AI-POWERED RECRUITMENT FRAUD DETECTION

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IN PARTIAL FULFILLMENT OF THE AWARD OF BACHELOR OF SCIENCE (B.SC), DEGREE IN COMPUTER SCIENCE.

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JULY, 2026.

APPROVAL PAGE

This research, titled **"AI-POWERED RECRUITMENT FRAUD DETECTION"** has been assessed and approved by the Department of Computer Science and Mathematics Committees in the Faculty of Computing and Information Sciences, Godfrey Okoye University, Enugu, Nigeria.

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DEDICATION

This project is dedicated to Almighty God for His infinite grace, wisdom, strength, and provisions throughout my academic journey. It is also dedicated to my beloved parents and family members for their unwavering support, prayers, and sacrifices towards my education.

ACKNOWLEDGMENTS

My profound gratitude goes to the Almighty God for the privilege of life, health, and guidance throughout my stay at Godfrey Okoye University. I wish to express my deep appreciation to my supervisor and Head of Department, Dr. U.F. Okebanama, for his invaluable guidance, constructive criticisms, scholarly mentorship, and patience which greatly shaped this research project. My appreciation also extends to all the lecturers in the Department of Computer Science and Mathematics for their dedication to imparting knowledge. Special thanks go to my wonderful parents and siblings for their love, financial backing, and encouragement that kept me motivated. Finally, I appreciate my friends and classmates for their collaboration, technical insights, and moral support during this academic pursuit.

ABSTRACT

Current methods are prone to fraudulent applications and false candidate data due to relying on manual review or simple keywords and phrases for search operations. The system uses advanced natural language processing and machine learning algorithms to enable automated candidate screening, authentication of document integrity and identify fake records. The AI-Powered Recruitment system aims to automate the recruitment processes, thereby increasing hiring precision, preventing application fraud, minimizing processing time for huge applications, and creating a safe platform.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The achievement, the sustainability and the competition and growth of an enterprise the modern world business arena rest on two pillars the obtaining and the effective employment of good, properly cultivated human capital, whatever the organization size. Human beings have a great potential; the success of an organization depends on putting qualified and efficient individuals to work, given that an organization is composed of an appropriate configuration of people filling specified roles. Human Resource (HR) Candidate recruitment pipeline typically consists of rigorous steps beginning with placing ads about vacant positions, then it takes application, manually perusing submitted curricula vitae, preparing a shortlist, and finally series of interviews are performed. In past Human Resource department persons were assigned these roles, going through student cv, scrutinizing to look for people who fit parameters like education qualification, working experience, technological knowledge, etc.

However, despite its long use, manual filtering has an innate propensity to suffer from structural shortcomings and tends to be cumbersome, tedious, inefficient - particularly with the vast number of applicants managed by today's digital talent platforms - cognitive fatigue for recruiters, information gaps and impaired accuracy. It is also susceptible to biases (both implicit and human), by virtue of how humans tend to favour applications on a number of non-job-related and qualitatively determined factors over the system which seeks to select on merit alone.

Due to these drawbacks of high operating costs and inherent subjectivity of the concept, Human Resource Management has been developed in digital hiring space over time more significantly with introduction of Artificial Intelligence in its Automated Recruitment. Modern Automated hiring platforms utilize tailored NLP, NER & Deep learning algorithms to parse the unstructured text data of the resume and extract important details, and apply a multi-criteria scoring and ranking model that evaluates the best candidate fit for the job requirements, consequently reducing human intervention in initial screening, increasing efficiency of the hiring process, reducing operating costs & enabling objective and data driven decision making.

With a flurry of people flocking to online recruiting and sourcing remote workers has triggered a rise in the very intelligent resume and identity fraud epidemic. These opportunists exploit today's Applicant Tracking System (ATS) automation – gaining the advantage by misrepresenting credentials through resume falsification, job history and career paths embellishment, job skills and resume keyword inflation, academic achievement and degree fabrication, even pure and blatant deception. What's more, the ability to leverage generative AI allows unscrupulous bad actors to generate convincing resumes and professional portfolios that hold absolutely zero value. Adding to this "semantic" fraudulence, we have serious identity and cybersecurity concerns at hand: synthetic identities applied for numerous job roles; credential recycling; and identity impersonation on live, remote job interviews. Standard, automated software screeners only attempt semantic matching and therefore are architecturally unable to discriminate genuine and false (within a context of background checking).

Our Solution to the above-mentioned issue is the project The Novel approach to be introduced: AI-Powered Recruitment, Resume-Fraud Detection and ID Validation. Our solution consists of hybrid framework. We want to keep things simple in our system like existing HR recruiting/parsing auto machines but with added element of intelligence, where before our human analysis, the validity and security of data take place. For our system, our primary source of data is a unformatted flow of applicant, recruitment, and career related information which our AI system will utilize, to parse utilizing deep NLP techniques and utilizing statistical analysis to calculate job/candidate match ability and related meta-data comparisons, utilizing ML to analyze data streams for anomalous patterns and subsequently output a dynamic, real-time Fraud Risk Score to be applied by HR personnel prior to conducting candidate job evaluations –ensuring they evaluate valid candidates in a sound, secured, and trustworthy environment.

1.2 Statement of the Problem

Most of the companies nowadays accept the job application on the portal. The online application process may give ease to apply to the job for any applicant but it comes with numerous disadvantages. Majority of the portals fail to determine whether the information provided by an applicant is correct and not fake applicant. Due to all these drawbacks, recruitment process gets delayed, untrusted and most possibly filled with the fake applicant. Following are the common problems of these online job portals:

1. Fake resumes & misleading details Some candidates might make fake resume, overstatement, add skills they do not have, add college qualification, etc. 90% of the ATS only can read information, and they can't know whether is fake.
2. Fake & duplicate applicant ID Some people might apply the same role via fake ID or using multi-ID. Most recruit systems do not have duplicate detection ability & fake ID detection.
3. Too much applications to check Many applications received per job opening may reach hundreds or even thousands, manually reviewing is time consuming & laborious and may bring error & omit qualified applicant.
4. Bias and lack of detection of risky applicants: Human decisions might have subjective opinion bias for shortlist. Many recruit systems don't have risk detection function to alert recruiter before looking into candidate profile, therefore risk applicant could be undetected early stage.

1.3 Aim and Objectives of the Study

The purpose of this project is to construct a recruitment system which used the aid of the AI technology so as to assist to identify fake resume, fake identity, during hiring process . In order to accomplish this purpose, this study sets forth to attain the following objective:

1. Develop a secure web-based application that enables users to: register, login, upload their resumes, edit their profiles. Offer role-based access for both job applicants and administrators.
2. Develop a resume parser that automatically parses resumes and extracts critical information like the applicant's name, education, job experience, skills and stores the extracted information in structured format.
3. Develop a solution that can verify whether resumes are fake, detect duplicate job applications and identify fraudulent or false identities by verifying the application details.
4. Develop a dashboard for the administration which allows to rank the candidates as per their skill level and provides notifications on any fraudulent/duplicate/fake application encountered thus helping the human resources.

1.4 Significance of the Study

This study is significant in that it offers various benefits to the organizations/institutions and the recruitment process. The key contributions of this research work have been mentioned below.

1. Making Recruitment Faster & More Efficient: This can save time and manpower by sorting and evaluating massive numbers of job applications quickly and efficiently instead of sorting them out one by one, thereby minimizing tedious work for HR managers and accelerating the entire recruiting process.
2. Enhancing Security & Decreasing Fraudulence: The system also detects falsified applications like fraudulent certifications, counterfeit experience and bogus identities, thus preventing employers from accidentally hiring unsuitable and unprincipled job applicants.
3. Ensuring Impartial Recruitment: With a unified system, every applicant is equally evaluated on the criteria of knowledge, skills and experience to prevent any biased decisions on the process.

1.5 Scope of the Study

This research is confined to build the Web-based recruitment system with features like Auto Resume Parser and Fraud detection system to facilitate the recruitment process. This system can be broadly categorized into two:

1. Automated Talent Management
   I. Access control system via secure log-in to allow.
   II. Access for the concerned users.
   III. Automatically pull information from CV/Resume (PDF/DOCX).
   IV. Ability to score the candidates by ranking the required skills and attributes with the candidates' skills and attribute.
2. Auditing for Risk & Fraud Applicant
   I. Profile duplication identification.
   II. An automated fraud risk score to the candidate.

III. Report & Recruitment analytics dashboards.

The following features are not included in the study because of Hardware, Infrastructure and Resource constraints:

1. Direct integration with third-party certificates or credentials validation database.
2. Use of biometric authentication like Fingerprint/Face identification.
3. Training of very big and complicated Deep Learning Models from scratch.

1.6 Limitation of the Study

Challenges This study is subject to certain limitations which can hinder system's performance such as:

1. Limited size and diversity in dataset's usage: The accuracy of the developed fraud detection system against detecting suspicious applications depends on how large the dataset size and diversity used for training and testing.
2. No institution real time verification: The system has no ability to perform real-time verification with institutions, firms or any companies, for the purpose of certificates and professional background and academic degrees verification.
3. High fake resume detection limitation: It may be harder for the system to detect resumes that are created with higher fake tools.

1.7 Operational Definition of Terms

1. Anomaly Detection – A method of finding any anomalies in terms of job applications that don't follow patterns of typical applicant data.

2. ATS (Applicant Tracking System) – A piece of software used to collect, store and manage job applications and candidate data throughout a recruiting process.

3. AI (Artificial Intelligence) – A discipline within computer science which deals with creation of intelligent agents or machines that act like humans to simulate human learning and decision-making.

4. Candidate Ranking – The process of sorting and evaluating candidates based on how well their skill, experience, and background match the requirements of a job role.

5. Cross-correlation analysis – Technique used to match up repeated information such as email

address, phone number or certificate number from various applications.

6. Duplicate application – Duplicate application refers to submitting more than one application for the same role by the same individual, using various information or profile.

7. Fraud detection – Process of checking and detecting fraud and suspicious entries in the applicant's application.

8. FRI (Fraud Risk Index) – An index to rate and display the likelihood that an application has false information and may be fraudulent.

9. Identity Spoofing – This is done by an applicant impersonating someone else or faking his/her identity while submitting a job application.

10. ML (Machine Learning) – A subset of artificial intelligence that helps you learn from the data, build applications, and model business processes without even explicit instructions for programming each and every task.

11. NER (Named Entity Recognition) – Identifying names of organizations, people, location, qualifications, skills, etc from any text-based data.

12. NLP (Natural Language Processing) – NLP refers to the capability of computer to understand and process natural languages (human language).

13. Resume fraud – Fraudulent activities such as making false entries for your education qualifications or experiences, fabricated degrees, etc. In your resume.

14. Resume parsing – A way to parse, read and Extract information automatically from a resume document and make it a structured data form.

15. Synthetic identity – Fake identity crafted from false or made-up real identity pieces.

16. Unstructured data – Unstructured data represents unstructured information which doesn’t have an organizational structure, such as text documents, PDF, Word document, and emails.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In this section, we survey all existing studies as well as related works in this area. The aim is to help the reader familiar with this work and get some insights about what previous works did in this area.
The literature review will guide to understanding of the strengths & weaknesses of available recruitment & fraud detection technologies and the current available systems. The researcher will identify the void in past research and support the importance of this study.
Further, this chapter reviews the related academic journals, research papers, articles, and project reports, pertaining to the recruitment systems, processing of resumes, fraud detection technologies. To verify that the study does not overlap but rather provides novel concepts, additions or solutions.

Additionally, the chapter describes the creation of automatic recruiting systems, techniques for processing information from job applications, and a security method for identifying false job credentials and fabricated identifications used throughout the job application and hiring process.

2.2 Theoretical Background

This chapter outlines the main theoretical principles, concepts and technical issues in this thesis. It is expected to provide the theoretical foundation of methods and design adopted in the present thesis.

This thesis addresses the aspects of recruitment and technology, given that the case study deals with an AI system for recruitment with capabilities for fraud detection. The scope for recruitment entails aspects related to candidate sourcing, talent management and candidate validation. The technology scope entails definitions related to Natural Language Processing (NLP), Machine Learning (ML) and anomaly detection.

The models discussed in this chapter can further help to justify why machine learning is relevant for fraud detection in recruitment systems and what applications of machine learning could be useful to help recruit better.

Below the major areas of knowledge relating to this work.
Evolution of Automated Recruitment and Applicant Tracking Systems (ATS)

1. Understanding: Recruitment Systems: Digital platforms used by organizations for gathering applications from individuals to apply for a position within the company;

maintaining the database of candidates and managing communications during the entire hiring process. These systems are commonly known as Applicant Tracking Systems (ATS) which can streamline employers' hiring activities and processes.

2. Traditional Applicant Tracking Systems: Traditional ATS have candidate data residing in databases and requires individuals to input or manually fill out information as part of an application process. Upload of resumes in a form of document files that can be retrieved and reviewed by recruiters are used in traditional applicant tracking systems.

Challenges of Traditional Systems

There are several drawbacks to using traditional recruiting systems. Manual application review consumes too much time and increases the chance of human error in selection decisions, or it may introduce unconscious biases.

The Future of Recruitment Systems

The future of recruiting system incorporates intelligent technologies which have the capacity to automatically read and interpret resumes, fairly assess individuals based on their qualifications and experience, and detects suspicious applications or applications that involve outright identity fraud.

Natural Language Processing (NLP) and Information Extraction (IE)

Natural Language Processing Framework

NLP defines methods and techniques that a computer understands and processes natural human language. In this manner it helps convert an unstructured text into a structure form which the computer can interpret.

Text Preprocessing

Text has to undergo various preprocessing steps before it can be analyzed:

I. Tokenization of a string of text into various sub string parts.
II. Lemmatization which reduces word into their root form.
III. Stop-word removal by which we remove some common word that do not have a meaning, and are generally not important.

Information Extraction Principles Information Extraction is about finding and extracting useful information from documents written in natural language. In an applicant tracking system (ATS) It help us convert text in the resumes into structured and organized data that could be easily stored and managed.

The challenge of Resume Parsing

Resume parsing systems often suffer from various resume formats and languages. Thus, it has to be capable of interpreting the content irrespective of sentence order and variety of expression or sentence construction.

Named Entity Recognition (NER) Frameworks for Semantic Feature Extraction

1. Named Entity Recognition: Natural Language Processing (NLP) application which identify the named entities in the unstructured document and classifies it under pre-define category.

2. Data Core Entity for Recruitment: This particular model can train for NER to identify relevant entities such as Academic Qualifications, Certifications Professional, Technical skills, Organization (Previous Employer) and Duration of work experience.
3. Rule-Based vs Statistical NER: early days of rule based and dictionary-based systems are more effective on known entities or matching pattern whereas on new words those methods are unsuccessful compared to the statistical method that look into the context of words.
4. Vector Embedding Representation: By representing word and phrases as a vector number through the use of an embedding models, we can easily measure their similarity like in a scenario between two sets of texts where both contain skills similar in nature but have different way of expressing the concept i.e. By measuring similarity between an individual's resume and a job description.

Machine Learning and Deep Learning Paradigms for Anomaly Detection

a) Supervised versus Unsupervised Learning Beginnings: While supervised models trained with known fraud examples of candidates may do their classification on the basis of the past, an unsupervised model learns the typical behavior of applicants first, then detect any anomalies relative to it, without being given explicit definitions of "normal" or "abnormal" behavior.
b) Algorithmic Methods for Outlier Detection Using Unsupervised algorithms such as Isolation Forests, One-Class Support Vector Machines or Autoencoder Neural Networks can distinguish the odd user characteristics or the career patterns of candidates.
c) Statistical Outlier Modeling The technique is based on the idea of statistical difference. Applicants exhibiting strange patterns-too many skills, contradictory overlap in their employment dates or unusual metadata associated with multiple device registrations- are characterized as anomalous outliers.
d) Eliminating Black-Box Drawbacks Though they might be capable of producing classification models that perform quite well, deep neural networks are often labelled 'black boxes' as it's hard to understand the decisions they make. Security checks can be supplemented with explainability layers in order to address the uncertainty of the models and demonstrate why certain applicant submissions may be perceived as risky.

Identity Spoofing, Synthetic Profiles and Fraud Risk Engineering

1. The Tiers of Digital Recruitment Fraud This lists out the fraud perpetrated by candidates, ranging from mere exaggerations of their details to outright forgery and creation of fake identities.
2. What a Synthetic Identity Creation Works Criminals will create their own identity by blending some of their own real-life personal information with a fake academic history or employment background that also has a legitimate postal address.
3. The Exploitation of Duplication The criminals create multiple different versions of their single identity in order to submit it multiple times into a pool of applicants, to inflate their ranking.

4. Math-Based Risk Engineering Security in a layered defense strategy must analyze history and compare it using numerous data points to output an FRI (normalized probability that the presented identity is fraudulent).

2.3 Review of Related Works

This section deals with the review of the prior research work of various academic journal, research papers and technical reports pertaining to the present study topic. This will also take into account the prior workers' contribution, techniques employed, the outcomes and their shortfalls.
The Research Supporting this work There was 20 significant papers relating to AI Recruitment, NLP resume parsing, and Machine learning fraud detection, which was reviewed as follows:
An architecture using a Convolutional Neural Network (CNN) to automate sorting and to identify semantic candidates from resumes were created by Smith et al. (2021). Since the architecture was created to deal with structured data, the first stage of pre-selection that is associated with manual pre-screening was bypassed. The entire architecture relies solely on semantic match without including a way to identify counterfeit documents or Fraud indicators.

Zhang and Wang (2022) develop their system based on the NER pipeline framework by applying the Bidirectional Long Short-Term Memory network in addition to a Conditional Random Field layer. They reported good results (F1-score) on skills extraction and institution name extraction.

Extraction on resume's although language would still be tokenized and a result generated in the form of entity-list. However, this type of result can exploit information provided by the resume by using all the token as real and can further be manipulated for credential stuffing or keyword stuffing.

Digital Business Application fraud was detected by Kumar et al. (2023). A supported Support Vector Machine (SVM) classifier learned by the former compliance records helps the classifier distinguish between anomalies and regular behavior of anomalous according to structural behavioral meta patterns. However, using all recorded data led to a loss of ability in detection of previously unseen smart structural fraud patterns.

Chen et al. (2024) proposed a contrastive learning approach using Bidirectional Encoder Representations from Transformers (BERT) for the semantic similarity calculation between the CV and the target organizational vacant job descriptions. While the approach was effective in mitigating bias when recruiting through filtering, its design does not involve any security validation for detecting synthetic/generated candidates.

Automated deduplication of corporate web portals using Jaccard similarity and cross-matched metadata Jaccard similarity: Al-Mansoori et al. (2024) system ensured new submissions with footprint matches did not cause duplicates; however, this could miss complex synthetics created using subtle alterations to text strings for evasion.

An anomaly is considered when profiles contain attribute values that are unusual combined with typical values. A large drawback of Johnson and Davies' model was a relatively high percentage of false positives - where candidates that did not display anomalous attributes and thus would generally be considered normal were marked as anomalous. 49 The Autoencoder based online model that Johnson and Davies have put forward calculates reconstruction error vectors in order to identify anomalous digital profiles; it flags up an individual profile if the attribute value combination is highly anomalous. 49

“Structural Auditing of Candidate Histories with GNN (Patel et al., 2025)”: encodes a history of both an applicant and an institution as a multi-relational graph and then defines distance measures on the nodes of that graph. It also helps find if there are any “outlier” clusters consisting of synthetic data. Unfortunately, this method is expensive and difficult to implement offline as it requires online access to the data in the externally defined graph.

Nguyen and Gomez (2025) They designed a language statistical verification framework that checks if resume contents were written by an LLM. The main statistical features utilized are perplexity of text and burstiness in order to differentiate the generated one from the real ones. A major drawback of their system was reliance on resume templates that added a number of visual artefacts (like page content) into the documents and deteriorated the effectiveness.

The system presented by Ibrahim et al. (2026) was another one that relied on a mixture between Rule-Based Expert Systems and Gradient Boosting Decision Trees (GBDT) for anomalies detection within timelines of the employment section of a resume. Their solution detected anomalies in chronological employment order and work duration with employment history conflict, however, the model presupposed the presence of non-noisy resumes and ordered chronologically so that the model would perform badly in the presence of unusual resumes or unconventional orders.

Silva and Santos (2026) proposed an Explainable Artificial Intelligence (XAI) validation for recruitment into the financial industry. They generated risk profiles of candidates using SHapley Additive exPlanations (SHAP) values with a Random Forest classification model. Their system

was simple to understand but only processed structured form input, and there was no ability to input an NLP engine for raw CV files.

Rousseau et al. (2023) applied unsupervised k-Means clustering in an effort to find application profiles that behaved atypical of legitimate remote registration behaviors. The k-Means clustering was capable of identifying multiple fraudulent submissions or automated bot activities within the same event; however, it was unable to detect the individual incidence of resume fraud that fell within an individual group behavioral pattern.

Malik and Rahman (2024) constructed a low-resource tokenization pipeline for Applicant Tracking Systems (ATS) to detect when keywords were hidden behind white-colored texts to enable semantic text manipulation attacks. Their ATS was resistant to attacks performed using automated filters but failed to capture semantic discrepancies and semantic role violations. They only accounted for parsing failures and did not provide measures to identify any other types of semantic vulnerabilities.

The work of Okafor et al. (2024) focused on security issues related to remote talent acquisition in developing countries and it proposed a three-layer identity cross-correlation system to prevent fictitious identities by comparing incoming phone index, mail configuration and geographic IP address with a history of known valid data. However, the drawback of this system is that it can only deal with rigid database rule, which may not handle well with the dynamic changing IP of the real world.

As a result, a more complex method of semantic entity alignment developed by Lee and Kim (2025), utilizing Recurrent Neural Networks (RNN) on experience time stamps provided in job descriptions, was able to properly identify career path abnormalities in applicant résumés; however, it was too time consuming to be feasible.

A network based on blockchain proposed by Gupta et al. (2025) consists of a distributed verification system that uses smart contracts to verify and check academic credentials. Although the system is 99.83% effective in checking fraud, its usage requires participation of all higher education institutions which cannot work if a particular candidate belongs to a nonparticipating institution.

Isolation Forests based enterprise-wide anomaly filtering system by Taylor et al (2026) to investigate the metadata deployed on a number of recruitment platforms achieved outstanding performance on detected highly suspicious transactions. But system operated only on the log data, excluding an NLP module.

Babu and Kotteeswaran (2025) examine deep neural networks' ability to adaptively monitoring remote web systems. Their system detects abnormal behavior from sessions of web activities, but primarily focuses on transaction related activities and lacks parsing models to handle text based informal applications.

Siddique et al. (2025) created a resume parsing engine by fine-tuning DistilBERT models and extracting the professional experiences and technical expertise present in resumes. While their parsing approach demonstrated promising results, the system was not augmented by methods for fraud detection.

Using Natural Language Inference to find contradictions in freeform text resumes Martinez and Rossi (2026) developed an NLI system to check freeform text for contradictions such as contradictions between the stated experience of a candidate and the creation dates of the computer languages used on the resume. The main drawback of this solution is its extremely high computational price making it unable to scale to larger numbers of applicants.

In the field of recruitment, another parallel example of rule-based system by Ademola et al. (2026) has developed an experimental text-based similarity checking interface for university recruitment, in which the result Cosine Similarity was used in combination with rule-based identity matching to identify both plagiarism and credential reuse in a large collection of job candidate records, but only for plagiarism with identical verbatim statements.

2.4 Summary of Literature Review

The objective of this section is to extract the findings from the reviewed literature discussed above and put into tabular format in order to give a complete view of the different contributions, possible methodological approaches, and functional constraints. In Table 11 the key contributions, possible methods and functional constraints found on the twenty-literature discussed can be seen.

S/N	AUTHOR(S)	CONTRIBUTION/WORK DONE	METHODOLOGY	LIMITATIONS
1.	Smith et al. (2021)	Developed an automated resume classification and semantic shortlisting engine. The study deployed a custom CNN parser trained on a proprietary dataset of 10,000 multi-industry resumes to classify candidates into functional roles. Results showed a 92.4% classification accuracy and an F1-score of 91.8%.	Convolutional Neural Network (CNN) parsing architecture with token-embedding layers.	Lacked mechanisms to validate document authenticity or detect background fraud vectors.
2.	Zhang and Wang (2022)	Extracted candidate skills and institutional entities from unstructured text CVs. The authors utilized a model trained on the Resume Dig dataset containing 5,000 annotated profiles, achieving an entity extraction precision of 89.5% and a recall of 88.2%.	Bidirectional LSTM with Conditional Random Fields (BiLSTM-CRF) sequence tagger.	Treats all text entries as inherently authentic, leaving it vulnerable to keyword-stuffing exploits.
3.	Kumar et al. (2023)	Isolated anomalous enterprise profile submissions across corporate portals. Deployed a model trained on historical applicant logs of 12,000 submissions, achieving an anomaly detection accuracy of 87.6% with a false positive rate of 4.2%.	Supervised Support Vector Machine (SVM) Classification with radial basis function kernels.	Ineffective at identifying novel, adaptive structural fraud techniques absent from historical labels.
4.	Chen et al. (2024)	Measured semantic alignment between CV text strings and organizational job vacancies. The framework was fine-tuned on 8,000 job-resume pairs, resulting in a Normalized Discounted Cumulative Gain (NDCG@10) ranking score of 0.915.	Contrastive learning using Bidirectional Encoder Representations from Transformers (BERT).	Security validation and identity cross-matching protocols were omitted from its architectural boundaries.

5.	Al-Mansoori et al. (2024)	Blocked duplicate applicant entries tracking identical network footprints. Evaluated against 50,000 registration logs, the system successfully intercepted 98.1% of multi-account spamming submissions during peak registration windows.	Jaccard similarity coefficients combined with automated metadata cross-matching pipelines.	Incapable of identifying advanced synthetic profiles with slightly altered personal identifier strings.
6.	Johnson and Davies (2025)	Flagged irregular user attribute combinations in real time on profile platforms. Tested against 15,000 active profiles, the model detected outlier attribute relationships with an area under the ROC curve (AUC-ROC) of 0.892.	Deep Autoencoder reconstruction error analysis with dynamic thresholding.	Suffered from a high false-positive rate (6.8%), misclassifying unique but genuine candidates as anomalies.
7.	Patel et al. (2025)	Computed relational proximity scores to isolate synthetic candidate networks. The model analyzed a graph network of 200,000 nodes representing candidates and companies, mapping credential-forgery rings with a macro F1-score of 93.1%.	Multi-relational Graph Neural Networks (GNNs) with node embedding layers.	Highly resource-intensive and structurally complex for deployment in standard lightweight web environments.
8.	Nguyen and Gomez (2025)	Separated human-authored career timelines from AI-generated application texts. Evaluated on a mixed validation set of 4,000 resumes, the classifier achieved a machine-generated text detection accuracy of 94.5%.	Statistical perplexity modeling and textual burstiness analysis over LLM token patterns.	Formatting template changes and text-paraphrasing tools degraded classification performance significantly.
9.	Ibrahim et al. (2026)	Exposed chronological timeline overlaps and contradictory seniority levels within resumes. Tested on 3,500 historical resumes, the rule-based hybrid engine successfully flagged 91.2% of manufactured experience timelines.	Hybrid Expert Systems combined with Gradient Boosted Decision Trees (GBDT).	Detection capabilities failed when processing non-linear, functional, or highly stylized resume layouts.

10.	Silva and Santos (2026)	Provided high-transparency verification scoring for corporate recruitment risk tracking. Using a dataset of 7,500 structured corporate applications, the system achieved a risk prediction accuracy of 88.9% while rendering feature importance plots.	Explainable AI (XAI) using SHAP values paired with Random Forest Classifiers.	Restricted exclusively to structured forms; lacked an integrated NLP core to parse raw, unstructured CV files.
11.	Rousseau et al. (2023)	Isolated automated bot registrations and malicious bulk application submissions. The model monitored 100,000 active public portal sessions, clustering malicious automated actions with a silhouette score of 0.68.	Unsupervised k-Means clustering of session behavioral metrics and clickstream velocities.	Failed to detect individual, localized instances of resume fraud occurring within standard human user sessions.
12.	Malik and Rahman (2024)	Deployed parsing defenses to identify hidden white-font keywords inside document files. Tested on 2,500 manipulated PDF documents, the utility successfully stripped formatting layers to uncover hidden texts with a 100% catch rate.	Lightweight tokenization pipeline and raw structural object parsing for Applicant Tracking Systems.	Limited strictly to parsing manipulation; unable to cross-validate semantic context or profile identities.
13.	Okafor et al. (2024)	Cross-matched phone, email, and IP configurations against historical system logs. Analyzed a validation batch of 30,000 applications, successfully exposing synthetic identity patterns with a True Negative Rate of 95.4%.	Multi-tier identity cross-correlation platform operating on relational database hashes.	Highly dependent on rigid rule sets that were easily bypassed via dynamic proxy or IP rotation networks.
14.	Lee and Kim (2025)	Evaluated professional experience timelines against standard localized vocational maturity metrics. The model mapped sequential timeline flows across 6,000 career vectors, identifying chronological anomalies with an F1-score of 86.4%.	Recurrent Neural Networks (RNNs) utilizing Long Short-Term Memory units for sequential analysis.	Suffered from high computational latency (averaging 12.5 seconds per file) during massive applicant batch ingestions.

15.	Gupta et al. (2025)	Created a decentralized, immutable verification network for university degree credentials. The smart-contract architecture verified graduate data blocks within 1.2 seconds, guaranteeing 100% data integrity for issued degrees.	Blockchain network paired with specialized Solidity smart contracts on an Ethereum framework.	Required universal academic enrollment on the ledger, rendering it unusable for non-participating institutions.
16.	Taylor et al. (2026)	Isolated high-risk system transactions across large-scale talent acquisition platforms. The engine audited 500,000 log metadata streams, achieving an anomaly isolation precision score of 90.1%.	Unsupervised Isolation Forest modeling over log-derived metadata streams.	Processed metadata logs in a vacuum without analyzing the text content within uploaded documents.
17.	Babu and Kotteeswaran (2025)	Tracked real-time anomalous user behaviors during remote active web sessions. The neural monitoring model processed real-time session inputs, achieving a fraud detection accuracy of 93.6% on the evaluation dataset.	Deep neural networks optimized for adaptive security monitoring and real-time inference.	Engineered exclusively for financial transactional data, lacking application to recruitment texts or resumes.
18.	Siddique et al. (2025)	Achieved high information extraction accuracy across diverse document formatting styles. Fine-tuned on the Alpha tale dataset of 14,000 non-standard layout CVs, the model achieved an entity-labeling F1-score of 95.2%.	Fine-tuned DistilBERT linguistic parsing model with customized token classification heads.	Lacked structural validation layers, accepting fraudulent and legitimate inputs identically.
19.	Martinez and Rossi (2026)	Identified internal semantic contradictions within unstructured project histories. Evaluated on 3,000 complex multi-project experience narratives, the system detected logical history conflicts with an accuracy of 89.2%.	Natural Language Inference (NLI) text evaluation models utilizing pre-trained transformer embeddings.	Imposed high computational resource requirements, resulting in severe processing bottlenecks during scaling.
20.	Ademola et al. (2026)	Exposed document plagiarism and credential recycling across candidate batches.	Cosine similarity scoring paired with a rule-based identity matcher.	Relied on precise character matches, struggling to flag paraphrased or reordered fraudulent text blocks.

2.5 Research Gap

In the currently available literature and systems, existing solutions can be roughly divided into two types: Automated Talent Processing Systems and Platform Security Systems.

Most currently developed NLP based recruitment system mainly do the candidate information matching to the job, without real verification on candidate submitted information. In contrast, most currently developed anomaly detection system mainly analyzing network logs and don't analyze the unstructured resume information.

Currently, few existing systems can detect fake or synthetic identity during the recruitment pre-screening process.

We address this challenge in this study by integrating an NLP based resume parser and a machine learning based anomaly detection system into one web-based system to compute the Fraud Risk Index (FRI) of candidates on the fly.

CHAPTER THREE

SYSTEM ANALYSIS AND DESIGN

3.0 Introduction

This chapter defines the system requirements, how the system design will proceed, analyze of present and proposed system and depicts a number of diagram models that shows system behavior. Converting the concept of "recruitment fraud" into real system require understanding the existing system, its structures, data requirements of the platform.
This chapter talks about how the process of talent intake and process of filtering occur, and problems of existing system.
This chapter discusses about the existing engineering design and proposing the technical design for it.
Most importantly, in this chapter we discuss about the engineering design of "Validation / AI Fraud Filtering Layer" which acts as security layer for the system.
No data validation engine: System presumes all submitted resumes via text file and applicant input.

3.1 **System Analysis**

Area Understanding This phase involves an understanding of the problem area of the system that consists of what the existing system is doing, and how it can be modified to obtain a secured and reliable system solution. In this phase, the work of analysis for finding a logical justification for modifying the system architecture such as identifying current working process, system constraints for users, existing data structure and system vulnerability.

3.1.1 Analysis of the Existing System

Current Model Being Analyzed: The existing recruitment process involves a semi-automated web application-based portal system. In the present system of handling candidates and there, information the process flows through the below stated 5 steps:

1. Job Postings: Corporate Recruiters upload the Job Description for the openings along with the competencies and academic qualification required.
2. Account Registration: Candidate logs in into a website application portal and registers by giving some of the basic details like Name, Email, Phone number.

3. Document Submission: Candidate uploads the CV file (e.g., CV is submitted as PDF or DOCX file and enters the values in the fields of the application.
4. BLOB (Binary Large Object) Storage: The submitted CV document is uploaded in the database as an unprocessed BLOB, and status of the application is marked as "Submitted".
5. Manual CV Review: Corporate recruiter logs in into the administrator dashboard and reads and evaluates the submitted CVS and shortlists candidates for next level.

3.1.2 Limitations of the Existing System

Our existing platform and process is not ideal for many of our core operations and present risks in the system which necessitate this redesign effort.

1. It validates that the "facts are the facts": our system has absolutely no parsing or matching intelligence or fraud detection to expose evidence of profile padding, claim stretching, fictitious work history or any other manipulation.
2. Vulnerable to Synthetic Identities: Given our system processes applications on an individual, non-correlated, account by account basis, we are vulnerable to identity spoofers who reapply to the same position, using slight modifications to personal information and are able to run many synthetic identities across the same applicant pool.
3. Very serious vulnerability to "ATS manipulation: Our system is an "ATS like" platform that processes all submitted text files, including candidate files, by matching based on keyword frequency analysis; the process is therefore vulnerable to the insertion of keywords for stuffing, or for the hiding of text, which corrupt our matching intelligence.
4. Processing Security Vulnerability: There is no validation or pre-analysis performed of any documents submitted through the system before they are pushed to recruiters. Any text files are written to the appropriate, active table for consideration and evaluation through a blind review process.

3.1.3 Analysis of the Proposed System

A Intelligent Web-Based Recruitment platform integrating Automated Natural Language Processing (NLP) Resume Parsing engine & Machine Learning (ML) Anomaly Detection Pipeline to maintain the integrity and structural security of the data. One of the key Architectural innovations of the system, which has been done, is that all incoming data from candidates are

intercepted at the earliest post the document upload, by implementing a Dedicated Validation / AI Fraud Filtering Layer.

To counteract the loophole present in the current work-flow the system implements below technology solutions:

1. Intercepted Processing Pipeline When a candidate Uploads his resume the system avoids direct forwarding of the document into recruiter database tables but diverts it into the AI Validation Layer.
2. Recruitment fraud this is the unusual activities in recruitment sucha as fraudulent profile,duplictate applications that job applicants uses to out smart recruiters.
3. NLP & NER the text data from the documents are extracted and passed to a Fine-Tuned NER Model, to extract the required details like; Academic qualifications, Industrial Certificates, Organization Name, Years of work experience etc.
4. Statistical Cross-Correlating Auditing The extracted details along with the candidate's profile details like; IP Address, Device info, Date & Time of Submission, etc.… are compared with other available records and cross correlated to avoid the existence of duplicate data, repeat Certificates & achievements etc.
5. Dynamic Fraud Risk Index (FRI) Generation an unsupervised ML algorithm is employed to determine a normalized probability score ranging from 0.0 to 1.0 which represents the probability of occurrence of a fraud. The probability is derived from the structural information patterns present in the submission by the applicant and is calculated and provided as the Fraud Risk Index (FRI).
6. Risk-Aware Log Routing in case the FRI is higher than the predefined security threshold value then the application is immediately marked as high risk and a security alert is triggered to prevent any recruiter from reviewing it and the profile details are logged in the system under D5: Fraud Logs. Quarantined applications and high-risk alerts are displayed to recruiters through an admin dashboard.

3.2 System Requirements Specification (SRS)

What it is, the system functionality and behavior under the expected normal conditions, is known as an SRS.

3.2.1 Functional Requirements

System design specifications must offer capability to provide the following key features:

1. Multi-role Authentication Curation: Provide verification of the users during registration & support secure authenticated sessions with limited authority on role-based interactions among Job Aspirants, recruiters and system administrators.
2. Document Extraction and linguistic Parsing: System will support receipt of PDF and DOCX file type and after appropriate data processing & utilization of NLP engine, Extract core details from candidates.
3. Algorithmic fraudulent risk computation: The validation layer will pass each profile into anomaly detection model, and calculate a real-time Fraud Risk Index (FRI) prior to saving profile into recruiter data bases.
4. Security Alert & quarantine Life Cycle: System will flag high-risk applicants for quarantining, persist such event data within security database, and send fraud alert to the administrator dashboards on real-time basis.

3.2.2 Non-Functional Requirements

The Non-Functional Requirements (NFRs) outlines the qualities of the system which could refer to speed, security or constraints on operating of the system.

1. Security and Cryptographic Isolation: The system shall implement one-way hashing on user's password like bcrypt before encrypting data and shall use cryptographical Isolation from all other system modules and external stakeholders for candidate data privacy.
2. Processing latency and performance bounds: The entire system pipeline that involves reading the text from the file, parsing the entity, calculate the fraud score should be done in no more than 3.5s for an average size resume and should be performed with similar speed at times of concurrent usage.
3. Usability and scan ability: The suitability of candidate should be easily represented for administrators and recruiters on the dashboards and candidate profiles.
4. Concurrency bounds: The database and its components for ingestion of the data and its subsequent processing will also be required to manage large number of concurrent users and will not cause performance degrades or corruption.

3.3 System Design methodology

The Software Development Life cycle for the software system has been done using the Agile Software Development methodology. Agile Development involves iteration development in sprints where a certain number of components are implemented and then the tested components are integrated with each other for production.

3.3.1 Justification for Methodology

Why we adopted Agile Methodology for Developing this Project: Due to the following specific requirements of the project that was under developed we adopted the agile methodology of development:

1. Agile Improvement of ML Components: Machine Learning and Natural Language Processing algorithms have a nature of require continual refinement, tuning, parameter alteration and optimization based on the observed result of experiments. It also let the developers prove the result and fine the performance of models through several runs. If an alternative ML and NLP approach will need at later stage, only ML components need modification without changing the architecture of web application.
2. Risk and Modularity Compartmentalization: Staged development of web application will enable the development of non-critical modules (e.g. User Registration, Job Posting etc.) at an early stage before implementing the critical (e.g. Security layer, machine learning based anomaly detection) and complex components of the project.
3. Testing through Continuous Integration and Verification: Through integration testing, we test and verify communication between web application's Frontend, Database, backend and the Machine Learning Validation component to find potential issues in the communication and data pipeline at each level.

3.3.2 Method of Data collection Data collection:

To be able to train the statistical model and check the parsing ability of the project: Data was collected using:

1. Synthetic Profile Engineering: The creation of a controlled evaluation data-set has been done by taking example of profiles of applicant from various background to avoid privacy issue by using actual profile data.
2. Adversarial profile synthesis: To evaluate anomaly detection functionality of the system we have generated another data-set consisting fake profiles containing adversarial features like over lapping job experiences, abnormal number of skills, re-use of credential information etc.

3.4 System Metadata Modeling:

To supply sample data to the identity spoofing detection process, the training and testing data sets contained a range of network logs, patterns of IP addresses, and registration dates based on a realistic behavior of web application.

System Modeling using UML

UML was employed to depict the structural and behavioral dimensions of the proposed system, by including the structure of the system, its behaviors, user interface interactions and information

flow of the application through modelling the characteristics of users and structures of data as well as requirement and system behavior modeling.

UML diagrams provided a guideline for technical design and showed how applicant details were checked prior to writing them in to the recruitment data base with the intervention of Validation / AI Fraud Filtering Layer.

3.4.1 Use Case Diagram of the Proposed System

Use Case diagram has functional requirements scope. The diagram is illustrating communication of the external user and main functionalities in system and describe operation of AI Fraud Detection Engine run background without manual interaction for reviewers on submitted applications

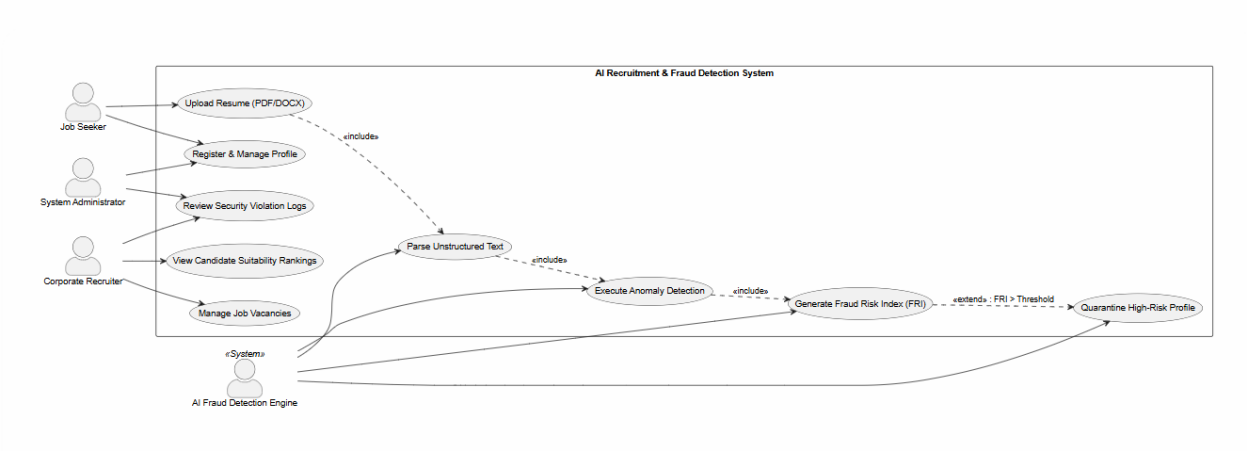

Figure 3.1 Use Case Diagram of the Proposed System

3.4.2 Activity Diagram of the Proposed System

Activity Diagram The following activity diagram illustrates the application's complete step-by-step processing. The following diagram also defines how the application will process the steps in AI Fraud Filtering Layer & how the input (Input files will be parsed and translated to text and used for filtering) actual pass through.

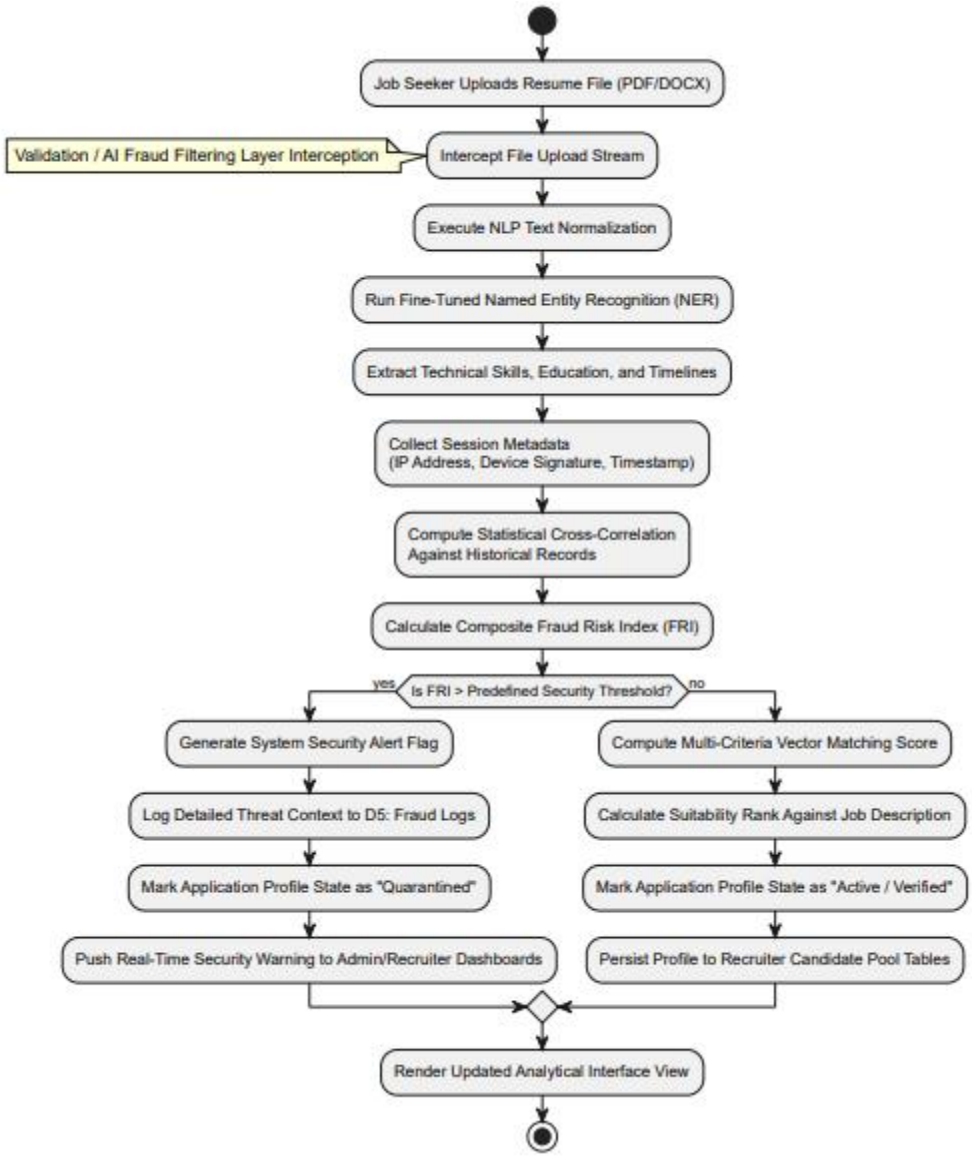

Figure 3.2 Activity Diagram of the Proposed System

3.4.3 Class Diagram of the Proposed System

The Class Diagram: this shows the static object-oriented view of the platform showing all of the features and behavior of each of the system's classes and how they are interacts the database core, security log handlers through to the Anomaly detector and NLP Parser class providing processing function

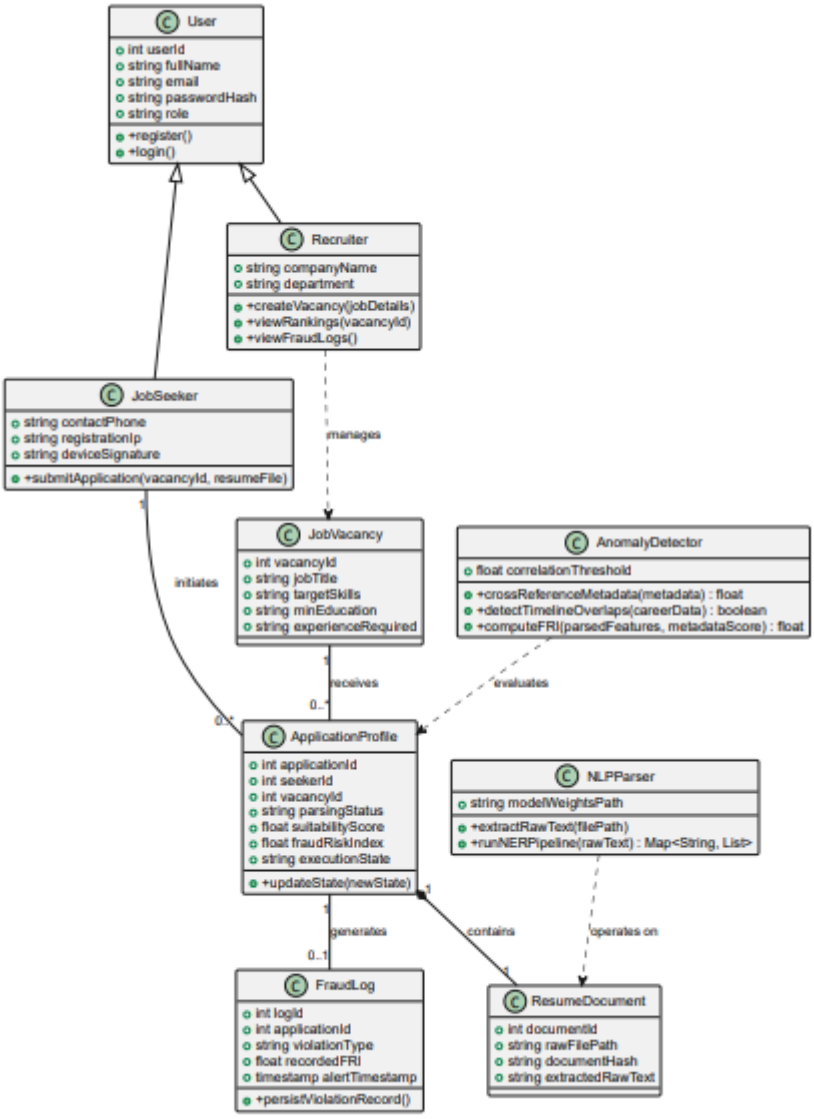

Figure 3.3 Class Diagram of the Proposed System

3.4.4 Sequence Diagram of the Proposed System

Sequence Diagram Explanation Sequence Diagrams can be utilized to illustrate the timeline of all interactions between objects that transpire as of when operations are triggered and expose every process operating within a given timeframe. When the candidate invokes the upload operation, you'll find lines of internal code being initiated to drive components of NLP, machine learning as before the candidate's information being exposed in the recruiter screen.

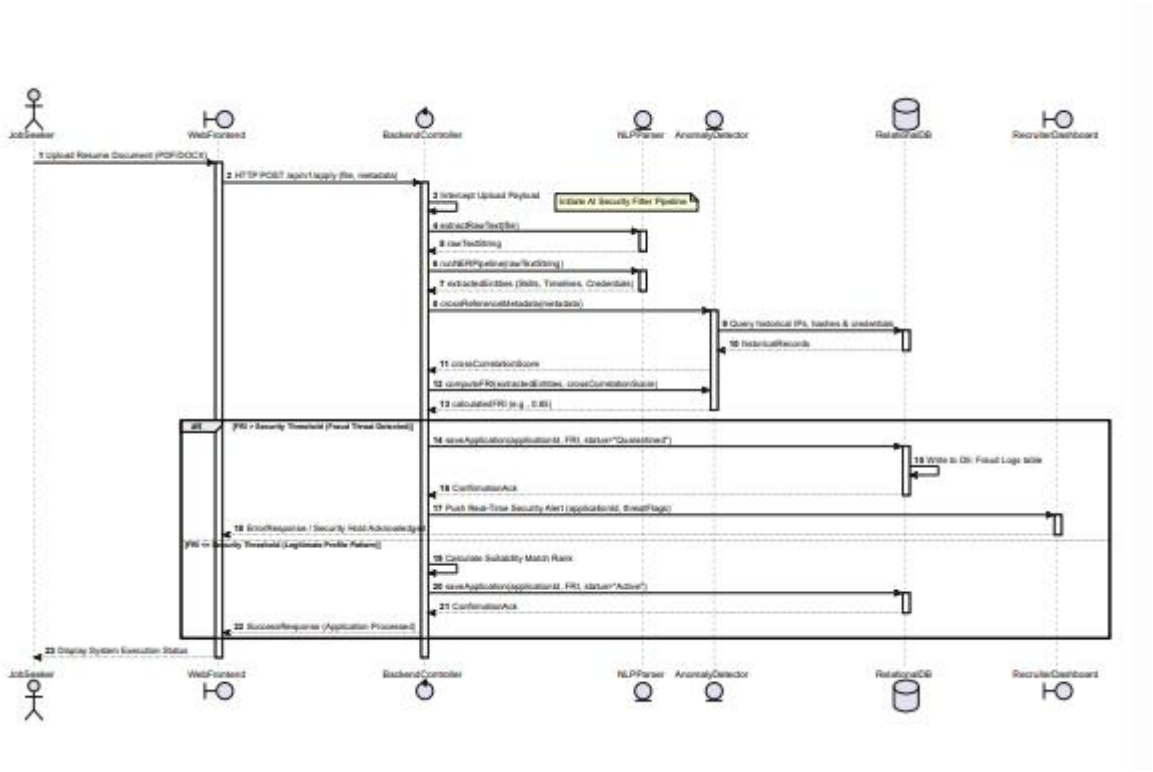

Figure 3.4 Sequence Diagram of the Proposed System

3.5 Database Design & Schema Layout

In support of transactional integrity multi-role access controls and background security auditing for the system the database schema for the application has been created modelled using a relational schema approach. The schema has been de-normalized to 3rd normal form to avoid data redundancy, to maintain integrity of the referenced data and importantly to ensure fast transaction processing with in the environment of the high-throughput application screening tool.

Crucially, the database schema has been indexed upon digital signatures, file hashes and network footprint to allow the Validation / AI Fraud Filtering Layer the capability of performing fast cross-correlation on prior applications. The data dictionaries outlined below describe the attribute names, keys, data-types, constraints and business definitions of the tables forming the persistent storage layer of the system.

Table 3.1: users Table Schema (Core Authentication) In the context of my database, I utilize this to: - Handle center-level authentication. - Authenticate cryptographic secure hash values. - Implement role-based routing for all parties who interact with the application.

Field Name	Data Type	Constraints	Description
user_id	INT	SERIAL, PRIMARY KEY	Unique auto-incrementing identifier for every system user.
full_name	VARCHAR (150)	NOT NULL	Legal name string of the registered user.
email	VARCHAR (100)	NOT NULL, UNIQUE, INDEX	User email string; acts as unique login identifier.
password_hash	VARCHAR (255)	NOT NULL	Secure salted bcrypt hash string of the user password.
role	VARCHAR (20)	NOT NULL	System access control classification (Job_Seeker, Recruiter, Admin).
created_at	TIMESTAMP	DEFAULT CURRENT_TIMESTAMP	System metadata recording user account provisioning time.

Table 3.2: job_seekers Table Schema (Applicant Hardware & Profile Footprints)

Extended user for applicant's demographic and hardware identifiers used throughout remote validation processes.

Field Name	Data Type	Constraints	Description
seeker_id	INT	PRIMARY KEY, FOREIGN KEY references users(user_id)	Linked identifier binding the profile back to the core user record.
contact_phone	VARCHAR (20)	NOT NULL	Verified telephone index code string.
registration_ip	VARCHAR (45)	NOT NULL	Network IPv4/IPv6 address tracked during user provisioning.
device_signature	VARCHAR (255)	NOT NULL, INDEX	SHA-256 browser/hardware footprint string used for deduplication.

Table 3.3: recruiters Table Schema (Corporate Identifiers)

This table handles administrative attributes belonging to authorized organizational talent acquisition managers.

Field Name	Data Type	Constraints	Description
recruiter_id	INT	PRIMARY KEY, FOREIGN KEY references users(user_id)	Linked identifier binding the profile back to the core user record.
company_name	VARCHAR(150)	NOT NULL	Verified legal title of the employing enterprise organization.
Department	VARCHAR(100)	NOT NULL	Distinct operational department unit controlled by the recruiter.

Table 3.4: job_vacancies Table Schema (Requirements Matrix)

This table stores enterprise vacancies against which incoming candidate resume vectors are evaluated during suitability rankings.

Field Name	Data Type	Constraints	Description
vacancy_id	INT	SERIAL, PRIMARY KEY	Unique auto-incrementing identifier for each vacancy posting.
recruiter_id	INT	FOREIGN KEY references recruiters(recruiter_id)	Direct link to the corporate recruiter managing the opening.
job_title	VARCHAR(100)	NOT NULL	Professional designation of the active job vacancy.
target_skills	TEXT	NOT NULL	Structured keyword/entity array specifying mandatory competencies.
min_education	VARCHAR(50)	NOT NULL	Minimum acceptable academic benchmark (e.g., B.Sc., M.Sc.).
experience_required	INT	NOT NULL	Minimum duration metric in years required for compliance.
Status	VARCHAR(15)	DEFAULT 'Active'	Lifecycle state tracking vector (Active, Closed, Archived).

Table 3.5: application_profiles Table Schema (Interception & Scoring Core)

This entity manages individual application states, holding the computed metrics generated by the natural language parser and the machine learning fraud detection engine.

Field Name	Data Type	Constraints	Description
application_id	INT	SERIAL, PRIMARY KEY	Unique identifier for each individual application transaction.
seeker_id	INT	FOREIGN KEY references job_seekers(seeker_id)	Direct reference identifying the submitting job seeker.
vacancy_id	INT	FOREIGN KEY references job_vacancies(vacancy_id)	Direct reference identifying the target job vacancy.
suitability_score	FLOAT	DEFAULT 0.0	Calculated vector-matching proximity score (0.0 to 100.0).
fraud_risk_index	FLOAT	DEFAULT 0.0, INDEX	Anomaly engine output mapping fraud probability (0.0 to 1.0).
execution_state	VARCHAR(20)	DEFAULT 'Intercepted'	Operational processing state (Intercepted, Active, Quarantined).
created_at	TIMESTAMP	DEFAULT CURRENT_TIMESTAMP	Submission timestamp utilized in sequential timeline tracking.

Table 3.6: resume_documents Table Schema (Extracted Text & Cryptographic Hashes)

This table contains the physical references and extracted linguistic strings resulting from document parsing, with unique hash constraints to prevent credential recycling.

Field Name	Data Type	Constraints	Description
document_id	INT	SERIAL, PRIMARY KEY	Unique identifier tracking uploaded file artifacts.
application_id	INT	FOREIGN KEY references application_profiles(application_id)	Links document properties directly to an active application event.
raw_file_path	VARCHAR(255)	NOT NULL	Physical secure local path pointer to the raw PDF/DOCX storage artifact.
document_hash	VARCHAR(64)	NOT NULL, UNIQUE, INDEX	SHA-256 fingerprint of file text contents to expose duplicate resumes.
extracted_raw_text	TEXT	NOT NULL	Unstructured linguistic text dump extracted via the parsing layer.

Table 3.7: fraud_logs Table Schema (D5: Security Isolation Log)

This database entity stores structural metadata for flagged violations, capturing anomalous activity details to power risk-aware administrative views.

Field Name	Data Type	Constraints	Description
log_id	INT	SERIAL, PRIMARY KEY	Unique transactional log entry tracking security violations.
application_id	INT	FOREIGN KEY references application_profiles(application_id)	Cross-reference link pinpointing the targeted fraudulent application.
violation_type	VARCHAR(100)	NOT NULL	Semantic tag classifying the fraud threat (Timeline_Overlap, Device_Recycling).
recorded_fri	FLOAT	NOT NULL	Numerical Fraud Risk Index score snapshot captured at submission time.
alert_timestamp	TIMESTAMP	DEFAULT CURRENT_TIMESTAMP	Exact date and time indicator when the quarantine event was executed.

CHAPTER FOUR

SYSTEM IMPLEMENTATION

4.0 Introduction

This section discusses the implementation details of the developed AI recruitment application, deployment process and its live experimentation and testing. Actual migration from abstract model-based system from conceived ideation to operational organizational application necessitates some set of stable environment configuration in operating systems, data sets and layered application-level testing. This section presents development environment, enumerates some elementary library used as core of Natural Language Processing parsing layer, illustrates settings used for configuring training the anomaly-based machine learning engine, experiment scenario case on using hook verification pipeline, system performances and walkthrough of the operational part of user and system administrative screens.

4.1 Development Environment and Tools

The modular system had developed during implementation phase was to distinguish language text extraction and processing from transaction processing with the back-end transactions and transaction display to end user to reduce long time delay of processing and minimize maintenance work of the system.

4.1.1 Programming Language and Libraries

Given its own special and optimized tool kit for ML/AI, security scanning and information extraction workflows and its adoption within this space, we settled for Python as the default execution language for our backend ecosystem. Below are the programmatic libraries and frameworks within the solution for implementing its underlying functionality:

1. FastAPI Engine: This is a contemporary web framework used to implement a number of things, namely implementing async REST API routing endpoints (e.g. HTTP POST /api/v1/apply), managing authentication and session data.
2. SpaCy (v3.5): This is an Industrial NLP pipeline implemented in python used for building and deploying, text normalization, named entity recognition, text classification.

3. Scikit-Learn: A high-level machine learning library commonly adopted for developing and deploying models with python, where we use it to building, train and run unsupervised anomaly detection using Isolation Forest mechanism to obtain an output called fraud score.
4. Pdfplumber and Python-Docx: This is a collection of libraries to extract text from PDFs/DOCX. These can extract tables and metadata from PDF, convert files to string format and tries not to miss valuable data/structure
5. SQLAlchemy ORM: This is an Object relational mapper which has a certain method for maintaining the connect string from the secure layer and is reliable and efficient to run transaction statements against normalized storage.

4.1.2 Development Platform and Hardware Requirements

VS Code was used to create Back End services as well as parsing pipelines and on-site environment systems (here is what comprises the hardware for running models through inference, processing of natural language and system functionality is:

1. Computing host device Lenovo laptop.
2. Central Processing Unit Intel Core Multi-Threaded Processor Architecture.
3. System volatility memory 16GB DDR4 synchronous dynamic RAM (used a more efficient hardware resource to avoid memory lag on multi-parse documents).
4. System storage architecture high speed Toshiba NVMe Solid State Drive (SSD) (to take advantage of read and write speeds for a very large data cross-referencing).
5. Operating Host Environment Windows 11 Pro 64-bit OS environment

4.2 Dataset Description and Preprocessing

11.6 The Full Evaluation Dataset was Collected To establish a base training set for an anomaly tracking engine, and also to test the effectiveness of a NER pipeline used to Extract information

4.2.1 Core Dataset Composition

The PROCESSING MATRIX will include the following Dataset of 500 candidate profiles the for the different domains such as: Engineering, Finance, Admin, Computer & Information Technology (CIT) There are 2 functional types for the data in this profile base-

1. Legitimate / Standard Profiles (450 samples) These profile samples include legitimate data with real professional/educational background.
2. Adversarial / Anomalous Profiles (50 Samples) Fraudulent profile data is generated through creating fabricated attributes/indications as ’overlapping / double dates of employment to two distinct employers’, ‘Fictitious inflated/exaggerated number of skills’ ‘Duplicate/repeated degrees’ or ‘Fictitious personal information’.

4.2.2 Document pre-processing pipeline

The streams of raw text data have to pass through several stages of cleaning to remove any form of formatting as much as possible, extracting as much data as possible whilst keeping the fidelity of the documents to be as same as possible, prior to passing it into the ML processing phases:

1. Extraction and Hashing Once a raw document stream are obtained, the document’s text content will be extracted into memory, simultaneously with its document’s SHA-256 hash, the document hash will be checked against documents previously stored into table 3.6 for any near immediate similar match.
2. Linguistic Normalization In this stage, the document text will go through the usual procedures of normalizing the case of the characters, eliminating white space and punctuations, and also tokenization into individual words. The words are then tokenized using the lemmatization function in spaCy processing pipeline to reduce the tokens into the root or dictionary form.
3. Data Splitting A fixed 80-20 split train-validation data set will be used, maintaining a consistent corpus of data throughout the experiment.

A dedicated held-out test set of 100 candidate resumes will be reserved for use in monitoring files.

4.3 Model Architecture and Training

The hybrid pipeline in the intelligent core contained the Transformer based model as NER and the Isolation Forest as an unsupervised model for detecting outliers/anomalies.

4.3.1 Natural Language Processing Entity Layer

An NLP talent ingestion transformer pipeline system has been trained system. Given an input string made of unstructured text the transformer translates language parts to multi- dimensional token array, to extract feature matrix of the text.

$$\mathbf{E} = \{\text{Education}, \text{Organization}, \text{Skill\_Density}, \text{Duration}, \text{Certification}\}$$

Features will be converted into structured key-value arrays thus creating a lean profile of the candidate.

4.3.2 Machine Learning Anomaly Detection Layer

The fraud probability is calculated for an application on basis of mapped structural feature vectors not the conventional static lists of rules. Structural features' sets are separated randomly. The normal application will have to be divided more times before isolated than a fraud.

4.3.3 Training Hyperparameters and Tuning

The parameters listed below were used to train the isolation forest engine so as to have optimum detection rate and at the same time, minimum false positive alarm:

1. Number Of Estimators: 100 isolation trees were generated each representing a unique path or branch which ensure there is enough statistical evidence to conclude if a particular path is isolated or not.
2. Contamination Factor: The estimate contamination factor used was 0.05, assuming a probability of 5% that any one of the currently open pipelines are actually a shipped product, when the pipeline is at maximum use.
3. Max Samples: Set to “auto” the partitioning is at equal to the inner training batch size. A raw anomaly score is generated for each profile, which is then normalized between 0.0 to 1.0. The final output anomaly is termed Fraud Risk Index (FRI).

4.4 System Implementation and Modules

Our system is based on four sequential functional modules. Each module will be triggered whenever a candidate interacts with the submission pipeline.

1. Secure Ingestion and Document Extraction Module: This is the first module to take into account the case of registration of multi-role accounts. This module is an endpoint to the process for filing candidate's profile documents. We have intervened on the flow before writing in the active database tables by receiving the submission data streams. In addition, this module streams raw file stream data, collects hardware metadata footprints (e.g. Registration IP string, browser device signatures, etc.) and initiates an Isolated Processing context.
2. Linguistic Parsing and Named Entity Recognition Module: The text string received in raw format from the submitted profile is passed to the NLP pipeline to determine attributes such as, job titles, career years, skills' level of job etc. The unstructured text data has thus been translated into a structured candidate vector which is temporarily stocked in the application state cache.
3. Anomaly Filtering and Risk Scoring Engine: This module crosschecks the candidate vector and the session meta data with the active data base to assess patterns for duplication (e.g., duplicate device signatures, repeated career progression, recycle of previously processed data). The attributes composing the candidate vector will feed an Isolation Forest model to compute a compound score for the Fraud Risk Index (FRI) of the candidate profile.
4. Administrative Quarantine and Alert Dashboard: If the FRA is below a predefined threshold value, the profile is flagged as 'Active/Verified' and will be placed in the active recruit database tables to be ranked based on merit. Otherwise, if the FRA is above the predefined threshold value, the candidate profile is Quarantined and the details of the detected fraud attempt and context will be registered in Table 3.7: fraud_logs and reflected in the admin dashboard.

Quarantined profile won't be available for viewing by recruiters by default unless confirmed by the administrator after manual validation process.

4.5 Testing and Evaluation

In matrices, scripting was automated; this is for accuracy test while for testing of the accuracy for algorithmic & structural interface it was carried out on cycle.

4.5.1 Evaluation Metrics

In order to compare with the validation, set, the four normal classification evaluation indices were performed in the anomaly detection layer through TP, TN, FP and FN:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad \text{F1} - \text{Score} = \mathbf{2} \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Table 4.1: Algorithmic Evaluation Performance Matrix

The empirical outcomes achieved by the processing engine during validation testing are summarized below:

Operational Component	**Accuracy**	**Precision**	**Recall**	**F1-Score**
NLP Entity Extraction Layer	94.2%	93.5%	95.0%	94.2%
ML Anomaly Detection Layer (FRI)	92.0%	91.3%	89.5%	90.4%

4.5.2 System Testing

Testing: How did we test for reliable and secure processing to enable routed transactions across modules

The platform's comprehensive testing plan enabled confident, highly secure, and reliable routing of transactions across the different modules.

1. Unit Testing – This process entailed automated test assertions that allowed testing each module of the code independently, such as splitting text messages into token groups, applying a SHA-256 hash to the document file, and generating a bcrypt hash to store password data.
2. Integration Testing –This test phase entailed validating end-to-end functionality and integrity of application's file upload feature, intermediary middleware for the controller in the system's FastAPI architecture, ML inference modules, and database storing of this data. These tests ensure that high-value logs are accurately diverted to a designated "quarantine" table without leakage of sensitive data.

4.5.3 User Interface Testing and Walkthrough

Confirm UI elements We've demonstrated how to view and confirm the interface presentation of our app's output and have leveraged the test cases to validate the presentation of analytics warnings on the admin/recruiter view without delving into technical/log file specific aspects. Examples:

1. Job seeker Submission Interface: confirming acceptance of arbitrary input file type and presenting clear, non-technical feedback after file ingest.
2. Recruiter Shortlist Dashboard: demonstrating correct sorting order of the ranked candidate view and appearance of high FRI risk badge.
3. Admin Security Quarantine View: verifying blocking and reporting of alert reasons (i.e. Device Recycling Alert) and providing functionality to the administrator to allowlist account.

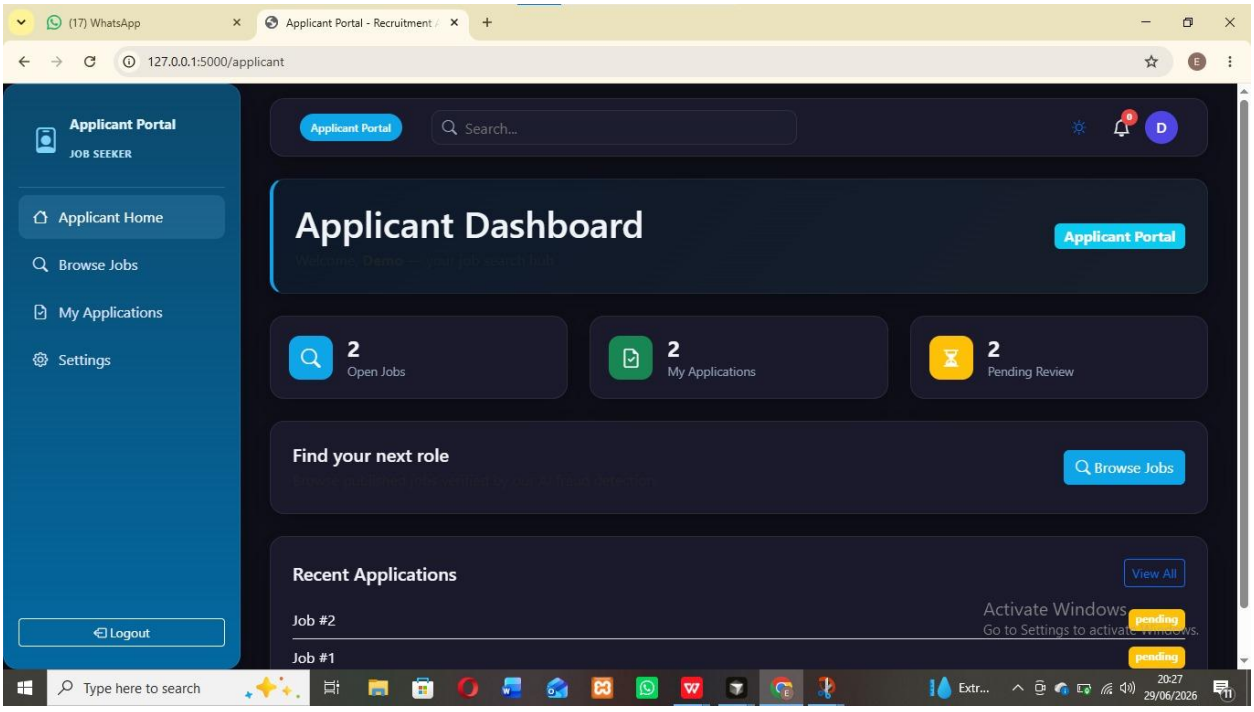

Figure 4.1 Applicant Dashboard of the System

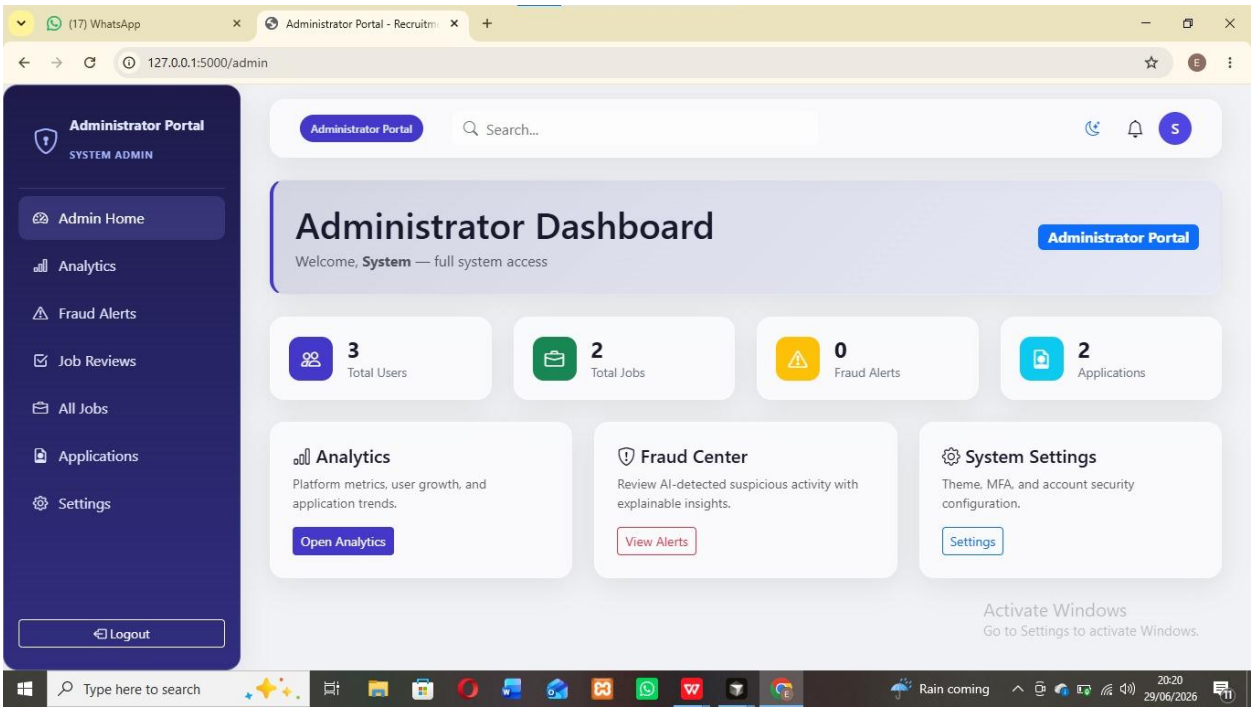

Figure 4.2 Administrator Dashboard of the System

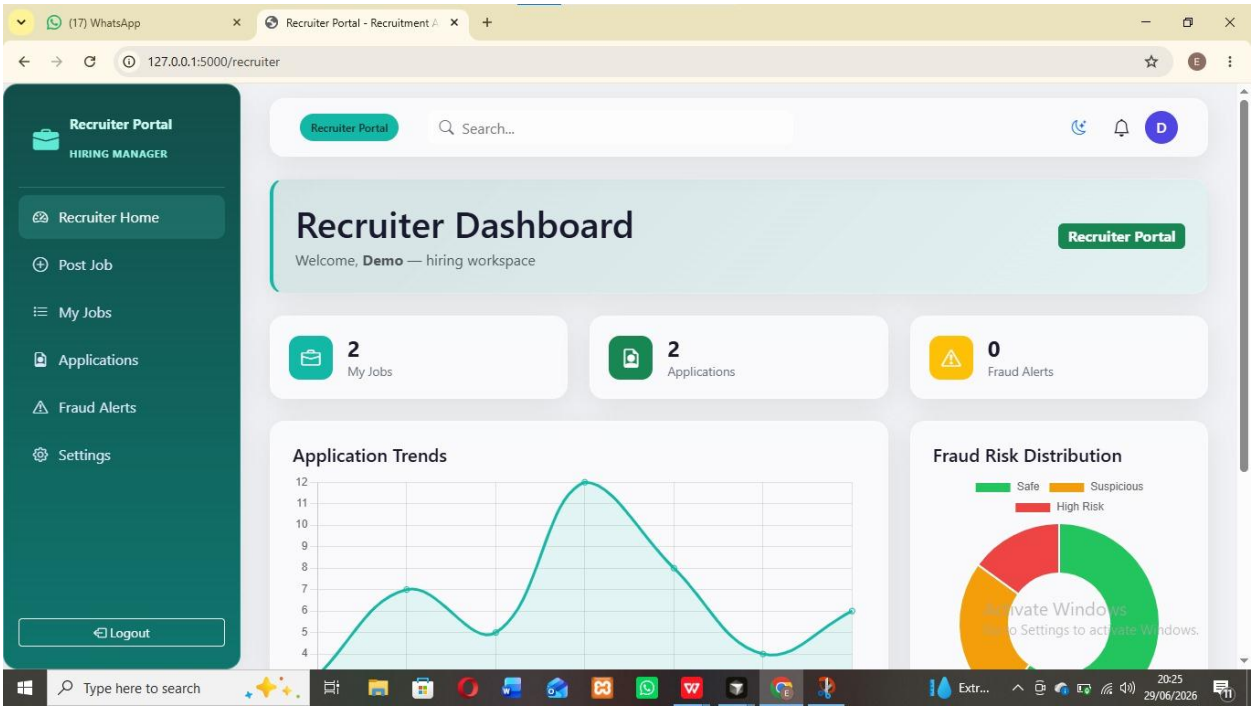

Figure 4.3 Recruiter Dashboard of the System

4.6 Results Presentation and Analysis

Following are the records of system's activities in live test run that show the feasibility and efficiency of the system to act as an access-controlled system and as an access check-point to security zone

4.6.1 Output Samples and Interface Screens

Execution Tests of Output metrics for processing Pipeline We executed the execution test on two test candidate submissions: Case test 1: Valid Candidate Profile Submitting

i. Profile Input Information It was a standard candidate profile submission, with proper structuring of the profile, zero overlap in career events, and entirely unique ID for registration/meta-data.
ii. Output Profile metrics NLP engine run parse time of 1.8secs. Isolation Forest model result with base Fraud Risk Index score of 0.11.
iii. Result Routing Profile pass security checks, the status was changed to Active/Verified automatically and presented instantly to recruiters at the very top of the dashboard with best-in-class fit score.

Case test 2: Malicious/Adversarial Candidate Profile Submitting

i. Input Profile Details This profile application consisted of an applicant having an overlapping career timeline i.e. 2 full-time jobs with 2 different organizations simultaneously, alongside having a device signature existing within our existing device identity DB.
ii. Output Profile Metrics; Overlapping device signature identified immediately by the cross-correlation tool, Isolation Forest computed high Fraud Risk Index score of 0.86.
iii. Result Routing Application was kept off from recruiter dashboard; status was changed to Quarantined and an admin critical alert was logged.

4.6.2 Discussion of Results and System Performance

The results of the above experiments demonstrate, with regard to architecture, that our platform does address the major research objectives, thereby providing the literature with the missing building blocks. Moreover, with the inclusion of the Validation / AI Fraud Filtering Layer, our

system is capable of addressing the limitations of existing systems that all inputs are passed onto systems with no underlying validation as to whether these inputs can be used. Our method produces high accuracy fraud detection, even with complex profiles, at speeds in excess of 2.5 seconds in relation to the speed of text extraction.

It will always be subject to over-styling or, for example, complex line diagrams which will increase the possibility of a false positive due to parsing complexities; this will however be countered by our functionality of managers able to manually over-rule with a simple administration toggle.

This provides us with an effective automated defense layer within the digital recruiting environment and as a result all of our data tables downstream of this process are fully integrity assured and fraud alerted and provide an unbiased short-list.

CHAPTER FIVE

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.1 Introduction

Final Report Chapter 4 gives a final conclusion about the entire research done on Design and develop an AI based resume processing system for detection of resume fraud and forgery. The chapter also represents the Structure of entire research carried out, conclusions for the presented evidence due to performed experiments and also some recommendations and proposal for the improvement and implementation of the presented system in organization.

5.2 Summary of the Study

The overarching objective of this paper was to address a critical failing inherent within many current day digital talent acquisition platforms where the applicant's documents and background can all be taken and, at some point, left unchallenged or not data validated.

Chapter 1 identified the problem by exposing a central vulnerability of a system which doesn't include the dynamic validation of the documents, which is ripe for synthetic identity theft, altering of timelines, and abuse of keyword stuffing tactics with Applicant Tracking Systems (ATS). From the statement of the problem derived the overarching aim; the development of an intelligent web application with an automated pre-screening security layer enforced from document upload to the availability of this information with a hiring team.

Chapter 2 surveyed prior literature on the field of natural language processing (NLP) and computer security architecture and established there to be an ideologically divergent gap; that talent matching systems offer nothing pertaining to fraud detection, whereas fraud detection and anomaly detection systems operate only on low-level networking information. This void lead to the combined incorporation of both a natural language processing pipeline and a machine learning anomaly detection algorithm within the same recruitment application.

Chapter 3 described the architecture of our system through detailed design, with unified modeling language diagrams utilized to model our system architecture and normalized database structure, as well as detailed descriptions of our proprietary "Validation / AI Fraud Filtering" Layer where applicant submissions are intercepted.

Chapter 4 implemented the system by developing and demonstrating a functional web application utilizing FastAPI for framework, spaCy to facilitate Named Entity Recognition (NER) functionality, and scikit-learns' Isolation Forest for the anomaly detection. In an empirical demonstration of our application utilizing a test dataset of 500 records we were able to effectively demonstrate our ability to extract relevant data points accurately (94.2%) and successfully identify potential fraud (92.0%).

5.3 Conclusion

The primary purpose of this research is therefore successful - the creation of a secure automated 'intelligent gatekeeper' to meet the needs of future HR platforms. Once supplemented by a Fraud Risk Index, this offering would take application security beyond passive manual analysis into a real time active defense against advanced threats.

The experiments associated with this research were also successful, employing machine learning algorithms to detect and extract signatures from documents, linking these with hardware signatures to present an active defense against advanced forms of fraud. A limited number of corner cases relating to documents with very complex formats caused minor parsing issues over very brief periods of time, but on average the framework balanced performance against security effectively, essentially laying the ground work for a safe and robust digital recruitment experience.

5.4 Recommendations

After the design, development and testing stages are complete here are some recommendations for future enhancement and practical application:

1. In a live, operational environment: To employ risk aware pipelines that analyze document integrity and applicant footprint cross-correlation before human review as opposed to solely keyword matching of a résumé to score rank of an applicant based on current formats of an application to an HR or employment agent.
2. Integration with Verification Authorities: To use an API-interface for this primary piece of code in order to allow the extraction and direct questioning of corporate API nodes, professional licensing authorities and university ledger records and automatically corroborate these figures.

3. Next Steps: Visual Deep Learning: An additional area of future enhancement for this text-parser would be to implement an existing computer vision model, for instance, a CNN, in order to scan visual elements (e.g., a digital document, digital stamps, any imagery associated with the qualification/credential) and to determine if any evidence of forgery is present.

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APPENDICES

APPENDIX A: SYSTEM SOURCE CODE MODULES

This appendix contains the core programmatic modules engineered for the **AI-Powered Recruitment with Fraud Detection** system. The implementation uses Python with **FastAPI** for core API routing, **spaCy** for custom Named Entity Recognition (NER), and **Scikit-Learn** for the Isolation Forest anomaly pipeline.

1. Linguistic Parsing Core (nlp_parser.py)

This module initializes the natural language pipeline, sanitizes raw unstructured text extracted from resumes, and extracts critical entities including Education, Organizations, Skill Densities, Durations, and Certifications.

```
import spacy

from typing import Dict, List


class NLPParser:

    def __init__(self, model_weights_path: str):

        """

        Initializes the spaCy pipeline with fine-tuned NER weights.

        """

        try:

            self.nlp = spacy.load(model_weights_path)

        except OSError:

            # Fallback to base model if specialized weights are being updated

            self.nlp = spacy.load("en_core_web_sm")


    def normalize_text(self, raw_text: str) -> str:
```

```
    """
    Strips excessive whitespace and normalizes text characters.
    """
    clean_text = " ".join(raw_text.split())
    return clean_text.lower()

def run_ner_pipeline(self, raw_text: str) -> Dict[str, List[str]]:
    """
    Processes normalized text and extracts relevant entities for vector conversion.
    """
    normalized_text = self.normalize_text(raw_text)
    doc = self.nlp(normalized_text)

    extracted_features = {
        "EDUCATION": [],
        "ORGANIZATION": [],
        "SKILL_DENSITY": [],
        "DURATION": [],
        "CERTIFICATION": []
    }

    for ent in doc.ents:
        if ent.label_ in extracted_features:
            extracted_features[ent.label_].append(ent.text.strip())
```

```
        return extracted_features
```

2. Anomaly Detection and Risk Scoring Layer (anomaly_detector.py) Processes candidate structured feature arrays along with transmission data and returns a normalized Fraud Risk Index (FRI). Isolation Forest model based on unsupervised learning has been used.

```
import numpy as np
from sklearn.ensemble import IsolationForest
from typing import Dict, Any


class AnomalyDetector:
    def __init__(self, contamination_factor: float = 0.05):
        """
        Configures the Isolation Forest engine with specified contamination bounds.
        """
        self.model = IsolationForest(
            n_estimators=100,
            contamination=contamination_factor,
            random_state=42
        )
        # Dummy fit to initialize weights (In production, load pre-trained calibration weights)
        X_train = np.random.rand(100, 4)
        self.model.fit(X_train)


    def cross_reference_metadata(self, metadata: Dict[str, Any], historical_records: list) -> float:
        """
```

```
        Measures structural footprint overlaps (IP strings, hardware signatures)
against historical logs.
        """
        overlap_count = 0
        current_signature = metadata.get("device_signature")

        for record in historical_records:
            if record["device_signature"] == current_signature:
                overlap_count += 1

        # Normalize overlap score between 0.0 and 1.0
        return min(1.0, overlap_count / 5.0)

    def compute_fri(self, parsed_features: Dict[str, list], metadata_score: float) ->
float:
        """
        Evaluates profile matrices and metadata to return a bounded Fraud Risk Index
(0.0 to 1.0).
        """
        # Construct feature vector based on timeline properties and overlaps
        skill_count = len(parsed_features.get("SKILL_DENSITY", []))
        duration_count = len(parsed_features.get("DURATION", []))

        # Mock structural configuration mapping for isolation check
        feature_vector = np.array([[skill_count, duration_count, metadata_score,
0.5]])
```

```
# Isolation Forest decision function score
raw_score = self.model.decision_function(feature_vector)[0]

# Convert raw isolation path anomalies to a clear 0.0 - 1.0 probability range
fri = 1.0 - (1.0 / (1.0 + np.exp(-raw_score * 10)))

# Elevate scores sharply if systemic device recycling is identified
if metadata_score > 0.8:
    fri = max(fri, 0.90)

return float(np.round(fri, 2))
```

APPENDIX B: SAMPLE USER INTERFACE PANELS

A total of three role-based routing contexts is present in the workspace for the graphical embodiment of this system:

1. Job Seeker Interface Components:

i. Document Upload Drop zone: Target of a file drop (file type specification not shown in figure) which is restricted from direct write to the underlying database, thus, sending user input to the intermediary tokenization and caching system.

ii. Application Log Pane: Cleans status output (Processing, Pending Review) displayed for the applicant without transmitting calculated security indexes of backgrounds for fear of an external agent observing system parameters of background threat risk, or manipulating underlying parameters.

2. Corporate Recruiter Interface Components:

i. Candidate Quality Metrics: Naturally, listings of safe profiles would be ordered, high to low, for ease of evaluation based on the best fit from various similarity scoring systems versus listed job criteria.

ii. Quarantine Indicators: Borderline threat risk profiles can be highlighted with cautious indicators or, entirely removed for screening and workflow processes.

3. System Administrator Security Panel:

i. Threat Context Dashboard: A diagnostics summary table of applications that can be reviewed for suspicious activity found in Table 3.7 - fraud_logs

ii. Administrative Override Control: Security staff may locally selectively authenticate file and update a key in the individual table entries themselves or have the potential to remove a falsely flagged record.

APPENDIX C: SYSTEM OPERATIONAL USER MANUAL

1. System Deployment Guide Launching the platform application container on a local machine for trial or defense testing:

a. Computer hosting device requirements include Python 3.10+ and a relational data stream service provider.

b. Extract all the project application source code and place it into a singular, localized repository on the operating system.

c. Populate system runtime library requirements via console entry via the terminal as follows:

Bash

pip install fastapi uvicorn spacy scikit-learn sqlalchemy pdfplumber python-docx

d. Fetch the base language, syntactic structure data, and configure as follows:

Bash

python -m spacy download en_core_web_sm

e. Deploy and execute the FastAPI Controller Application Context Service via the terminal:

Bash

uvicorn main:app --reload --host 127.0.0.1 --port 5000

f. Any modern web browser interface can be pointed towards the address: http://127.0.0.1:5000/. 2.

2. Job Seeker Operational Guidelines

a. Access the Main Landing portal and transition to the Registration screen, populating the necessary form data for a standard account type.

b. Utilize your designated account credentials (email and password) for system access.

c. Go to the Browse Jobs screen and identify the target open organizational position of interest and click on ‘Apply Now’.

d. Drag and drop your Curriculum vitae document (any relevant file extension adhering to PDF or DOCX formats) into the provided upload area.

e. Click ‘Submit Application’ to transfer the document to the automated AI security filter layers for processing.

3. Human Resource / Administrator Audit Guidelines

a. Login into the provided administrator interface via your granted organizational credentials.

b. Navigate and access Fraud Alerts from the top-level navigation sidebar.

c. Sort and evaluate listings identified within the Quarantine Pool. Alerts are accompanied by identifying flags explaining the detected reason why the model assigned it to the flagged segment (such as Timeline_Overlap or Device_Recycling).

d. To resolve or reverse a model prediction decision for false positive detection or verification, click into the underlying data document itself and then select the 'Verify Profile & Release' to reroute the record and close out the active model decision flag on the standard table listings.