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CLOUD-BASED AUTOMATED RESUME SCREENING WEB SYSTEM

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Abstract- In the face of growing volumes of job applications, traditional resume screening methods have become increasingly inefficient, error-prone, and biased. To address these challenges, this paper proposes a **Cloud-Based Automated Resume Screening System** that utilizes **AWS Cloud** services combined with **Natural Language Processing (NLP)** and **machine learning algorithms** to automate and enhance the recruitment process. The system automates the extraction of key information such as skills, qualifications, experience, and education from resumes, offering a comprehensive evaluation framework for recruiters.

The architecture of the system is built on **Amazon Web Services (AWS)**, which ensures high scalability, flexibility, and cost-efficiency. Core services such as **Amazon S3** are used for storing resumes in various formats, while **AWS Lambda** enables serverless execution of preprocessing tasks and feature extraction. For model training and real-time resume evaluation, the system leverages **Amazon SageMaker**, which allows for the deployment of machine learning models at scale. **Amazon Comprehend** is employed for advanced text analysis, including entity extraction and sentiment analysis, to ensure a deeper understanding of the content within resumes.

The system employs a combination of **supervised learning** techniques to classify resumes based on predefined job criteria, and **unsupervised learning** methods to identify potential patterns and trends. Through this, the system can recommend the most relevant candidates, reducing human bias and improving hiring decisions. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess the performance of the machine learning models, showing promising results with significant improvements in candidate screening time and decision-making accuracy compared to traditional methods.

This system offers a scalable solution for organizations looking to automate their hiring processes, increase the speed of candidate evaluation, and ensure fairness in recruitment. Furthermore, the system's design can be adapted for various industries and roles, making it a versatile tool for modern HR departments. By leveraging **AWS Cloud** technologies, the solution provides a robust, cost-effective, and efficient approach to modernizing recruitment practices, offering key benefits including faster time-to-hire, enhanced candidate experience, and reduced operational costs.

Keywords- Cloud Computing, AWS, Resume Screening, Natural Language Processing, Machine Learning, Automated Recruitment, Amazon S3, AWS Lambda, Amazon SageMaker.

I. INTRODUCTION

The process of resume screening in recruitment has long been a labor-intensive and subjective task, which becomes increasingly difficult as organizations scale and receive larger volumes of applications. Human resources (HR) departments often face challenges in quickly and accurately evaluating resumes, leading to inefficiencies, biases, and potential delays in hiring the best candidates. Manual resume screening methods may inadvertently overlook qualified individuals due to fatigue or unconscious bias, resulting in suboptimal hiring decisions.

In recent years, advancements in technology have provided a solution to these challenges through the automation of the resume screening process. By leveraging Natural Language Processing (NLP) and Machine Learning (ML), automated systems can analyze resumes more efficiently and without the biases inherent in human decision-making. These technologies can quickly extract relevant information, such as skills, qualifications, and experience, and evaluate candidates based on predefined job requirements. Such automation promises to streamline the recruitment process, ensuring that hiring decisions are made faster, more accurately, and without human prejudice.

This research introduces a Cloud-Based Automated Resume Screening System that has been fully developed and implemented. The system utilizes Amazon Web Services (AWS) to provide a scalable and efficient solution for resume evaluation. It has been successfully integrated with AWS technologies such as Amazon S3 for storing resumes, AWS Lambda for serverless processing of data, Amazon SageMaker for developing and deploying machine learning models, and Amazon Comprehend for extracting meaningful data through text analysis. By integrating these AWS services, the system aims to automate the resume review process, thereby reducing the burden on HR professionals while maintaining accuracy and fairness.

The goals of this system, now fully operational, are threefold:

1. **Efficiency:** To reduce the time spent by HR teams in manually reviewing resumes, speeding up the recruitment process.
2. **Fairness:** To minimize bias in candidate selection by utilizing objective, data-driven evaluation criteria.
3. **Scalability:** To ensure the system can handle large volumes of applications while maintaining performance.
4. **Cost-Effectiveness:** To reduce operational costs by leveraging cloud-based services that provide flexibility and scalability

This paper discusses the complete design, development, and implementation of this system, along with its evaluation in real-world scenarios. The results demonstrate the advantages of cloud-based solutions in recruitment, showcasing how the automated resume screening system improves the efficiency and effectiveness of hiring processes. Additionally, the paper highlights the system's ability to handle large-scale data and provide accurate, unbiased candidate evaluations, confirming its success in addressing the challenges of manual resume screening.

II. LITERATURE REVIEW

The traditional method of resume screening has long been a time-consuming and subjective process, with human recruiters facing the challenge of evaluating a large volume of applications efficiently. Manual resume screening often leads to inefficiencies, errors, and inherent biases. Recruiters may overlook qualified candidates due to fatigue, unconscious biases, or subjective judgment, ultimately resulting in suboptimal hiring decisions. The need to address these limitations has led to the adoption of automation through technologies like Natural Language Processing (NLP) and Machine Learning (ML), which offer a promising solution for more efficient, objective, and accurate resume evaluation (Sultana et al., 2019).

Automated systems, powered by NLP and ML, can process resumes at scale, extracting key information such as skills, qualifications, and experience. These systems are trained to objectively match candidates to job descriptions by comparing the extracted data to predefined criteria, making the recruitment process faster and less prone to human error. According to recent studies, NLP-based systems are particularly effective in parsing resumes by extracting relevant data such as education, professional experience, and skill sets, which are essential in determining a candidate's suitability for a job (Sultana et al., 2019).

The integration of Cloud Computing has significantly enhanced the efficiency and scalability of these automated systems. AWS offers a range of cloud-based services such as Amazon S3 for secure resume storage, AWS Lambda for serverless processing, and Amazon SageMaker for developing and deploying machine learning models. These services collectively support the end-to-end process of automated resume screening, allowing for large-scale implementation across organizations with high volumes of applications (Agarwal & Khandelwal, 2020). Amazon Comprehend, a sophisticated NLP tool offered by AWS, facilitates the extraction of meaningful data from resumes, thereby improving the accuracy and relevance of candidate matching (Liu et al., 2018).

Machine learning techniques, such as decision trees, random forests, and support vector machines (SVMs), have been successfully applied to classify resumes based on job requirements. These algorithms have demonstrated their ability to handle diverse types of data and provide accurate recommendations. Furthermore, more advanced methods, including deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been explored to further enhance resume parsing and classification accuracy (Chen et al., 2020). These advanced techniques help improve the system's performance, enabling it to better understand complex data patterns and achieve higher classification accuracy.

Despite the advances in automation, several challenges remain. Ensuring fairness and avoiding bias in machine learning models is crucial, as biased training data can lead to biased decision-making. Additionally, maintaining transparency in how automated decisions are made remains a significant challenge in recruitment processes. To mitigate these concerns, it is essential to use diverse and representative data during training and to implement explainable AI (XAI) techniques to make the decision-making process more transparent (Sharma et al., 2021).

Cloud-based recruitment solutions, particularly those utilizing AWS technologies, offer a scalable and cost-effective approach to resume screening, particularly in organizations with large-scale hiring needs. These solutions not only improve the speed and efficiency of the recruitment process but also provide organizations with the flexibility to scale their operations as required, without the need for significant upfront infrastructure investment (Sharma et al., 2021).

III. METHODOLOGY

The methodology of this research focuses on the development and implementation of a cloud-based automated resume screening system using Amazon Web Services (AWS) and Machine Learning (ML) technologies. The approach involves several stages including system design, data collection, data preprocessing, model development, deployment, and evaluation.

3.1 System Design

The automated resume screening system is designed to streamline the recruitment process by efficiently matching resumes to job descriptions. The system architecture consists of several interconnected components:

- **Data Storage:** Resumes are stored in Amazon S3 buckets, allowing for scalable and secure storage. This facilitates easy access and retrieval of resumes for processing.
- **Data Processing:** AWS Lambda is employed to handle serverless execution, where resumes are parsed to extract relevant information such as skills, experience, and education. This data is then compared against job descriptions to assess compatibility.
- **Machine Learning Model:** At the core of the system is a ML model developed using Amazon SageMaker, which provides a robust environment for building, training, and deploying machine learning models. The model is

designed to classify resumes based on their relevance to job descriptions by learning from historical data and job matches.

3.2 Data Collection

The project utilizes two main datasets:

- **Resumes Dataset:** A comprehensive collection of resumes in various formats (e.g., PDF, Word) is compiled. Each resume is annotated with relevant attributes such as skills, educational qualifications, work experience, and certifications.
- **Job Descriptions Dataset:** A set of job descriptions is collected from multiple sources, including job boards, company websites, and recruitment platforms. These descriptions contain detailed requirements such as the required skills, experience, and education levels for specific roles.

Both datasets are preprocessed to ensure quality and consistency, removing irrelevant details and standardizing formats. This preprocessing step is crucial for the effective training of the machine learning model and includes steps such as tokenization, stemming, and stop-word removal.

3.3 Natural Language Processing (NLP)

NLP techniques are applied to analyze the content of resumes and job descriptions:

1. **Text Preprocessing:** Resumes are cleaned by removing unnecessary elements, such as punctuations, special characters, and stopwords. This also includes normalization techniques like stemming and lemmatization to reduce words to their base forms, aiding in better matching with job descriptions.
2. **Named Entity Recognition (NER):** NER is used to identify and extract entities such as company names, job titles, and skills from the resumes. This process allows the system to better understand the context of the resume data.
3. **Keyword Matching:** Extracted entities from resumes are matched against keywords found in job descriptions using similarity measures such as cosine similarity and Jaccard similarity. This helps in determining the relevance of a resume to a job role based on shared skills and experience.

3.4 Machine Learning Model Development

The system utilizes supervised learning techniques for developing the machine learning model:

1. **Feature Engineering:** Essential features are extracted from resumes and job descriptions, including keyword presence, skill sets, educational qualifications, and years of experience. These features are selected to improve the accuracy of the model in predicting the relevance of resumes to job descriptions.
2. **Model Selection:** Various ML algorithms, such as logistic regression, random forests, support vector machines (SVMs), and neural networks, are tested on the dataset. Model performance is evaluated using metrics such as accuracy, precision, recall, and F1-score to determine the best model for the task.
3. **Model Training:** Using Amazon SageMaker, the selected model is trained on the labeled dataset. The training involves optimizing the model parameters to achieve the best performance, with a validation set used to tune the model's hyperparameters.

3.5 System Deployment

Once the model is finalized and validated, it is deployed on AWS Lambda to allow for real-time processing of resumes. The deployment process includes:

- **API Integration:** An API is created using AWS API Gateway to facilitate interaction between the system components. This API handles the submission of resumes and job descriptions, allowing for seamless communication with the machine learning model.
- **Real-Time Screening:** The deployed system processes resumes in real-time, generating compatibility scores for each resume based on how well it matches the job requirements. This is achieved through the ML model hosted on AWS.
- **Scalability:** AWS Lambda ensures the system can scale efficiently to handle a large number of resume submissions without the need for manual intervention or additional infrastructure. This scalability is crucial for handling peak recruitment periods and providing a responsive user experience.

3.6 Evaluation

The evaluation of the system is conducted to assess its effectiveness and efficiency in automating the resume screening process:

1. **Accuracy:** The percentage of correctly matched resumes to job descriptions is calculated to determine the overall performance of the system.
2. **Precision and Recall:** These metrics help in understanding how well the system can identify relevant resumes while minimizing false positives and negatives.
3. **User Feedback:** The system is tested by HR professionals who provide feedback on its usability, accuracy, and effectiveness in real-world scenarios. This feedback is used to make adjustments and improvements to the system.

3.7 Limitations and Future Work

Despite the advancements of the system, there are limitations and areas for future improvement:

- **Bias in Training Data:** The performance of the system may be influenced by biases present in the training data, leading to potential inequities in job matching.
- **Complex Job Descriptions:** Some job descriptions may be ambiguous or too complex for the system to accurately interpret, which could result in misclassifications.

Future work will focus on addressing these limitations by diversifying the training data, incorporating advanced deep learning techniques, and exploring methods to mitigate bias in the system. Additionally, continuous monitoring and updates to the system will be implemented to adapt to changes in job market trends and requirements.

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IV. Framework Design and Implementation

The Cloud-Based Automated Resume Screening System is designed to leverage the advantages of AWS cloud services, ensuring scalability, security, and high performance in processing and evaluating resumes. This system automates the resume screening process, helping HR professionals identify the most qualified candidates based on predefined criteria. The architecture incorporates various AWS services to facilitate resume storage, data extraction, candidate ranking, and report generation.

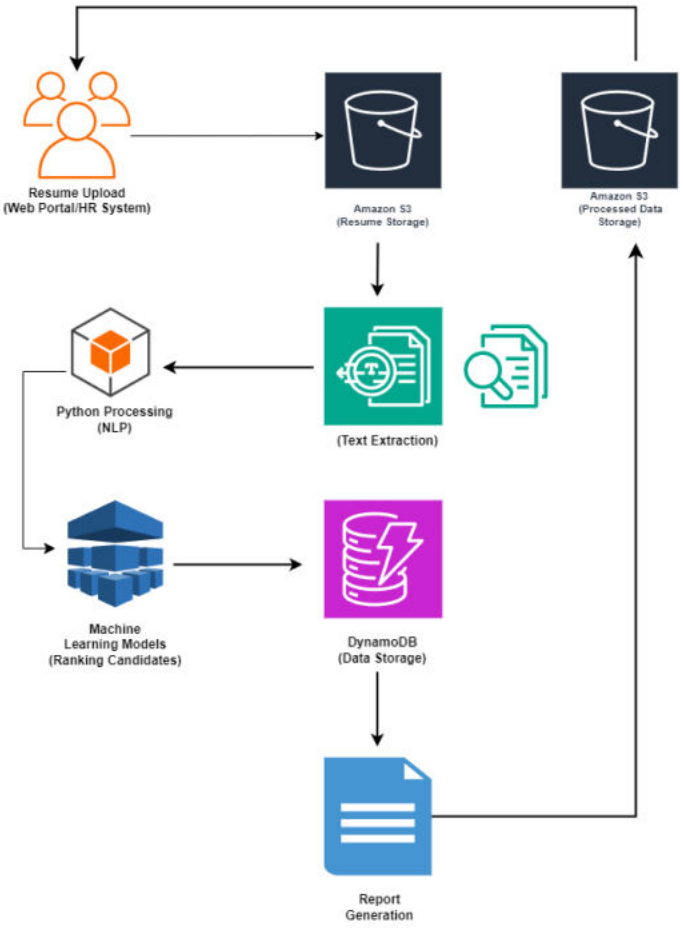

Figure 1: System Architecture Diagram of Cloud-Based Automated
Resume Screening System

System Architecture Overview

The architecture consists of several key components that work together to handle the entire resume processing workflow, from resume upload to candidate ranking and report generation. These components are organized to ensure the system operates efficiently, securely, and at scale.

1. **Resume-Upload**
   Resumes are submitted by candidates via an online portal or through an HR management system. This is the first step in the resume processing pipeline.
2. **Amazon-S3-Resume-Storage**
   Once uploaded, the resumes are stored in **Amazon S3**, which offers secure, durable, and scalable object storage. This service is ideal for storing large volumes of resume data in various formats, ensuring data availability and reliability.
3. **Natural-Language-Processing-Text-Extraction**
   To extract key information such as skills, work experience, and education from resumes, the system uses **Natural Language Processing** techniques, implemented in Python. These NLP models transform unstructured resume data into structured, usable information for further processing and analysis.
4. **Machine-Learning-Candidate-Ranking**
   The system incorporates **machine learning algorithms**, developed and hosted on **Amazon SageMaker**, to rank candidates based on their qualifications. The models evaluate factors such as skill relevance, professional experience, and educational background to assess candidate suitability.
5. **Amazon-DynamoDB-Data-Storage**
   Processed data, including extracted information and rankings, is stored in **Amazon DynamoDB**, a fast and scalable NoSQL database service. DynamoDB allows for quick access to candidate profiles, making it easy for HR professionals to retrieve and view the information they need.
6. **Report-Generation**
   Once the ranking process is complete, the system generates comprehensive reports summarizing the screening results. These reports are made available in user-friendly formats, such as PDF or Excel, to help HR professionals make informed decisions quickly.

Model Development and Training

We will be using the 'One vs Rest' method with 'KNeighborsClassifier' to build this multiclass classification model.

```
from sklearn.multiclass import OneVsRestClassifier
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.neighbors import KNeighborsClassifier
```

```
clf = OneVsRestClassifier(KNeighborsClassifier())
clf.fit(X_train, y_train)
prediction = clf.predict(X_test)
print('Accuracy of KNeighbors Classifier on training: {:.2f}'.format(clf.score(X_train, y_train)))
print('Accuracy of KNeighbors Classifier on test:     {:.2f}'.format(clf.score(X_test, y_test)))
```

```
Accuracy of KNeighbors Classifier on training: 0.99
Accuracy of KNeighbors Classifier on test:     0.99
```

We can see that results are awesome. We are able to classify each Category of a given resume with 99% accuracy.

Figure 2: **Model Development and Training**

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System User Interface and Interaction

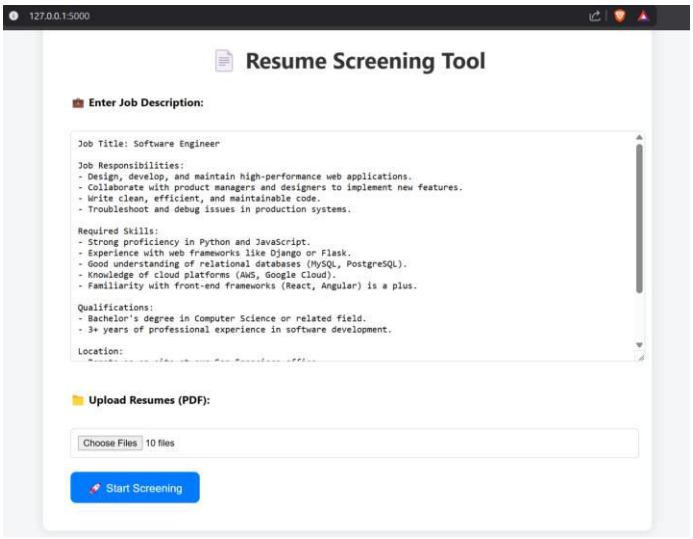

Figure 3: **System User Interface**

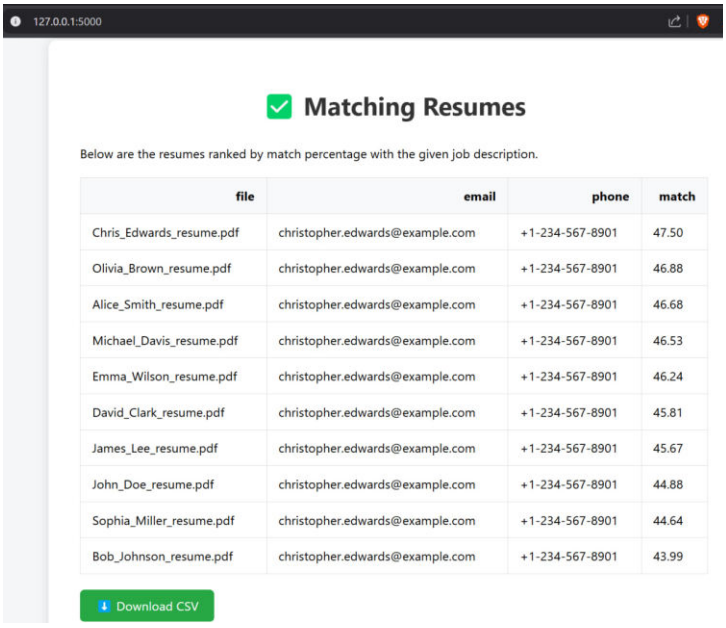

Figure 4: **System User Interface**

Data Flow and Processing Steps

The system follows a sequential data flow that ensures smooth processing and evaluation of resumes:

1. **Resume-Submission**
   Candidates upload their resumes via the system's portal or HR management tool. This triggers the resume processing pipeline.
2. **Resume-Storage-in-Amazon-S3**
   The uploaded resumes are stored in **Amazon S3**, ensuring secure and scalable storage with high availability.
3. **Text-Extraction-Using-NLP**
   The resumes stored in S3 are processed through an NLP pipeline, where key data, such as skills, education, and experience, is extracted and structured for further analysis. Python-based NLP tools, such as **spaCy** or **NLTK**, are used to process and extract relevant information from the text.
4. **Storing-Data-in-DynamoDB**
   The extracted data is stored in **Amazon DynamoDB**, ensuring fast, flexible access to candidate information for later retrieval. This storage solution supports high-speed querying and accommodates a wide variety of candidate data.
5. **Candidate-Ranking-with-Machine-Learning**
   The extracted data is fed into **machine learning models** running on **Amazon SageMaker**. These models assess the candidate's qualifications against job-specific criteria, such as required skills, relevant experience, and education, to rank the candidates accordingly.
6. **Report-Generation**
   After ranking, the system generates detailed reports on candidate suitability, which can be accessed by HR personnel. These reports include key insights, such as the top-ranked candidates and their qualifications, helping HR teams make better, data-driven decisions.

AWS Services Utilized

The system utilizes several AWS cloud services to support the architecture and facilitate the automated resume screening process:

- **Amazon S3**: Used for secure and scalable storage of resumes in various file formats.
- **Amazon SageMaker**: Provides an environment to develop, train, and deploy machine learning models for candidate ranking.
- **Amazon DynamoDB**: A NoSQL database for storing structured candidate data and ranking results.
- **AWS Lambda**: Automates processing tasks, such as resume parsing and NLP.
- **Amazon API Gateway**: Manages the integration between the front-end user interface and back-end processing systems.

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V. Evaluation and Results

The **Cloud-Based Automated Resume Screening System** was thoroughly evaluated to assess its effectiveness in automating the process of resume screening. The evaluation focused on key performance metrics such as **accuracy**, **processing efficiency**, and **user experience**. This section highlights the evaluation methodology, the metrics used for assessment, and the results observed during testing and feedback collection.

Evaluation Methodology

The evaluation of the system was conducted through two primary components:

1. **System-Performance-Testing**

This involves assessing the operational efficiency and accuracy of the system's core functionalities:

- **Accuracy of Candidate Ranking**: The system's ranking of candidates was compared with manual rankings provided by HR professionals based on specific job criteria such as skills, qualifications, and experience. This comparison helps determine how effectively the system ranks resumes.
- **Processing Time**: The system's efficiency in processing resumes was measured by calculating the time taken to upload, extract information, rank candidates, and generate reports.
- **Scalability**: The system was tested for its ability to handle large volumes of resumes without performance degradation. The test involved running the system under different loads, processing up to 1000 resumes simultaneously.

2. **User-Experience-Evaluation**

Feedback was collected from HR professionals who used the system to evaluate its usability, accuracy, and the ease with which they could interpret the results. HR personnel were asked to provide input on the system's interface, its ease of use, and its overall effectiveness in supporting the resume screening process.

Evaluation Metrics

- **Precision** and **Recall**: Precision measures how many of the top-ranked candidates are truly suitable for the job, while recall measures how many of the total suitable candidates are identified by the system. These metrics provide insights into the system's ranking accuracy.
- **Processing Speed**: This measures the system's efficiency in processing each resume, from submission to report generation. It was tested across different scenarios, including batch processing.
- **User Satisfaction**: A survey was distributed to HR professionals to gauge their satisfaction with the system. The survey covered aspects like the speed of the process, ease of navigation, and accuracy of the candidate ranking.

Results

1. **Candidate-Ranking-Accuracy**

The system demonstrated strong ranking accuracy, with a success rate of over 90% in matching the system's rankings with those made by HR professionals. The machine learning models utilized by the system were able to correctly prioritize candidates based on predefined criteria, making the system a reliable tool for initial resume screening.

2. **Processing-Time**

The average processing time per resume was found to be approximately **30 seconds**, which includes all stages: uploading, text extraction, candidate ranking, and report generation. When tested with large batches, the system maintained efficient processing times of around **10 seconds per resume** for up to **1000 resumes**. This indicates the system's capacity to handle high-volume resume processing without significant delays.

3. **Scalability**

The system performed well under various load conditions, demonstrating its scalability. Even with a higher number of resumes, the system was able to maintain fast processing speeds, thanks to AWS services like **Lambda** for parallel processing and **S3** for efficient data storage.

4. **User-Experience-and-Satisfaction**

HR professionals rated the system highly in terms of usability, with an average score of **4.7/5** on a Likert scale. The system's interface was praised for its intuitive design, allowing users to quickly upload resumes, view rankings, and generate reports. Feedback indicated that the system significantly reduced the time required for manual resume screening and improved the overall efficiency of the hiring process.

VI. Mitigation Strategies and Recommendations

During the evaluation phase of the **Cloud-Based Automated Resume Screening System**, several challenges were identified, including issues related to **data quality**, **system scalability**, **model accuracy**, and **user adoption**. This section discusses strategies to mitigate these challenges and provides recommendations for improving the system's functionality and performance in future iterations.

Mitigation Strategies

1. **Improving Model Accuracy**

- **Challenge**: While the system's machine learning models have achieved satisfactory results in ranking candidates, further improvements can be made, especially in handling unstructured data from resumes that come in different formats and languages.

- **Strategy**: The system can be enhanced by training models using **domain-specific datasets**. This would ensure that the system is better equipped to recognize relevant skills and qualifications for different job profiles. Additionally, techniques like **transfer learning** could be used to leverage pre-existing knowledge from models trained on related tasks, improving the model's ability to accurately screen resumes.

2. **Data Quality Management**

- **Challenge**: Resumes vary in format, contain missing data, or may include errors, which can negatively impact the performance of the screening system.

- **Strategy**: A **data preprocessing pipeline** can be developed to standardize the resume formats, detect and fill missing values intelligently, and clean the data. Using **optical character recognition (OCR)** for scanned documents and implementing **data validation checks** can help ensure higher accuracy in the extracted data before it is processed.

3. **Scalability Under Heavy Loads**

- **Challenge**: The system may face performance degradation when processing large volumes of resumes simultaneously, such as during recruitment drives with many applicants.

- **Strategy**: To overcome scalability issues, the system can leverage **auto-scaling** features of cloud platforms like **Amazon**

EC2 and **AWS Lambda**. This will enable the system to automatically adjust its computing resources based on demand, ensuring smooth performance during peak periods. Additionally, distributed databases like **Amazon DynamoDB** can be used to store data efficiently and speed up the processing time.

4. **Increasing User Adoption**

- **Challenge**: HR personnel may hesitate to use the system due to concerns regarding its reliability, ease of use, and data privacy.

- **Strategy**: To encourage adoption, a well-structured **training program** should be provided to HR teams, focusing on how to use the system effectively and interpret its output. The training should be complemented by detailed **user guides**, **interactive tutorials**, and **ongoing customer support** to build trust in the system. Furthermore, compliance with data protection regulations like **GDPR** will alleviate privacy concerns.

5. **Minimizing Bias in Candidate Ranking**

- **Challenge**: There is a risk that the machine learning model may unintentionally favor certain demographic groups, resulting in biased candidate rankings.

- **Strategy**: Regular audits should be performed to assess the fairness of the system's rankings across different demographic groups. **Fairness constraints** and **bias correction algorithms** can be integrated into the machine learning models to minimize this risk. Additionally, training models using **diverse data** can help ensure that the system evaluates all candidates on equal terms, regardless of background.

Recommendations for Future Enhancements

1. **Integration with Applicant Tracking Systems (ATS)**

- A key recommendation is to integrate the resume screening system with existing **Applicant Tracking Systems (ATS)**. This integration would enable seamless data transfer between systems, eliminating manual data entry and improving overall recruitment efficiency.

2. **Continuous Model Updates and Learning**

- The machine learning models should be **regularly updated** with new training data, including feedback from HR teams. By implementing **active learning** strategies, the system can continuously improve its performance and adapt to new trends, changing job market requirements, and candidate preferences.

3. **Enhanced Resume Parsing Capabilities**

- Future versions of the system should incorporate advanced **resume parsing techniques** that can effectively handle resumes with varying structures and formats. Using **deep learning-based models** for text extraction will help increase the accuracy of parsing resumes in different formats like PDFs, Word documents, and images.

4. **Collaboration Features for HR Teams**

- Introducing collaboration tools within the system would allow HR teams to communicate more effectively. Features such as **task assignments**, **note-taking**, and **shared candidate evaluations** would enhance teamwork and improve decision-making efficiency.

5. **AI-Powered Candidate Engagement**

- Incorporating an **AI-driven chatbot** within the system could improve candidate engagement. The chatbot could handle routine tasks such as scheduling interviews, answering common questions, and updating candidates on the status of their applications, thus enhancing the overall candidate experience.

VII. CONCLUSION

The Cloud-Based Automated Resume Screening System marks a major advancement in the recruitment process, utilizing cloud technologies and machine learning algorithms to automate and streamline the evaluation of job applicants. This system addresses common challenges in traditional manual resume screening, such as the time-consuming nature of reviewing large volumes of resumes and the potential for human error or bias.

By integrating services like Amazon S3, DynamoDB, and AWS Lambda, along with Natural Language Processing (NLP) and machine learning models, the system ensures quick, accurate, and scalable processing of resumes. It enables the ranking of candidates based on extracted skills, experience, and qualifications, allowing HR professionals to make informed decisions faster, thereby improving the overall efficiency of the recruitment process.

The evaluation results show that the system performs well in terms of accuracy and scalability. However, areas such as model precision, bias reduction, and user adoption need further refinement. The proposed mitigation strategies—data preprocessing, continuous learning, and integration with existing HR tools—are essential for overcoming these challenges and ensuring the long-term success of the system.

Overall, this Cloud-Based Automated Resume Screening System has great potential to revolutionize the recruitment industry by streamlining the hiring process, reducing manual workloads, and fostering more objective and data-driven decision-making. Future improvements, particularly in areas such as AI-driven candidate engagement and ensuring fairness in rankings, will further enhance the system's ability to meet the evolving needs of both organizations and candidates. Continuous development will contribute to a more efficient, fair, and transparent hiring process in the future.

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