Applied AI Letters

WILEY

LETTER OPEN ACCESS

Developing an Intelligent Resume Screening Tool With AI-Driven Analysis and Recommendation Features

K. L. Abhishek[1] | M. Niranjanamurthy[1] | Shonit Aric[2] | Syed Immamul Ansarullah[3] | Anurag Sinha[4] | G. Tejani[5,6] | Mohd Asif Shah[7,8,9,10]

[1]Department of Artificial Intelligence & Machine Learning, BMS Institute of Technology Affiliated to Visvesvaraya Technological University, Bangalore, Karnataka, India | [2]Software Engineer, Fidelity Investments, Bangalore, India | [3]Department of Management Studies, University of Kashmir, North Campus, Srinagar, Jammu and Kashmir, India | [4]Tech School, Computer Science Department, ICFAI University, Ranchi, Jharkhand, India | [5]Department of Computer Science, RC University Palamue, Bishrampur, Jharkhand, India | [6]Jadara University Research Center, Jadara University, Amman, Jordan | [7]Dean of Faculty, Department of Economics, Kardan University, Kabul, Afghanistan | [8]Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India | [9]Chitkara Centre for Research and Development, Chitkara University, Baddi, Himachal Pradesh, India | [10]Division of Research and Development, Lovely Professional University, Phagwara, Punjab, India

Correspondence: Mohd Asif Shah (m.asif@kardan.edu.af) | Anurag Sinha (anuragsinha257@gmail.com)

Received: 21 October 2024 | **Revised:** 9 February 2025 | **Accepted:** 22 February 2025

Funding: The authors received no specific funding for this work.

Keywords: natural language processing | parsing | resume analysis | tokenization

ABSTRACT

Current resume screening relies on manual review, causing delays and errors in evaluating large volumes of resumes. Lack of automation and data extraction leads to inefficiencies and potential biases. Recruiters face challenges in identifying qualified candidates due to oversight and time constraints. Inconsistent evaluation criteria hinder decision-making. These issues result in prolonged hiring processes, missed opportunities, and potential bias in candidate selection. The goal of this project is to develop an AI-powered Resume Analysis and Recommendation Tool, catering to the trend of recruiters spending less than 2 min on each CV. The tool will rapidly analyze all resume components while providing personalized predictions and recommendations to applicants for improving their CVs. It will present user-friendly data for recruiters, facilitating export to CSV for integration into their recruitment processes. Additionally, the tool will offer insights and analytics on popular roles and skills within the job market. Its user section will enable applicants to continually test and track their resumes, encouraging repeat usage and driving traffic. Colleges can benefit from gaining insights into students' resumes before placements. Overall, this AI-powered tool aims to enhance the resume evaluation process, benefiting both job seekers and employers. The primary aim of this project is to develop a Resume Analyzer using Python, incorporating advanced libraries such as Pyresparser, NLTK (Natural Language Toolkit), and MySQL. This automated system offers an efficient solution for parsing, analyzing, and extracting essential information from resumes. The user-friendly interface, developed using Streamlit, allows for seamless resume uploading, insightful data visualization, and analytics. The Resume Analyzer significantly streamlines the resume screening process, providing recruiters with valuable insights and enhancing their decision-making capabilities.

1 | Introduction

The Resume Analyzer project is a Python-based tool that aims to revolutionize the resume screening process by automating the traditionally laborious and time-consuming task of manually reviewing resumes. Leveraging the power of Pyresparser, NLTK (Natural Language Toolkit), and MySQL, the system offers a comprehensive solution for parsing, analyzing, and extracting key information from resumes. The tool utilizes natural language processing techniques from NLTK and Pyresparser to extract vital details from resumes, such as contact information, work experience, education, skills, and certifications. By automating this extraction process, the Resume Analyzer saves valuable time for recruiters and HR professionals, enabling them to focus on evaluating candidates rather than sifting through piles of documents. To facilitate user interaction and create a seamless experience, the Resume Analyzer integrates Streamlit, a user-friendly web application framework. Through the Streamlit-powered interface, users can effortlessly upload resumes, view parsed data, and access insightful visualizations and analytics. The intuitive nature of the interface ensures that recruiters can quickly navigate the tool and make informed decisions based on the extracted resume data. The extracted resume data is efficiently stored in a MySQL database, providing easy access, retrieval, and the potential for further analysis. Recruiters can access candidate information in a structured and organized format, enabling them to compare and evaluate applicants based on predefined criteria easily. Moreover, the system introduces a unique feedback loop that allows applicants to receive actionable recommendations for improving their resumes. This feature not only enhances the quality of resumes but also empowers job seekers to better align their profiles with market demands. For recruiters, the tool provides detailed analytics on popular roles, in-demand skills, and emerging trends in the job market, enabling data-driven decision-making. By offering these dual benefits, the AI Resume Analyzer bridges the gap between job seekers and employers, fostering a more efficient and equitable hiring process. With its ability to streamline the resume screening process, the Resume Analyzer proves to be a valuable asset for organizations of all sizes. By saving time and effort in the initial screening stages, recruiters can focus on identifying top candidates and conducting more meaningful interviews. The tool's efficient parsing and analysis capabilities increase the accuracy of candidate evaluation, ultimately leading to better hiring decisions. The project also aims to provide valuable insights and analytics to aid recruiters in their decision-making process. By aggregating data on popular skills, experience levels, and educational backgrounds, the tool empowers organizations with essential information to optimize their recruitment strategies. In addition to its technical innovations, the AI Resume Analyzer addresses critical challenges in the recruitment landscape, such as bias reduction and scalability. By relying on objective, data-driven criteria for candidate evaluation, the system minimizes unconscious biases that often plague manual screening processes. Furthermore, its scalable architecture ensures that it can handle large volumes of resumes without compromising performance, making it suitable for both small businesses and large enterprises. These features position the AI Resume Analyzer as a transformative tool in the recruitment industry, offering a competitive edge to organizations and job seekers alike. Overall, the Resume Analyzer project strives to be a reliable, efficient, and user-friendly solution that simplifies the resume screening process and enhances decision-making for recruiters. By automating the analysis and organization of resumes, the tool contributes to a more efficient, effective, and data-driven approach to talent acquisition, ultimately leading to better hires and stronger organizations.

The current resume screening process relies on manual review by recruiters, leading to time-consuming and labor-intensive evaluations of large volumes of resumes. This method is prone to human error and potential oversights, hindering the identification of qualified candidates. Moreover, the lack of automation and efficient data extraction mechanisms contributes to inefficiencies and potential biases in the process. To address these limitations, the proposed Resume Analyzer leverages AI, NLP, and ML technologies. It automates resume scanning, extracting relevant information such as education, work experience, and skills. This eliminates manual efforts and accelerates candidate evaluation. The system organizes and stores data in a centralized database, facilitating easy retrieval and analysis for future reference. By comparing candidate qualifications with job requirements, the Resume Analyzer ensures recruiters focus on the most suitable candidates, enhancing decision-making. Moreover, it minimizes biases by relying on objective criteria. Additionally, the system offers detailed analytics, insights, and candidate rankings, aiding recruiters in identifying top talents efficiently. Customizable and integral, the Resume Analyzer streamlines the hiring process, promoting efficiency and data-driven recruitment decisions. With continuous learning capabilities, it continually improves its performance and aligns with organizational preferences.

The proposed system, "AI Resume Analyzer," is a comprehensive solution designed for both applicants and recruiters to analyze resumes and gain valuable insights. The system utilizes natural language processing techniques to understand the content of resumes and extract relevant information. This information is then parsed and stored in a database for easy retrieval and further analysis. For applicants, the system provides predictions, tips, and recommendations based on the parsed resume information. This feature helps applicants improve their resumes by suggesting modifications, optimizing keywords, or highlighting areas that require attention. By leveraging the system's intelligent analysis, applicants can enhance their chances of securing job opportunities. On the other hand, the AI Resume Analyzer offers powerful analytics and informative data for recruiters or administrators. The system generates valuable insights and statistics derived from the resumes of applicants. These insights can include trends in job roles, in-demand skills, education patterns, and more. The analytics enable recruiters to make data-driven decisions, identify top candidates, and streamline their hiring process effectively. Overall, the AI Resume Analyzer serves as a valuable tool for both applicants and recruiters. It empowers applicants with personalized recommendations and predictions, while providing recruiters with powerful analytics and informative data, thereby enhancing the efficiency and effectiveness of the resume screening and hiring processes.

AI Resume Analyzer tool offers several valuable features and benefits. Firstly, it allows organizations to extract all resume data and transform it into a structured tabular format, making it suitable for analysis and export to CSV. This enables organizations to utilize the data for analytics purposes, gaining valuable insights into their talent pool. Secondly, the tool provides recommendations, predictions, and an overall score for resumes. This empowers users to improve their resumes by incorporating suggested changes and continuously testing their effectiveness using our tool. Furthermore, the inclusion of a user section in the tool can generate increased traffic. Users can create accounts, access their resume history, and benefit from personalized recommendations and insights, enhancing their user experience and engagement. Colleges can also leverage our tool to gain insights into their students' resumes before placements. This enables them to better understand students' profiles, skills, and experiences, facilitating more effective career counseling and placement support. Additionally, the tool offers the ability to analyze which job roles users are primarily interested in. This information can be valuable for understanding market trends, identifying popular career paths, and tailoring recruitment strategies accordingly. To continuously improve the tool, it actively seeks feedback from users. By incorporating user suggestions and addressing their needs, we ensure that the tool remains relevant, efficient, and user-friendly, providing a valuable resource for both applicants and recruiters [1, 2].

2 | Literature Survey

Text mining [3] is the process of extracting meaningful information from large amounts of text data. This can be used for a variety of purposes, including resume analysis. There are two main approaches to text mining for resume analysis: supervised learning and unsupervised learning. Supervised learning requires a training dataset of resumes that have already been labeled with the desired information. Unsupervised learning does not require a training dataset. Instead, it uses statistical techniques to identify patterns in the text data. There are a number of challenges associated with text mining for resume analysis, such as the format of resumes varying widely, the language used in resumes being informal and unstructured, and the quality of resumes varying widely. However, text mining for resume analysis has a number of potential benefits, such as it can help to automate the resume screening process, it can help to identify qualified candidates who might otherwise be overlooked, and it can help to ensure that all candidates are evaluated fairly. Overall, text mining for resume analysis is a promising approach that can help HR departments to improve the efficiency and effectiveness of their hiring process.

The Smart Resume Analyzer System [4] is a text mining application that uses keyword matching algorithms to analyze resumes and identify potential candidates for interviews. The system uses a personalized dictionary of keywords to match against the terms in the resume. The necessary data is extracted and placed in a database, and the complete information is sorted using multiple criteria. The system then schedules interviews based on the generated sorted list. The system has several benefits. It can help graduates identify and correct any flaws in their resumes. It can also help graduates highlight their skills and experience in a more effective way. Additionally, the system can help graduates get more interviews and increase their chances of getting a job. However, the system is still under development, and there are some limitations to the system. For example, the system only works with resumes that are written in English. Overall, the Smart Resume Analyzer System is a promising tool that can help graduates improve their resumes and increase their chances of getting a job.

Machine learning [5] is a powerful tool that holds great promise in predicting student employability outcomes, benefiting both career advisors and students in making better education and career decisions. By analyzing large datasets of student information, machine learning can identify patterns that lead to better predictions of employability compared to traditional static resume audits, which focus solely on academic performance and skills.

In one notable study, a hybrid model of Multi-Layer Perceptron Neural Network (MLPNN) and Radial Basis Function Neural Network (RBFNN) was employed to predict the employment outcomes of graduate students in engineering colleges. The model achieved an impressive accuracy rate of 88.38%, showcasing the potential of machine learning to improve employability predictions. Furthermore, this hybrid model can be adapted and extended to other academic streams, making it a versatile solution for various educational domains. Though the application of machine learning for student employability prediction is still in its early stages, it already shows immense potential for revolutionizing career centers' operations. By leveraging machine learning algorithms to analyze diverse student data, career advisors can provide more accurate and personalized advice to individual students. This tailored guidance can significantly enhance students' chances of achieving their career goals and finding suitable employment opportunities. Moreover, as machine learning continues to advance, it can potentially transform the landscape of career services in educational institutions. By continuously learning from vast datasets and identifying emerging patterns and trends, machine learning algorithms can stay up-to-date with the ever-changing job market. This agility ensures that students receive the most relevant and timely advice on industry trends, job openings, and skill requirements. Despite the exciting possibilities, it is essential to acknowledge that the field of using machine learning for student employability prediction is still evolving. As researchers delve further into this domain, they must address ethical considerations related to data privacy and fairness in decision-making algorithms. Transparent and ethical implementation of machine learning models will be crucial in building trust between students, career advisors, and educational institutions. In conclusion, machine learning holds tremendous potential for improving student employability prediction, enabling career centers to offer more effective and personalized guidance to students. As the field continues to evolve, the responsible use of machine learning in career services can pave the way for a more inclusive and successful transition from education to employment for students across various academic streams. By harnessing the power of machine learning, the future of career advising looks promising and transformative.

Open and distance learning systems [6], like Anadolu University's Open University System, cater to a vast number of learners, necessitating comprehensive learner support for effective and sustainable education. According to Tait (2000), this support can be categorized into cognitive, affective, and systemic aspects. Cognitive support helps learners in their learning process, affective support fosters self-respect and loyalty, and systemic support ensures smooth management of learning processes. Understanding the student profile is crucial for effectively providing these supports. Anadolu University's Open University System is a prominent mega university worldwide, serving approximately 1.5 million students.

To optimize the system's effectiveness and longevity, it is essential to know the learners comprehensively. This involves data on their prior education, entry type, scores, rankings, as well as demographic details like age, gender, nationality, and contact information. Furthermore, learners can voluntarily give feedback throughout the learning process, allowing continuous improvement. Research by Hakan et al. focuses on understanding Open Education Faculty (OEF) learners and their preferences for learning and communication environments, serving as an example of efforts to know learners at OEF. In conclusion, gathering and utilizing information about learners is fundamental in providing tailored support within large-scale open and distance learning systems like Anadolu University's Open University System. Understanding learners' needs and preferences enhances the system's effectiveness, contributing to a successful educational journey for millions of students.

Open and distance learning systems [7] require learner support in order to be effective. This support can be cognitive, affective, or systemic. In order to provide effective support, it is important to know the learner profile well. The study found that artificial neural networks can be used to predict the success of OEF students. The most important variables that predict the success of the students were gender, nationality, educational status, and graduation from vocational school. The results of this study can be used to improve the support provided to OEF students and to increase their success rates. For example, the results suggest that OEF should provide more support to female students, students from certain nationalities, and students who have not graduated from a vocational school. Overall, this study provides valuable insights into the factors that contribute to the success of OEF students. The results can be used to improve the support provided to students and to increase their success rates.

The paper [8] introduces "EXPERT," an advanced e-recruitment tool designed to efficiently screen job candidates using ontology mapping. Traditionally, e-recruitment tools have been used primarily for storing contact information, but EXPERT aims to take the process further. The tool operates in three main phases. In the first phase, EXPERT collects resumes from candidates and creates an ontology document that represents the key features and characteristics of each applicant. The second phase involves representing job openings and requirements as an ontology. Finally, in the third phase, EXPERT maps the job requirement ontology onto the candidate ontology document, enabling it to identify and retrieve the most suitable and qualified candidates for the specific job. By utilizing ontology mapping, EXPERT significantly improves the accuracy of candidate job requirement matching. This advanced approach helps streamline the candidate screening process, saving valuable time for companies and increasing the likelihood of finding the right fit for a job opening. As a result, EXPERT presents a promising and intelligent solution to enhance the e-recruitment process and improve the overall efficiency of candidate selection in the job market.

This work presents a novel approach [9] to evaluating job applicants in online recruitment systems by utilizing machine learning algorithms to address the candidate ranking problem. The researchers have implemented their approach in a prototype system, which has been tested in a real-world recruitment scenario. The proposed system takes advantage of LinkedIn profiles to extract a set of objective criteria from the applicants' information. Additionally, the system performs linguistic analysis on the candidates' blog posts to infer their personality characteristics. By combining these sources of data, the system aims to make more informed and objective decisions about applicant ranking. The evaluation of the prototype system demonstrated that it consistently performs on par with human recruiters [10]. This finding implies that the system's automated candidate ranking and personality mining capabilities can be trusted. As a result, the system shows promise as an efficient tool for assisting recruitment processes, providing valuable insights into applicants' qualifications and personality traits, thereby helping companies make better-informed hiring decisions. By automating parts of the recruitment process, the system could potentially save time and resources for employers while ensuring a fair and objective evaluation of applicants [11].

Applicant Tracking Systems (ATS) are widely used in recruitment processes to manage and streamline the hiring workflow. These systems are designed to parse resumes, store candidate data, and facilitate communication between recruiters and applicants. However, traditional ATS systems have several limitations. They often rely on rigid keyword matching algorithms, which can lead to the exclusion of qualified candidates whose resumes do not precisely match the predefined criteria. Additionally, ATS systems typically lack advanced analytics and personalized recommendations for candidates, limiting their ability to provide actionable insights to both recruiters and job seekers.

In contrast, the proposed AI Resume Analyzer offers several advantages over traditional ATS systems. Firstly, it leverages advanced Natural Language Processing (NLP) and Machine Learning (ML) techniques to extract and analyze resume data more accurately and contextually. This allows the system to identify relevant skills, experiences, and qualifications even when they are phrased differently or presented in unconventional formats. Secondly, the AI Resume Analyzer provides personalized recommendations to job seekers, helping them optimize their resumes based on industry trends and job requirements. This feature is particularly beneficial for candidates who may not be aware of the specific keywords or formatting preferences favored by ATS systems. Finally, the AI Resume Analyzer offers recruiters detailed analytics and insights into the job market, such as trending skills, in-demand roles, and candidate demographics. These insights enable recruiters to make data-driven decisions and refine their hiring strategies, ultimately improving the efficiency and effectiveness of the recruitment process.

By addressing the limitations of traditional ATS systems and incorporating advanced AI-driven features, the proposed AI Resume Analyzer represents a significant step forward in resume screening and candidate evaluation. It not only enhances the accuracy and fairness of the recruitment process but also empowers both job seekers and recruiters with valuable tools and insights to achieve their respective goals.

3 | Methodology

The system architecture adopts a three-tier framework, constituting the presentation layer, application layer, and data layer. The presentation layer serves as the interface through which users engage with the system. This stratum encompasses various user interface (UI) components, encompassing web pages or application screens. Here, users can input their personal information, upload their resumes, and provide feedback. UI development relies on a combination of HTML, CSS, and JavaScript, with potential utilization of web frameworks such as Flask or Django for server-side rendering. This layer's primary role involves interacting with users, managing their inputs, and relaying necessary information to the application layer for further, processing Figure 1 shows the flow graph [12].

In the application layer, the system's business logic and processing take center stage. This segment encompasses server-side application components responsible for tasks such as resume analysis, statistical computations, and managing user requests. Machine learning libraries such as scikit-learn can be harnessed for the intricate process of resume analysis and the extraction of pertinent details. Collaboration between the presentation layer and the application layer ensures the translation of user-initiated actions into concrete resume analyses, with subsequent presentation of analysis outcomes. Furthermore, this layer might extend its functionalities by integrating with external services or APIs, thereby augmenting the system's capabilities and enhancing user experience [13].

The data layer stands as the foundation of the architecture, responsible for the storage and retrieval of the data essential to the system's operation. To this end, a proficient database system, such as MySQL, is employed. This database houses an array of crucial information, ranging from user profiles and resume records to feedback and statistical metrics. The data layer's operations align closely with the application layer's demands, covering crucial aspects like data insertion, retrieval, and updates. Effective database design plays a pivotal role, ensuring the optimization of data storage and efficient organization [14].

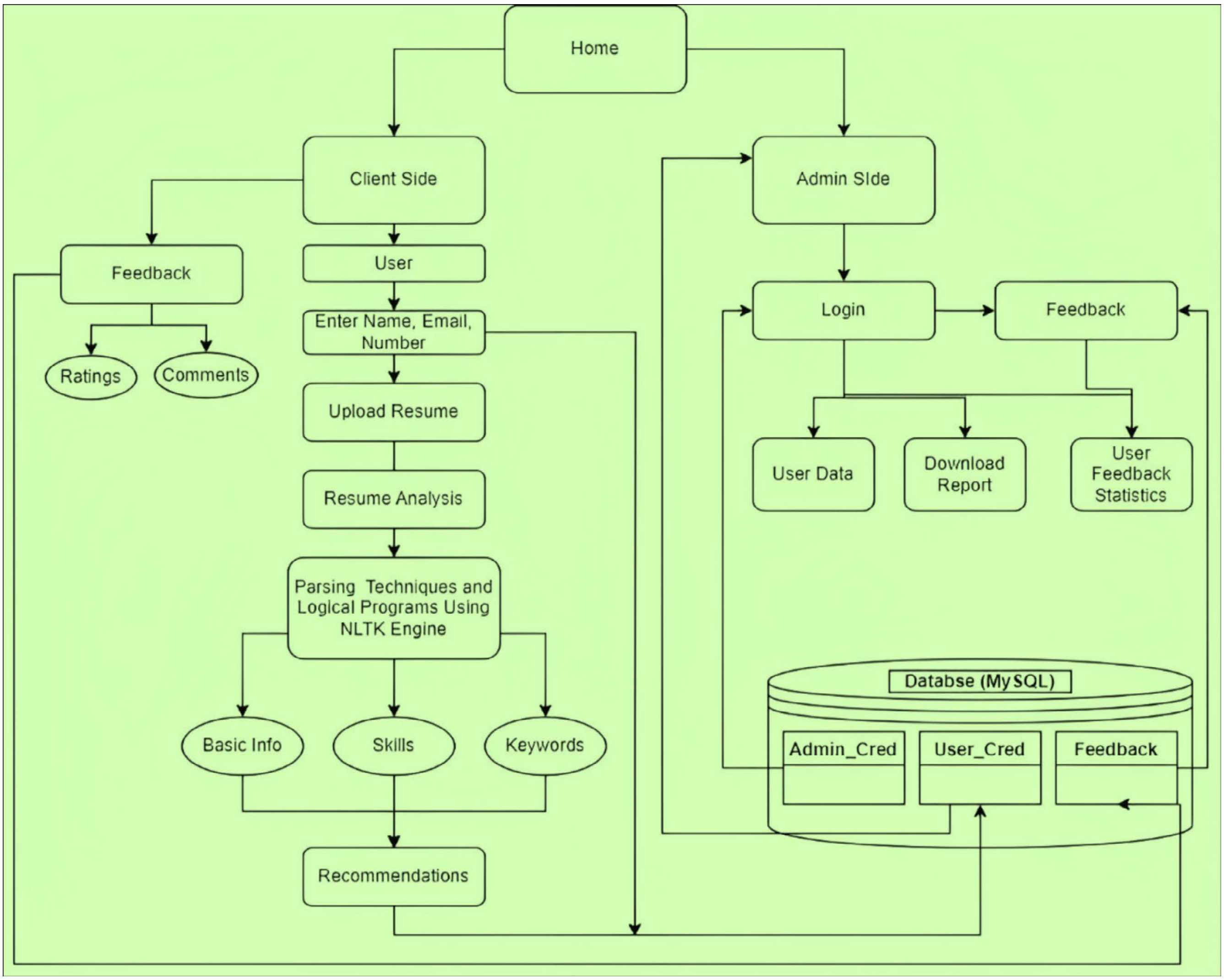

FIGURE 1 | Flow graph.

3.1 | Multi-Layer Perceptron Neural Network (MLPNN)

In the context of Back Propagation [5], the process of updating weights involves adjusting them in proportion to the derivatives of the nonlinear activation functions. In a Multi-Layer Perceptron Neural Network (MLPNN), the activation function used for neurons is often of the sigmoid type, characterized by its bell-shaped derivatives. The objective is to strategically choose the weights in a way that minimizes the performance criterion [15].

$$E_q = \frac{1}{2}\left(d_q - x_{out}^{(s)}\right)^T \left(d_q - x_{out}^{s}\right) = \frac{1}{2}\sum_{h=1}^{n}\left(d_{qh} - x_{out,h}^{s}\right)^2 \quad (1)$$

In the context of a Multi-Layer Perceptron Neural Network (MLPNN) with a sigmoid activation function, denoted as "g," and considering "s" as the number of network layers, the learning algorithm can be outlined as follows [15]:

a. Begin by adjusting the weights in the network using the standard initialization process.
b. Utilize the training data set to generate the network's response to each training pattern [16].
c. Compare the selected network output with the predetermined output of the network, and subsequently compute the local error.

$$\text{For output layer: } \delta_i^s = \left(d_q - x_{out,i}^s\right) g\left(u_i^s\right) \quad (2)$$

$$\text{For hidden layer: } \delta_i^s = \sum_{h=1}^{n2} \delta_h^{s+1} w_{hi}^{s+1} g\left(u_i^s\right) \quad (3)$$

d. The network weights can be modified as follows:

$$\mathrm{W}_{\mathrm{ij}}^{s}(\mathrm{t}+1) = \mathrm{W}_{\mathrm{ij}}^{s}(\mathrm{t}) + \mu \delta_{\mathrm{i}}^{s} \mathrm{X}_{\mathrm{out,j}}^{s} + \alpha\left[\mathrm{W}_{\mathrm{ij}}^{s}(\mathrm{t}) - \mathrm{W}_{\mathrm{ij}}^{s}(\mathrm{t}-1)\right] \quad (4)$$

e. If the network has reached convergence, halt the iteration process; otherwise, return to step 2 and continue.

The initial stage of the research pertains to the preprocessing of the secondary datato guarantee the quality and appropriateness for further analysis. The steps taken into account for preprocessing include normalization and imputation of missing values, as these procedures facilitate the creation of a coherent dataset [17]. A cornerstone in data preparation is the data standardization that guarantees that all features have a balanced impact during the PCA. Standardization is mathematically expressed as shown in Equation (5):

$$Y = \left(\frac{X - \mu}{\sigma}\right) V \quad (5)$$

where X: Original data matrix (samples × features). μ: Mean vector of the features. σ: Standard deviation vector of the features. V: Matrix of eigenvectors (from PCA). Y: Transformed data in the principal component space [18].

To begin, the relationships among the features are quantified using the covariance matrix, which is calculated by Equation (6):

$$\sum = \frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \mu\right)\left(x_i - \mu\right)^T \quad (6)$$

where Σ: Covariance matrix (a square, symmetric matrix). n: Number of data points. xi: The i-th data point (a vector). μ: Mean vector of the features. $\left(x_i - \mu\right)\left(x_i - \mu\right)^T$: Outer product of the deviation vector [19].

The next step involves computing the eigenvalues (λ) and eigenvectors (v) of the covariance matrix. This is achieved by solving the Equation (7):

$$\sum v = \lambda v \quad (7)$$

where Σ: Covariance matrix (computed from the data). v: Eigenvector (defines the direction of a principal component). λ: Eigenvalue (indicates the variance captured by the principal component).

By arranging the eigenvalues in descending order and selecting the top components, the data is transformed into a lower-dimensional space using Equation (8):

$$X' = XV \quad (8)$$

where X: Original dataset (size $n \times pn \times p$, where nn is the number of samples and pp is the number of features). V: Matrix of eigenvectors (size $\mathrm{p} \times \mathrm{k}p \times k$, where k$k$ is the number of principal components). X': Transformed dataset (size $\mathrm{n} \times \mathrm{k}n \times k$, where k$k$ is the number of principal components).

To assess the significance of each principal component, the proportion of variance explained (PVE) is calculated using Equation (9):

$$\nabla \theta J(\theta) = E\tau \sim \pi\theta\left[\nabla \theta log\pi\left(as = Xt'; \theta\right) \cdot R(\tau)\right] \quad (9)$$

1. PCA transformation:
   a. The original dataset X is transformed into the reduced feature space $X' = \mathrm{XV}_{\mathrm{k}}$, where V_{k} contains the top k eigenvectors. This reduces dimensionality while preserving 98.7% of the variance.
2. State representation:
   b. Each row of X' represents a state s in the reinforcement learning environment [20].
3. Policy gradient objective:
   c. The policy π(a|s;θ) is optimized to maximize the expected reward J(θ). The gradient of the objective ∇θJ(θ) is computed using the policy gradient theorem.
4. Connection to PCA:
   d. The state is in the policy π(a|s;θ) is derived from the reduced feature space X', which is the result of PCA.

The optimization objective is to maximize the expected cumulative reward, expressed in the form of Equation (10) as:

$$\nabla \theta J(\theta) = E\tau \sim \pi\theta\left[\sum_{t=0}^{T} \nabla \theta log\pi(at \mid st; \theta) \cdot \left(\sum_{t'=t}^{T} Rt'\right)\right] \quad (10)$$

where τ: A trajectory (sequence of states and actions), $\tau = (s0, a0, s1, a1, ..., sT, aT)$. Rt: The reward obtained at time step t. T: The total number of time steps in the trajectory. $\pi\theta$: The policy parameterized by θ.

The gradient is computed as presented in Equation (11):

$$\nabla\theta J(\theta) \propto E\tau \sim \pi\theta \left[\sum_{t=0}^{T} \nabla\theta log\pi(at \mid st; \theta) \cdot Gt \right] \tag{11}$$

where: $Gt = \sum t' = tTRt'$: The cumulative future reward from time step t to the end of the trajectory T. $\nabla\theta \log\pi(at|st;\theta)$: The gradient of the log-probability of taking action at at in state st. $E\tau\sim\pi\theta$: The expectation over trajectories $\tau\tau$ generated by the policy $\pi\theta\pi\theta$.

3.2 | Functionalities of the System

3.2.1 | File Upload for Extraction

The updated Data Flow Diagram (DFD) in Figure 2 illustrates a streamlined process for capturing user information and resume data. The user interface facilitates the collection of essential details like name, email, mobile number, and a resume PDF file. This information is subsequently channeled to the User Input API, which manages the submission process. The API then transmits both the user input and the resume file to the Resume Parser component [21].

Within the Resume Parser, cutting-edge techniques like machine learning and parsing are employed to extract pertinent details from the resume. These details encompass crucial elements such as skills, work experience, and educational background. Following this extraction, the relevant data is made accessible for further actions or storage within the Extracted Data component. This refined DFD elegantly outlines the seamless progression of information from initial user input to the intricate process of resume parsing, culminating in the acquisition of valuable extracted data [21].

3.2.2 | File Extraction to Recommender

In Data Flow Diagram Figure 3, the flow of information involves the extracted data transitioning to the Sorting & Analyzing component. This pivotal element is responsible for categorizing, sorting, and conducting a comprehensive analysis of the data to unveil insights and detect meaningful patterns. Subsequently, the organized and analyzed data becomes a vital resource for the Recommender component, which harnesses this information alongside the user's profile and extracted details to craft personalized recommendations.

Moreover, the Sorting & Analyzing component facilitates a reciprocal flow of its output to the User Data component, thereby enabling real-time updates to the user's profile. This streamlined DFD encapsulates the sequential journey of data, spanning from its extraction and progressing through the phases of sorting, in-depth analysis, personalized recommendation generation, and ultimately culminating in the dynamic enhancement of user data records.

3.2.3 | Feedback

In the Data Flow Diagram depicted in Figure 4, the process entails the user furnishing their name, email, feedback rating, and comments. This user-generated data is subsequently routed to the Data Analysis component, which undertakes a diverse array of analytical operations on the feedback dataset. These operations encompass intricate calculations, aggregations, or other pertinent analytical procedures aimed at extracting meaningful insights from the feedback.

The outcomes of this comprehensive analysis are then conveyed to the Analysis Results component. Here, a visual representation of the feedback ratings is presented, employing tools such as charts, graphs, or concise summaries. These visual aids effectively illuminate trends, patterns, and statistical details intertwined with the feedback. Through this visual portrayal, stakeholders are empowered to garner valuable insights into user sentiments, thereby facilitating well-informed decisions

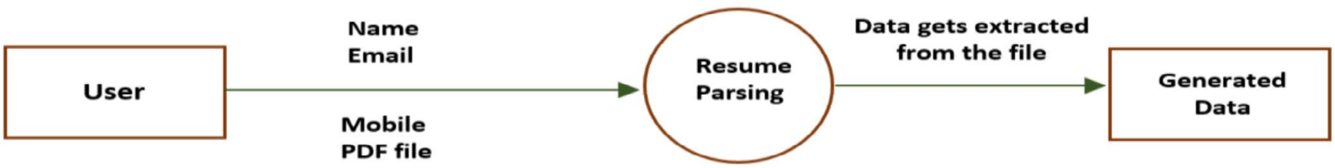

FIGURE 2 | Data flow diagram (DFD) file upload for extraction.

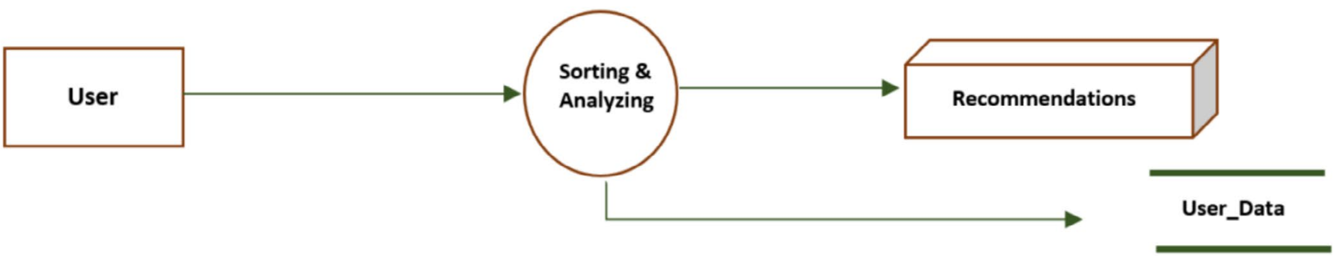

FIGURE 3 | Data flow diagram (DFD) file extraction to recommender.

grounded in the feedback information. This streamlined Data Flow Diagram captures the fundamental trajectory of information, commencing with user inputs and proceeding through the stages of meticulous analysis. The subsequent display of the analysis results serves as an instrumental gateway for stakeholders to delve into user perspectives, enabling a deeper comprehension of received feedback and facilitating astute decision-making based on this insightful data [22].

3.2.4 | Admin

Within the Data Flow Diagram depicted in Figure 5, the administration process entails the admin inputting their user ID and password, serving as authentication credentials. These credentials are subsequently relayed to the Authentication component, where a validation process is conducted to ascertain their legitimacy. Upon successful verification, the admin attains authorized entry to the login system, facilitated by the Login component [23].

This DFD succinctly outlines the pivotal stages intrinsic to the admin login procedure, encompassing the essential sequence from initial credential submission through the verification process, culminating in the conferment of access to the admin interface. It is important to acknowledge that the specific implementation might entail additional security protocols and functionalities to bolster the overall security and reliability of the admin login experience [24].

In Figure 6, the system engages with resume data through a dynamic process involving extraction, analysis, and personalized recommendation generation. Resumes are acquired either from user uploads or fetched from a database. Pertinent information, including skills and experience, is meticulously extracted from these resumes. The system then employs advanced algorithms and analytical techniques to thoroughly analyze the extracted data. This analytical prowess allows it to derive meaningful insights and patterns, empowering it to make informed assessments of each user's professional profile. Based on this comprehensive analysis, the system crafts individualized recommendations tailored to each user's unique attributes. These recommendations encompass a range of possibilities, spanning job opportunities that align with their skillset or specialized skill development programs to bolster their professional prowess.

The culmination of this intricate process sees the recommendations seamlessly presented to users through an intuitive user interface or via email notifications. Ultimately, this use case serves as a potent avenue for the system to harness the power of resume data, furnishing users with invaluable insights and actionable suggestions that have the potential to shape and elevate their career trajectory.

In Figure 7, the system facilitates seamless admin access through secure login credentials. Upon successful authentication, the admin gains comprehensive visibility into user data, encompassing vital details like names, emails, and feedback ratings. The system empowers the admin with versatile tools to efficiently navigate this data, including filtering, searching, and sorting functionalities. Furthermore, the system extends the admin's capabilities by enabling the generation of insightful reports. Leveraging these reports, the admin can specify parameters such as date ranges or specific data categories, tailoring the analysis to their needs. The system then diligently compiles and presents these reports, affording the admin a clear and comprehensive overview of user interactions.

This use case strategically equips the admin with the means to expertly manage and assess user data, providing the foundation for informed decision-making. By seamlessly amalgamating

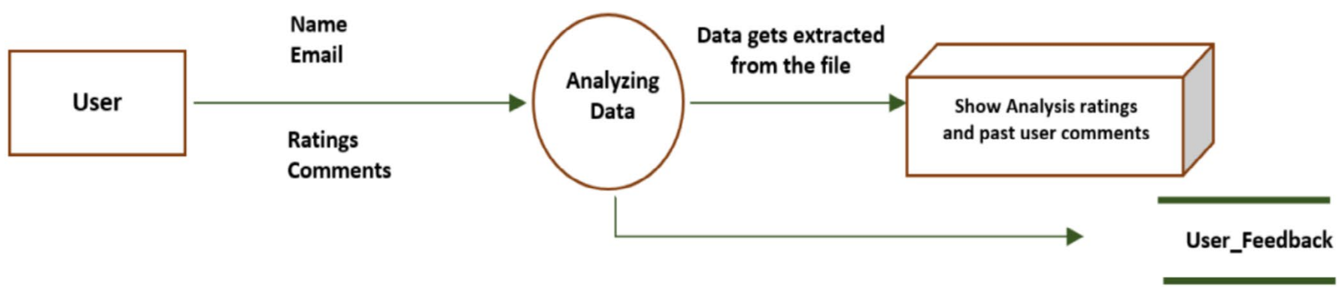

FIGURE 4 | Data flow diagram (DFD) feedback.

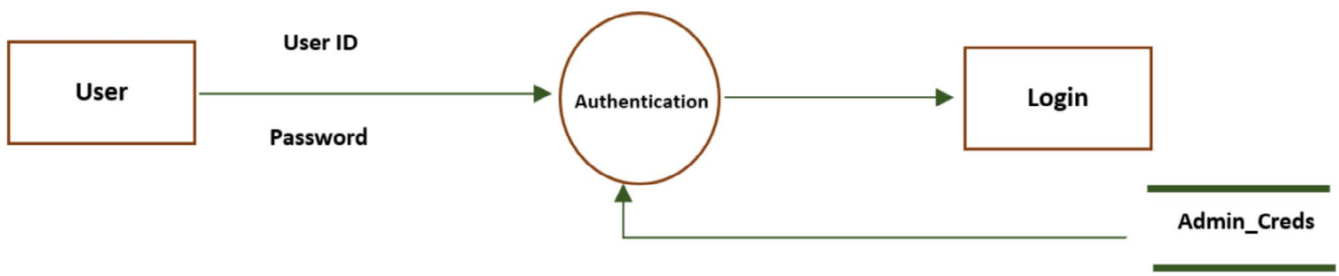

FIGURE 5 | Data flow diagram (DFD) admin.

data exploration, filtering, and report generation, the system fosters a dynamic environment for admin-driven insights and enhancements.

In Figure 8, users engage with the system through streamlined actions of resume upload and feedback provision. Within the user interface, individuals upload their resume files, initiating a process where relevant information is extracted and associated with their profile. This extracted data is efficiently stored within the system for future reference. Furthermore, users are empowered to contribute feedback, enhancing user engagement. Through ratings, comments, and suggestions, users provide valuable insights. This feedback is thoughtfully cataloged and linked to their profile, allowing for a comprehensive understanding of user sentiments. This use case fosters seamless resume submission, data extraction, and feedback channels, resulting in enhanced user interaction. By enabling easy resume uploads and facilitating meaningful feedback, the system elevates user engagement and iteratively enhances its performance.

In the sequence of interactions depicted in Figure 9, the user's engagement initiates with the pivotal step of uploading their resume file to the system. The system seamlessly processes the uploaded document, embarking on a journey to extract pertinent details encompassing skills, experience, and more.

Following the data extraction, the user is granted the opportunity to contribute their feedback, which is facilitated through a rating mechanism complemented by optional comments. This valuable feedback is meticulously captured and intricately linked to the user's profile, providing a holistic view of user sentiments. On the administrative side, the administrator accesses the system through authentication, ensuring security and accountability. Subsequently, the admin navigates to the report generation section, where they wield the power to fine-tune parameters and

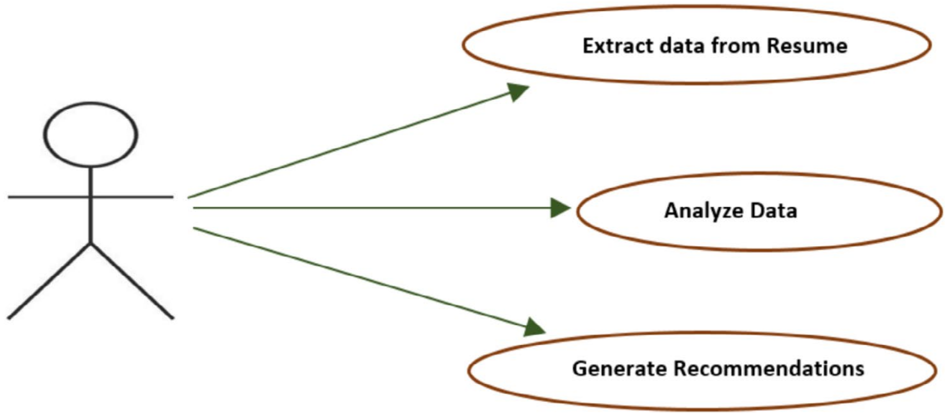

FIGURE 6 | Use case diagram for system.

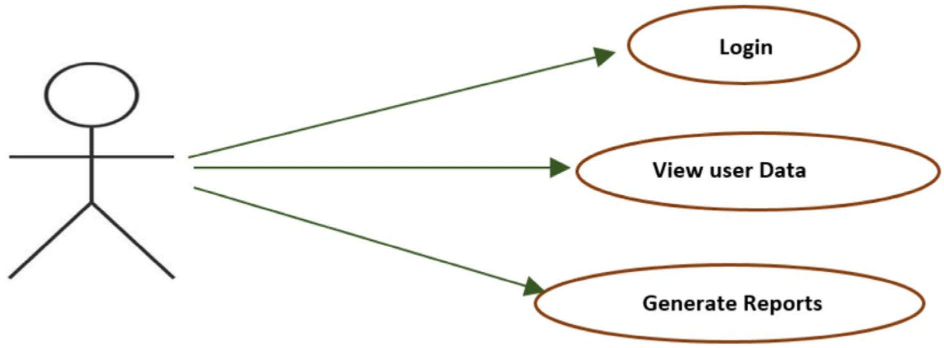

FIGURE 7 | Use case diagram for admin.

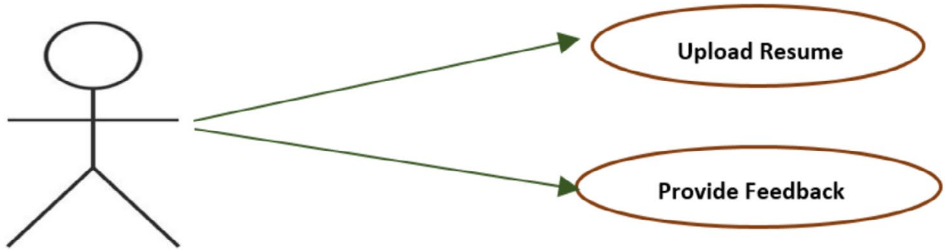

FIGURE 8 | Use case diagram for user.

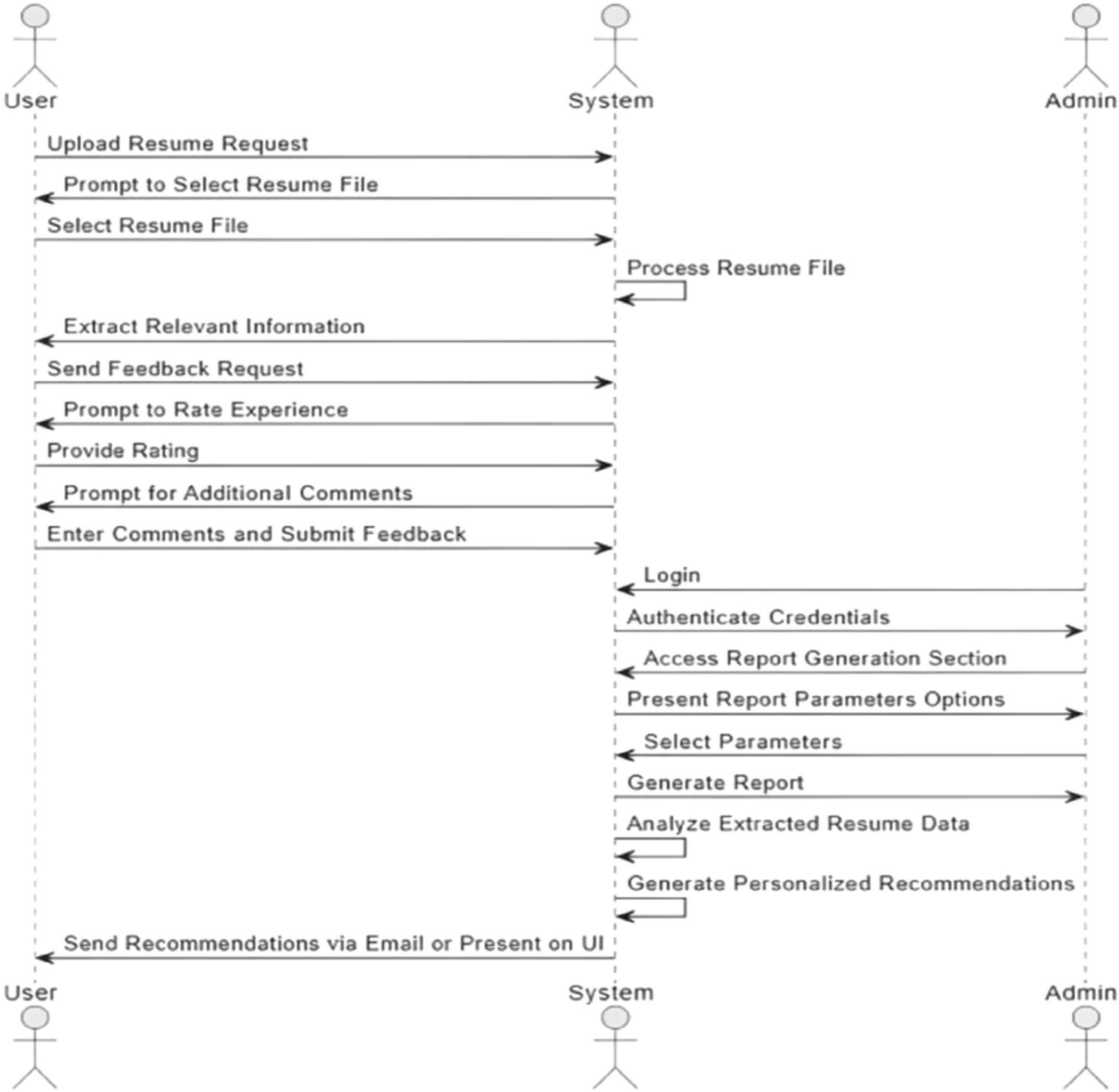

FIGURE 9 | Sequence diagram of resume analyzer.

specifications for generating customized reports. Meanwhile, the system doesn't rest; it employs its analytical prowess to analyze the extracted resume data. Armed with this insight, the system adroitly generates personalized recommendations that align with the user's unique attributes. These tailored recommendations are thoughtfully presented to the user, either through the user interface or delivered directly via email [25].

Collectively, this intricate sequence of interactions forms a dynamic cycle, where user-initiated resume uploads, data extraction, feedback collection, admin authentication, report generation, and personalized recommendation delivery converge. This comprehensive process encapsulates the project's essence, expertly harmonizing user engagement, data utilization, and system functionality to provide a seamless and enriching experience for both users and administrators alike.

4 | Results and Discussion

The client-side code provided offers an intricate and user-centric experience, revolutionizing the way individuals approach job applications and interviews. By seamlessly integrating multiple functionalities, the system empowers users with invaluable insights and recommendations to enhance their resume's effectiveness. Upon selecting the "User" option, users are prompted to input essential personal details, including name, email, and mobile number. The system then generates a secure token, harnessing advanced security measures. It goes further by collecting system-specific information such as the host name, IP address, device user, and OS version, ensuring a comprehensive understanding of the user's context. The code's highlight is its ability to analyze and extract information from uploaded PDF resumes. Leveraging cutting-edge parsing techniques, it accurately retrieves vital data, including the candidate's name, contact information, educational background, and more. The system astutely predicts the candidate's experience level based on the resume's content, allowing users to gauge where they stand in the competitive job market.

Additionally, the code offers targeted recommendations for skills and courses based on the predicted experience level. This feature is invaluable, as it provides users with specific actionable steps to enhance their professional profile and align it with their desired field. A notable aspect of the code is its holistic approach to evaluating the completeness of the resume. By assigning a resume score, the system quantifies the quality of the document, motivating users to ensure they include critical sections like objectives, education, experience, skills, achievements, certifications, and projects. While the code showcases an impressive array of features, it does have room for improvement. For instance, it could benefit from more robust error-handling mechanisms to gracefully manage unexpected issues during data extraction or parsing. In conclusion, the client-side code is a comprehensive tool that transforms the traditional resume-building process. Its sophisticated analysis, personalized recommendations, and engagement-enhancing videos equip users with the knowledge and resources needed to create compelling resumes and succeed in job interviews, ultimately propelling them toward their desired career goals.

In Figure 10 of the application's workflow, the user engages with the system by opting for the “Upload Resume” feature. This action triggers a pivotal interaction where users can seamlessly choose their resume document from their local device. The ensuing dialogue prompts users to select the desired file, initiating a streamlined process.

Upon file selection, the application undertakes several crucial steps. Firstly, it diligently processes the uploaded content, ensuring the data's integrity and conformity. This includes rigorous validation checks to confirm the file's format, verifying that it adheres to the stipulated requirements, such as being in PDF format. Once the file successfully passes the validation stage, the application securely manages the storage aspect. Employing robust data management protocols, the system either transfers the resume to a designated storage repository or safely retains it on the server. This strategic approach ensures the confidentiality and accessibility of the document while also mitigating potential security risks.

As the resume upload concludes, the user receives an affirmative confirmation message. This message acts as a tangible indicator of a triumphant resume upload, reinforcing user confidence and facilitating a positive user experience. Overall, the “Upload Resume” function stands as a pivotal junction within the application, expertly facilitating seamless, secure, and user-friendly integration of user-generated content into the platform's ecosystem.

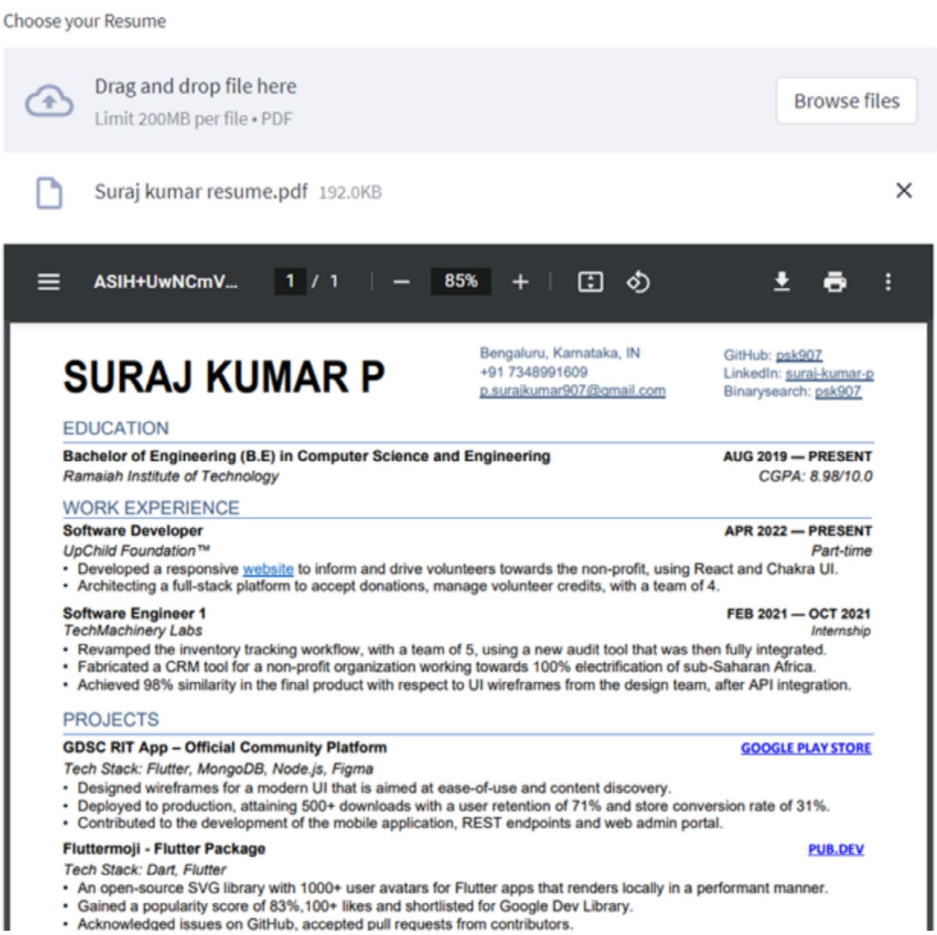

FIGURE 10 | Uploading resume in resume analyzer.

Once the user uploads their resume, the system triggers a pivotal analysis process, as depicted in Figure 11, designed to meticulously extract crucial information from the resume. This intricate process involves parsing the uploaded resume file and adeptly retrieving pertinent details encompassing skills, experience, education, and other contextual data. Employing advanced algorithms and techniques, the system ensures accurate extraction and meticulous structuring of these details, setting the stage for comprehensive analysis.

The extracted information serves as a linchpin in generating valuable recommendations, aligning job requisites, and furnishing vital insights to both users and system administrators. These insights become instrumental in making informed decisions, whether it is optimizing job matches or enhancing system functionality. Ultimately, this analysis-driven process forms the cornerstone of the project, facilitating meaningful interactions, data-driven insights, and enhancing the overall user experience.

In Figure 12, leveraging the user's uploaded resume as a point of reference, the system embarks on a meticulous content analysis, discerning and pinpointing the skills embedded within. Drawing insights from this analysis, the system dynamically generates a spectrum of skill recommendations that seamlessly align and complement the user's existing proficiencies.

These recommendations encompass a diverse array of skills, spanning technical prowess, soft skills, and industry-specific proficiencies that remain in high demand or harmonize with the user's envisioned career trajectory. This strategic output empowers users by guiding them toward areas of potential skill development, thereby elevating their employability quotient. The system's skill recommendations act as a compass, steering users toward relevant market trends and job requisites, ultimately bolstering their readiness to navigate the dynamic professional landscape. Through this symbiotic process, the system enriches user skillsets, enhances employability, and cultivates alignment with prevailing industry demands.

In the administrative realm illustrated in Figure 13, a dynamic process unfolds wherein user data is seamlessly retrieved from the database, heralding a trove of insights and information catering to administrative needs. The system adeptly executes database queries, extracting a rich tapestry of user-specific particulars, encompassing names, contact details, feedback appraisals, skills, experience, and other pertinent attributes.

This wealth of information is elegantly presented to the admin, thoughtfully structured and meticulously organized. Such presentation equips the administrator to navigate user profiles, delve into analytical exploration, generate comprehensive reports, and thus, wield informed decision-making capabilities. By harnessing and leveraging the robust reservoir of user data stored within the database, the administrator becomes the steward of effective system management and monitoring. This strategic grasp empowers the admin to oversee system performance, gauge user engagement, and strategically propel the system's overarching trajectory, thereby orchestrating an environment of holistic progress and continual enhancement.

In Figure 14, pie charts are utilized to present statistical information in a visually appealing and informative manner. These charts provide a graphical representation of data distribution,

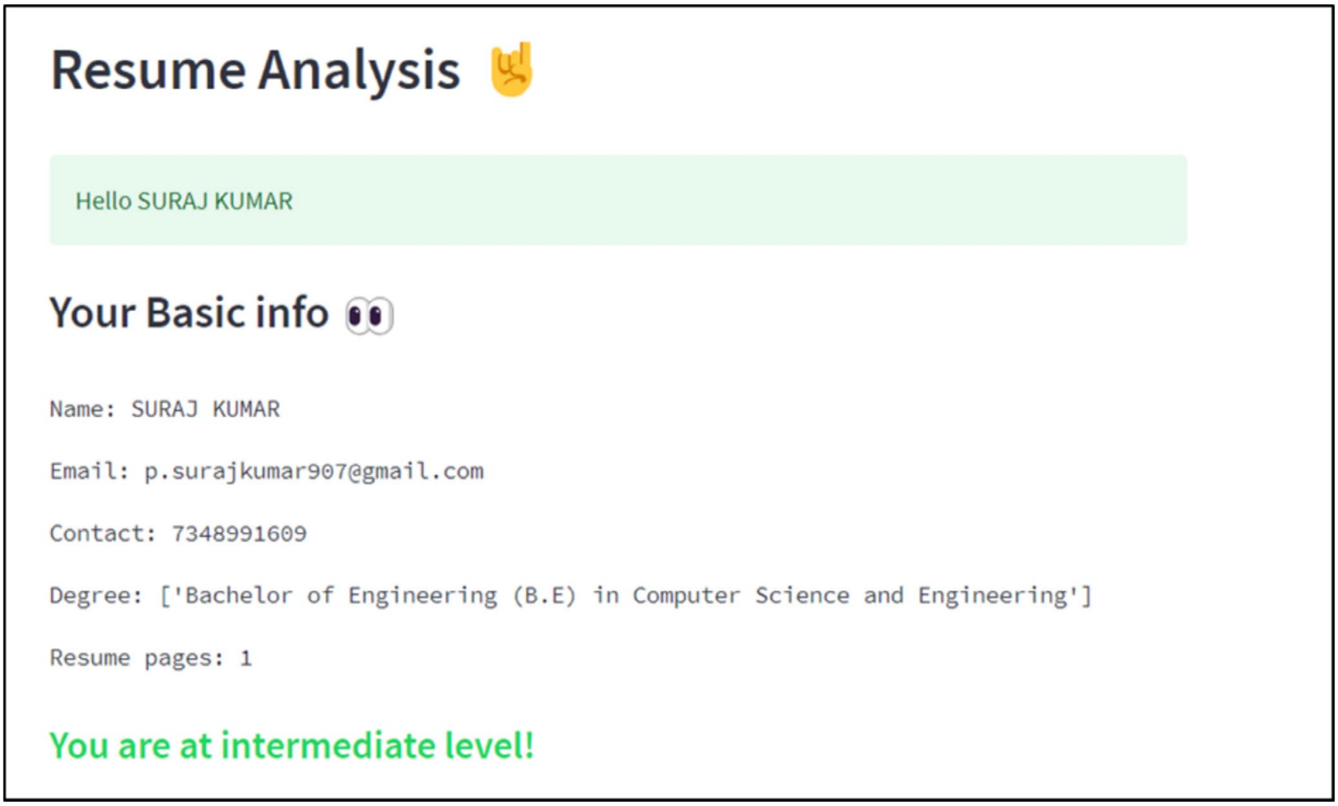

FIGURE 11 | Resume analysis in resume analyser.

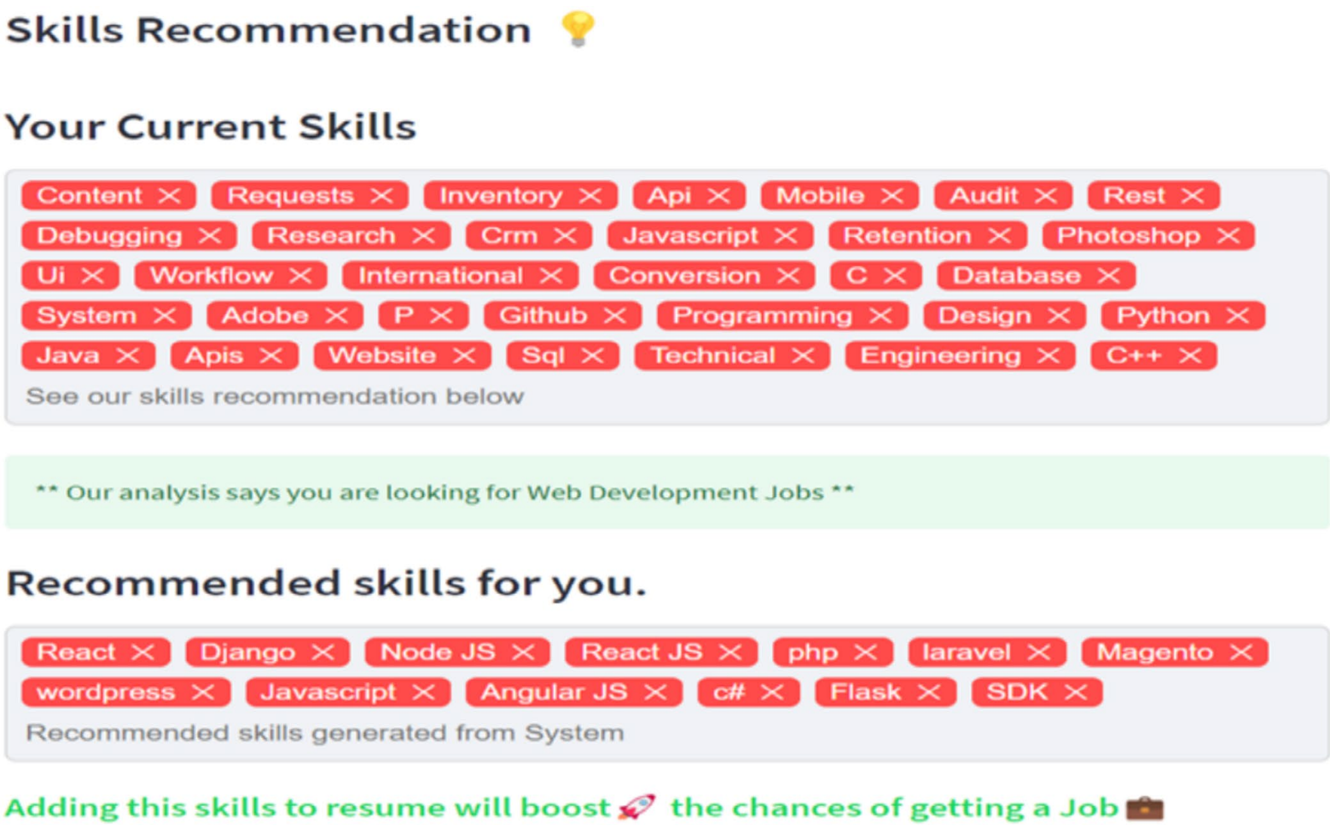

FIGURE 12 | Skill recommendations in resume analyzer.

User's Data

	ID	Token	IP Address	Name	Mail	Mobile Number	Predicted Fie
0	1	WSozt5wffO1igMAO	192.168.137.1	demo	demo@gmail.com	12345678890	Web Develop
1	2	b5tYQJ9X2RlOQm1X	192.168.137.1	demo	demo@gmail.com	12345678890	Web Develop
2	3	QJWwK7Gu1DvFqFVe	10.20.30.236	athul	athul@gmail.com	9876543210	UI-UX Develc
3	4	eYu-3FJbhFBjWwOS	10.20.30.236	demo000	d@gmail.com	584758652	NA
4	5	Uoux6Ae3QD4UjrwW	10.20.30.236	demo000	d@gmail.com	584758652	Web Develop
5	6	OtOVB_5u4XnGvzfo	192.168.137.1				NA
6	7	mnhwOrJ2a07eJxL9	192.168.137.1				Web Develop
7	8	UkvjYy6ZygLGFSIv	192.168.137.1	yukthi	yukthi@gmail.com	8885454752	NA
8	9	3RhWno9w-6H0uljH	192.168.137.1				NA
9	10	OZ90KWOHJywSe92N	192.168.137.1				NA

Download Report

FIGURE 13 | User data in resume analyzer.

enabling users to easily understand and interpret key statistics. Pie charts are used to depict various categories such as feedback data, skills in resumes, experience levels, or geographical distribution of users. The size of each pie slice corresponds to the proportion or percentage of data within each category. This visual representation allows users, including admins, to quickly grasp the overall trends, patterns, and distributions, aiding decision-making, identifying areas of focus, and gaining insights into the system's performance and user demographics.

While Hloom and ZipRecruiter offer a range of benefits for job seekers, there are also some disadvantages to consider. One major limitation of Hloom is that its free resources and tools are limited, and users may need to upgrade to a premium subscription to access more advanced features. Additionally, some users have reported that Hloom's resume builder and cover letter templates can be somewhat generic and lacking in customization options. ZipRecruiter also has some drawbacks, including the fact that its job search engine can be overwhelming to navigate, with too many job listings to sift through. Furthermore, some users have reported that ZipRecruiter's resume analyzer tool can be overly critical, providing feedback that is not always accurate or helpful. Finally, both Hloom and ZipRecruiter have been criticized for their lack of transparency regarding their data collection and usage practices, which can be a concern for job seekers who value their online privacy. Overall, while Hloom and ZipRecruiter can be valuable resources for job seekers, it is essential to be aware of their limitations and potential drawbacks. Additionally, Hloom's focus on providing generic resume and cover letter templates can lead to a lack of personalization, making it difficult for job seekers to stand out in a crowded job market. Furthermore, some users have reported difficulty in canceling their premium subscriptions, with some experiencing unexpected charges or difficulties in getting refunds.

ZipRecruiter also has some limitations in its job matching algorithm, which can sometimes prioritize job openings based on factors such as location or job title, rather than the job seeker's actual skills or qualifications. This can lead to job seekers receiving irrelevant job recommendations, which can be frustrating and waste valuable time. Moreover, both Hloom and ZipRecruiter have been criticized for their lack of customer support, with some users reporting difficulty in getting help with technical issues or other concerns. This can be particularly problematic for job seekers who are relying on these platforms to find employment. In terms of data security, both Hloom and ZipRecruiter have faced criticism for their handling of user data. Some users have reported concerns about the security of their personal and professional information, particularly in light of high-profile data breaches in recent years. Finally, both Hloom and ZipRecruiter have been accused of using aggressive marketing tactics, including sending unsolicited emails or making unwanted phone calls to job seekers. This can be annoying and intrusive and may deter some job seekers from using these platforms altogether. The below Table 1 gives the limitations of Hloom and ZiZi [25].

The graph in Figure 15 presents a comparison of three resume analyzer tools: Own Tool, Hloom Resume Analyzer, and ZipRecruiter. The tools are evaluated based on three performance metrics: accuracy, processing time, and precision.

The results show that Own Tool outperforms the other two tools in terms of accuracy, with a score of 85%. Hloom Resume Analyzer and ZipRecruiter follow closely, with accuracy scores of 80% and 78%, respectively. In terms of processing time, ZipRecruiter takes the longest time to analyze resumes, with an average processing time of 4.1 s. Hloom Resume Analyzer and Own Tool have relatively faster processing times, with averages of 3.2 and 2.5 s, respectively. Precision is another important metric evaluated in this comparison. Own Tool achieves the highest precision score of 90%, followed by Hloom Resume Analyzer and ZipRecruiter, with scores of 85% and 83%, respectively [26].

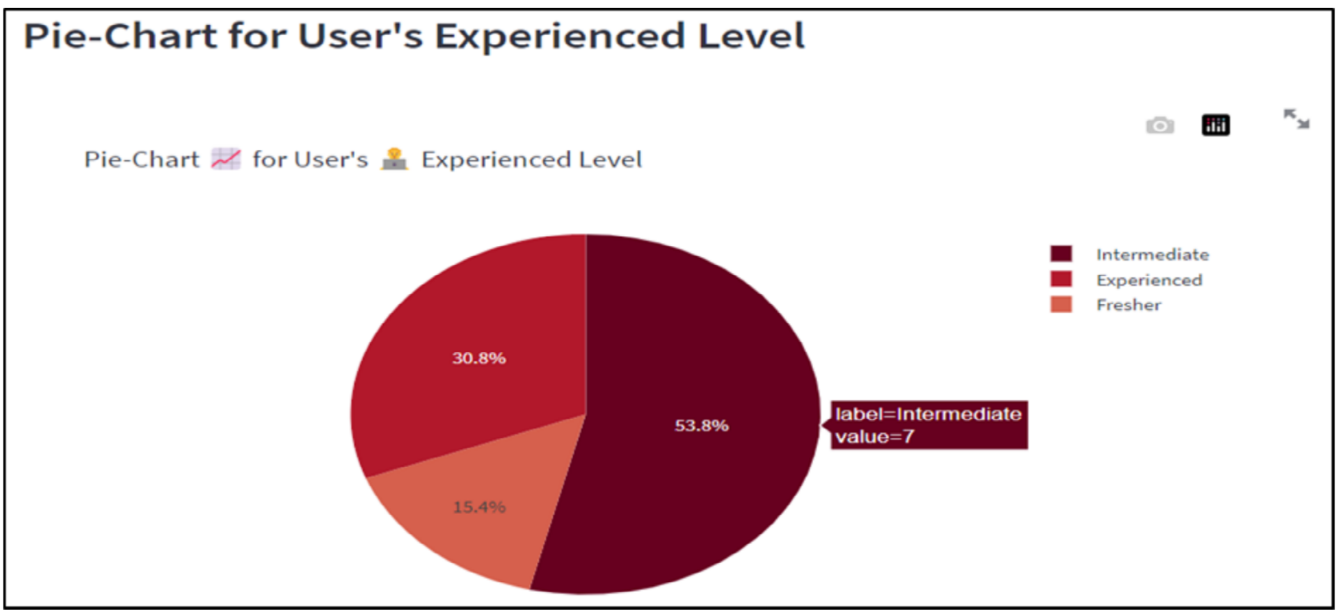

FIGURE 14 | Pie charts in resume analyze.

TABLE 1 | Comparison of Hloom and ZipRecruiter.

Category	Hloom	ZipRecruiter
Limited free features	Free tools are restricted; requires premium for advanced features	N/A
Generic templates	Resume and cover letter templates lack customization and personalization	N/A
Subscription issues	Some users face difficulties canceling premium plans and getting refunds	N/A
Job search overload	N/A	Too many job listings can be overwhelming
Job matching issues	N/A	Algorithm may prioritize location or job title over relevant skills
Resume feedback	N/A	Resume analyzer can be overly critical and not always helpful
Customer support	Reports of poor customer service and difficulty in resolving issues	Similar complaints about lack of support for technical problems
Data security concerns	Users worry about data handling and security risks	Similar concerns, especially given past data breaches
Transparency issues	Lack of clarity in data collection and usage practices	Same issue—concerns about privacy and data use
Aggressive marketing	Users report unsolicited emails and calls	Similar complaints about intrusive marketing tactics

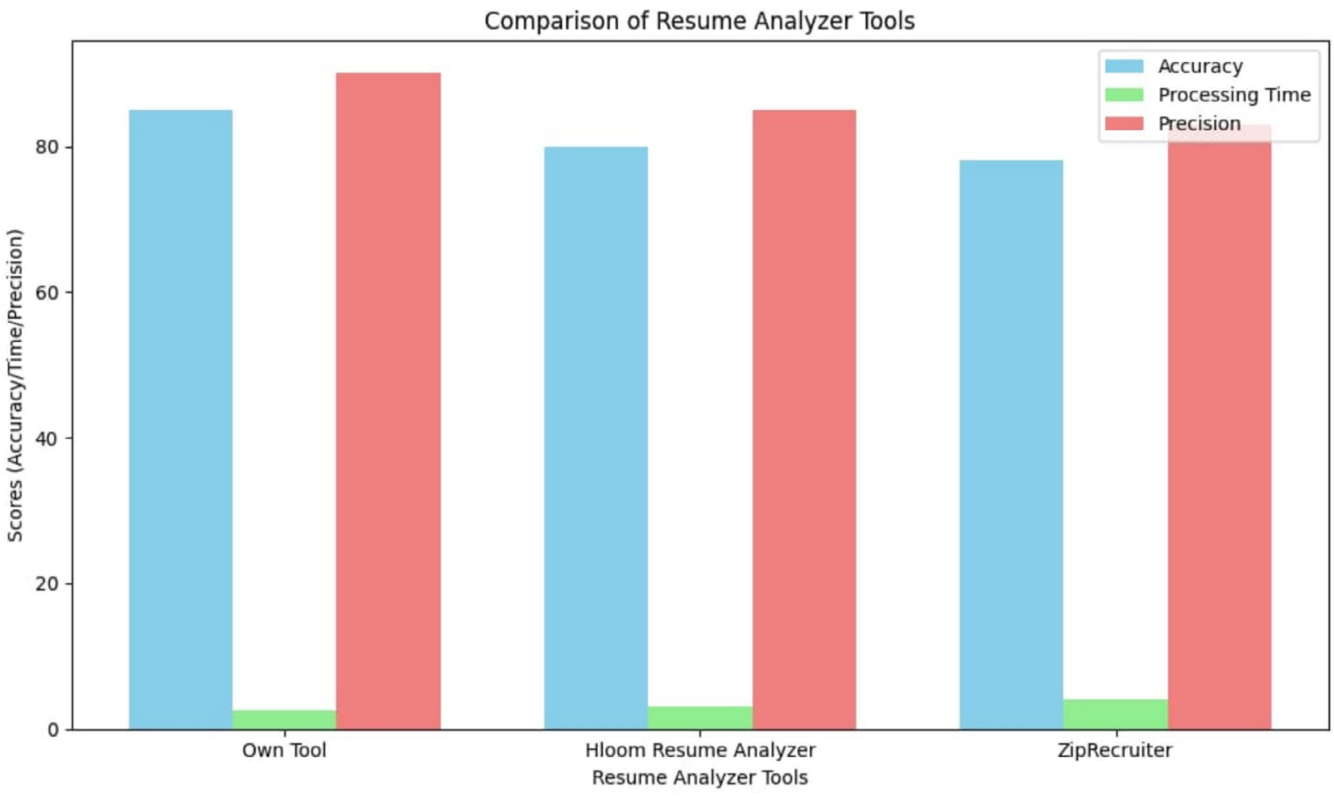

FIGURE 15 | Comparison of resume analyzer tools.

Overall, the results suggest that Own Tool is the most effective resume analyzer tool among the three, with high accuracy, fast processing time, and high precision. Hloom Resume Analyzer is a close second, with competitive accuracy and precision scores, although its processing time is slightly slower than Own Tool. ZipRecruiter, while still a viable option, trails behind the other two tools in terms of accuracy, processing time, and precision. These findings have significant implications for individuals and organizations seeking to utilize resume analyzer tools. By selecting the most effective tool, users can optimize their resume screening processes, saving time and improving the quality of candidate selection. Furthermore, the results of this comparison can inform the development of future resume analyzer tools, highlighting areas for improvement and innovation [12].

5 | Conclusion

The proposed system focuses on assisting users in improving their employability by providing resume analysis, skill recommendations, and feedback functionalities. By analyzing uploaded resumes, the system extracts relevant information and generates insights that help users understand their strengths and areas for improvement. The skill recommendations provide valuable guidance on enhancing skill sets and aligning them with industry requirements. Furthermore, the feedback feature allows users to receive valuable input and suggestions for refining their profiles. The system also caters to the administrative side by providing access to user data, generating reports, and presenting statistical information through visually appealing pie charts. Admins can gain valuable insights into user demographics, feedback ratings, skill distribution, and other important metrics. This empowers admins to make data-driven decisions and enhance the overall effectiveness of the system. Throughout the development process, testing has been crucial in ensuring the system's functionality, performance, and security. Unit testing, integration testing, user interface testing, and other testing methodologies have been employed to identify and address any issues, resulting in a robust and reliable system. The human interface design prioritizes user-friendliness, clear instructions, and intuitive interactions. By providing a seamless and user-friendly experience, users can easily upload resumes, provide feedback, and navigate through the system with ease. Overall, this project aims to improve user employability outcomes by leveraging the power of resume analysis, skill recommendations, and user feedback. By empowering users with valuable insights and guidance, and providing administrators with comprehensive data and analysis, this system strives to bridge the gap between job seekers and recruiters, ultimately increasing the chances of successful employment.

To elevate our resume analysis and skill recommendation system, we propose a multifaceted approach. Firstly, we aim to enhance accuracy by implementing sophisticated machine learning algorithms. By harnessing natural language processing techniques and deep learning models, we can extract nuanced insights from resumes, providing a comprehensive understanding of candidates' skills and experiences. Secondly, integration with popular job portals will seamlessly connect users with relevant job opportunities. This direct linkage streamlines applications, aligning user profiles with job requirements to offer tailored recommendations. Moreover, sentiment analysis will be elevated through advanced techniques such as sentiment classification, topic modeling, and sentiment trend analysis, enabling deeper insights from user feedback. Thirdly, gamification elements will be introduced to motivate users. Badges, challenges, and virtual rewards will incentivize skill development and course completion. Fourthly, a user-friendly mobile application will enable on-the-go resume uploads, feedback submission, and skill tracking, enhancing accessibility and engagement. Lastly, data visualization will be enriched with interactive charts and graphs, offering intuitive representations of user data and feedback trends. In amalgamating these advanced strategies, our system will stand at the forefront of innovation, providing users with a comprehensive, user-centric, and technologically advanced solution for resume analysis, skill enhancement, and career progression.

Conflicts of Interest

The authors declare no conflicts of interest.

References

1. A. Aggarwal, S. Jain, S. Jha, and V. P. Singh, "Resume Screening," *International Journal for Research in Applied Science and Engineering Technology* 134 (May 2022): 66–88.

2. K. Tejaswini, V. Umadevi, S. M. Kadiwal, and S. Revanna, "Design and Development of Machine Learning Based Resume Ranking System," *Global Transitions Proceedings* 3 (October 2021): 371.

3. B. Kelkar, R. Shedbale, D. Khade, P. Pol, and A. Damame, "Resume Analyzer Using Text Processing," *Journal of Engineering Sciences* 11, no. 5 (May 2020): 22–45.

4. V. Nawander, S. Elma, A. Karthikeya, M. K. Yadav, S. K. Kotala, and M. D. N. Akash, "Modern Resume Analyserfor Students and Organisations," *JETIR* 10, no. 5 (May 2023): 116–126.

5. V. Krishnaiah and Y. H. Kadegowda, "Undergraduate Engineering Student's Employment Prediction Using Hybrid Approach in Machine Learning," *International Journal of Electrical and Computer Engineering* 12, no. 3 (June 2022): 2783–2791.

6. Y. Aybek and S. Hilal, "Anadolu University Turkey Okur, M. Recep Open Education Faculty Anadolu University Turkey. Predicting Achievement With Neural Networks: The Case of Anadolu University".

7. R. Parser, S. Er, F. Khan, et al., "Resume Parser and Summarizer 442, 447," (April 2023).

8. A. R Sankar, "Towards an Automated System for Intelligent Screening of Candidates for Recruitment Using Ontology Mapping (EXPERT)," *International Journal of Metadata, Semantics and Ontologies* 8, no. 1 (2013): 56, https://doi.org/10.1504/ijmso.2013.054184.

9. E. Aliagka, K. Ramantas, A. Tsakalidis, and G. Tzimas, "Application of Machine Learning Algorithms to an Online Recruitment System, ICIW 2012: The 7th International Conference on Internet and Web Applications and Services, 215–220," (2012).

10. S. Lokesh, S. Mano Balaje, E. Prathish, and B. Bharathi, "Resume Screening and Recommendation System Using Machine Learning Approaches," *An International Journal (CSEIJ)* 12, no. 1 (February 2022): 1–7.

11. A. Anand and S. Dubey, "CV Analysis Using Machine Learning," *International Journal for Research in Applied Science and Engineering Technology* 16 (May 2022): 115–157.

12. S. Sanyal, S. Hazra, S. Adhikary, and N. Ghosh, "Resume Parser With Natural Language Processing," *International Journal of Engineering Science and Computing* 14 (February 2017): 4484.

13. P. K. Roy, S. S. Chowdhar, and R. Bhati, "A Machine Learning Approach for Automation of Resume Recommendation System," *Procedia Computer Science* 167 (2020): 2318–2327.

14. R. Nimbekar, Y. Patil, R. Prabhu, and S. Mulla, "Automated Resume Evaluation System Using NLP," in *2019 International Conference on*

Advances in Computing, Communication and Control (ICAC3) (IEEE, December 2019), 1–4.

15. S. Amin, N. Jayakar, S. Sunny, P. Babu, M. Kiruthika, and A. Gurjar, "Web Application for Screening Resume," in *2019 International Conference on Nascent Technologies in Engineering (ICNTE)* (IEEE, January 2019), 1–7.

16. J. A. A. Zubeda, M. A. A. Shaheen, G. R. N. Godavari, and S. Z. A. M. S. Naseem, "Resume Ranking Using NLP and Machine Learning," *Computer Science and Engineering: An International Journal (CSEIJ)* 12, no. 1 (February 2022): 1–6.

17. J. Chen, C. Zhang, and Z. Niu, "A Two-Step Resume Information Extraction Algorithm 1–10," (2018).

18. S. Maheshwary and H. Misra, "Matching Resumes to Jobs via Deep Siamese Network," in *Proceedings of the Web Conference, International World Wide Web Conferences Steering Committee* (2018), 87–88.

19. A. M. Shahiri, W. Husain, and N. A. Rashid, "A Review on Predicting Student's Performance Using Data Mining Techniques," *Procedia Computer Science* 72 (2015): 414–422, https://doi.org/10.1016/j.procs.2015.12.157.

20. R. Ade and P. R. Deshmukh, "Efficient Knowledge Transformation System Using Pair of Classifiers for Prediction of Students Career Choice," *Procedia Computer Science* 46 (2015): 176–183, https://doi.org/10.1016/j.procs.2015.02.009.

21. M. Nie, L. Yang, J. Sun, et al., "Advanced Forecasting of Career Choices for College Students Based on Campus Big Data," *Frontiers of Computer Science* 12, no. 3 (2018): 494–503, https://doi.org/10.1007/s11704-017-6498-6.

22. S. Al-Sudani and R. Palaniappan, "Predicting Students' Final Degree Classification Using an Extended Profile," *Education and Information Technologies* 24, no. 4 (2019): 2357–2369, https://doi.org/10.1007/s10639-019-09873-8.

23. B. M. Rao and B. V. R. Murthy, "Prediction of Student's Educational Performance Using Machine Learning Techniques," in *Data Engineering and Communication Technology* (Advances in Intelligent Systems and Computing, 2020), 429–440.

24. E. T. Lau, L. Sun, and Q. Yang, "Modelling, Prediction and Classification of Student Academic Performance Using Artificial Neural Networks," *SN Applied Sciences* 1, no. 9 (2019): 982, https://doi.org/10.1007/s42452-019-0884-7.

25. R. Ishizue, K. Sakamoto, H. Washizaki, and Y. Fukazawa, "Student Placement and Skill Ranking Predictors for Programming Classes Using Class Attitude, Psychological Scales, and Code Metrics," *Research and Practice in Technology Enhanced Learning* 13, no. 1 (2018): 7, https://doi.org/10.1186/s41039-018-0075-y.

26. VanshNawander, S. Elma, K. Andhoju, M. K. Yadav, S. K. Kotala, and M. D. N. Akash, "Modern Resume Analyser for Students and Organisations," *International Research Journal of Engineering and Technology (IRJET)* (October 2022): 188–192.