thorough examination. In Figure 9, the perceptive algorithms of the system exhibit a discriminating observation, revealing a characteristic of utmost importance - Openness. This specific characteristic, known for its complex nature, was revealed with a significant numerical value of 0.59745115. The revelation of the trait of Openness, which essentially holds greater value, provides a profound understanding of the candidate's demonstrative disposition exhibited during the interview. This process might be likened as gaining insight into a candidate's psychological composition, as if the system has temporarily removed the barrier concealing their deepest thoughts and revealed an aspect of their character that is typically obscured in conventional assessments.

```
                                                                                Python
... Trait with the highest value: openness
    Highest value: 0.59745115
```

Figure 9: Output - Personality Evaluation

This finding demonstrates the system's aptitude in evaluating candidates' traits based on their responses. The Resume Parser equipped with contextual understanding showcased its proficiency by providing a nuanced match analysis. The system reported that the candidate's resume aligns by 46.15% with the job description, indicating a comprehensive contextual understanding. Figure 10, shows the output of the resume parser and job description matching score. Given similarity score is multiplied by hundred and rounded off to two decimal points.

```
Similarity Score:
[[1.         0.4614666]
 [0.4614666 1.        ]]

Your Resume matches46.15% to the Job Descipriton
```

Figure 10: Output - Resume Job Description Similarity Score

As the Figure 11, the implementation of the YOLOv5 algorithm in conjunction with the Unauthorized Object Detection - OIDv4 dataset has significantly improved the detection of unauthorized objects in interview videos. By leveraging this advanced technology, the evaluation process now includes a robust method for identifying and flagging any prohibited items present during interviews. This enhancement not only strengthens the ethical evaluations conducted but also ensures a fair and transparent assessment of candidates' behavior and adherence to interview guidelines. The integration of YOLOv5 with the OIDv4 dataset showcases the potential of cutting-edge algorithms in bolstering ethical benchmarks during interviews, thereby contributing to a more rigorous and effective candidate evaluation process.

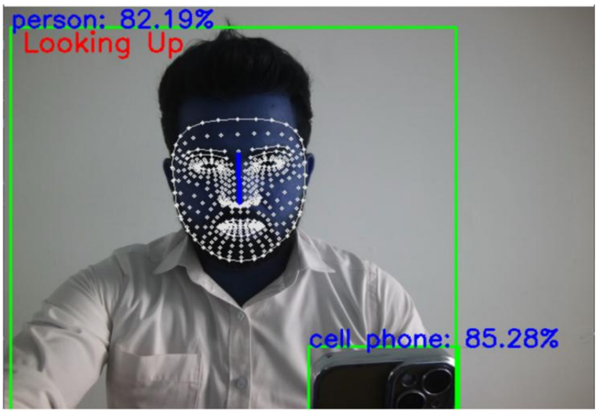

Figure 11: Output Unauthorized Objects Detection

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Collectively, these outcomes underscore the robustness and efficacy of the Positive Mindset Evaluation component within IntelliHire. The system excelled in gauging positive mindsets, confidence levels, and contextual congruence between resumes and job descriptions. The advanced methodologies and cutting-edge technologies, including NLP techniques and sentiment analysis models, played a pivotal role in achieving these outcomes. The successful integration of these elements fortified the system's capacity to assess and interpret emotional nuances, sentiments, and confidence expressed by candidates. The findings from the Positive Mindset Evaluation module underscore its potential to revolutionize the hiring landscape. By automating the assessment of positive mindsets and confidence levels, IntelliHire significantly expedites the candidate evaluation process. This automation eliminates subjectivity and biases inherent in manual evaluations, ensuring consistency and impartiality. These positive results not only validate the efficacy of automated systems but also illuminate a new era in hiring practices. The incorporation of advanced technologies and methodologies, as demonstrated in IntelliHire's Positive Mindset Evaluation component, empowers organizations to make astute hiring decisions. The system's capability to discern positive mindsets and confidence levels among candidates offers a data-driven approach to candidate selection, underscoring IntelliHire's transformative role in shaping the future of recruitment.

V. CONCLUSION AND FUTURE WORKS

The application of IntelliHire, an innovative automated assessment and behavioral analysis system, has significantly transformed recruitment processes by providing advanced tools to evaluate candidates' ethical standards, language proficiency, and role suitability. Empowered by intricate architecture and advanced algorithms, IntelliHire extracts insightful information from interviews, enabling informed decision-making for successful talent acquisition. IntelliHire employs the Facial Expressions Behavioral Evaluation (FER 2023) and Positive Mindset Evaluation - First Impressions V2 datasets for its facial expressions and personality evaluation component. Through CNN models, candidates' facial expressions are categorized into emotional groups, yielding behavioral insights from images of faces and hand gestures, enhancing understanding of nonverbal cues. IntelliHire integrates datasets and cutting-edge technology to assess candidates' ethical integrity and language fluency. Utilizing the YOLOv5 algorithm with the Unauthorized Object Detection - OIDv4 dataset, unauthorized objects in interview videos are detected, enhancing ethical evaluations. The language_tool_python package assesses language fluency by analyzing transcribed audio text for grammatical errors.

IntelliHire's architecture includes a potential component for evaluating cognitive abilities, using cognitive assessment tools to measure problem-solving, critical thinking, and cognitive skills. This holistic approach provides a comprehensive evaluation of candidates' suitability for roles. Acknowledging the importance of evaluating ethical benchmarks and language competence, IntelliHire assesses candidates' ethical principles and language proficiency. This involves establishing evaluation standards for ethical conduct and applying advanced language processing to analyze vocabulary, grammar, and fluency. IntelliHire’s continuous research and development efforts aim to enhance system functionalities, incorporating advancements in computer vision, NLP, and ML architectures. Expanding datasets to encompass diverse scenarios and candidate profiles will enhance accuracy and robustness. By automating examination and behavioral analysis, IntelliHire revolutionizes recruitment, offering impartial evaluation through components addressing fluency, cognitive ability, ethics, and expressions.

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