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Optimizing Recruitment and Job Sourcing with a Multilayer Perceptron Classifier-Based Recommendation System for More Effective Hiring Decisions

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تحسين عملية التوظيف باستخدام نظام توصية يعتمد على مصنف متعدد الطبقات لاتخاذ قرارات توظيف أكثر فاعلية

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Abstract:
With the increase in technological development, most jobs have specific advantages and specifications, and the size of the offer and the number of those wishing to hire have increased significantly, and the pace of increasing the number of job managers has also increased in the direction of obtaining a distinguished employee who is ready to fill the desired job. This paper focuses on building a recruitment system that aims to serve both parties in the job equation, to serve the job seeker, and to serve the job managers in finding the right employee. The research of this paper lies in building a job recommendation system based on the skills written in the employee's CV, and then the system provides a suggestion of vacant jobs that the employee can go to. This paper also provides a short presentation on the traditional prevailing framework within an important institution, which is the Misurata Free Zone. Where initially, the system works to clean the information by expelling incomplete information, or those with missing or duplicate parts. Then, job recommendations are provided to targeted applicants based on their preferences or on what is determined by the Human Resources Management Office in the Misurata Free Zone. It uses different machine learning procedures, the results of which show that artificial intelligence systems give the highest accuracy in predictions, especially when compared to traditional systems. The recommendation framework based on multiple attributes including geography is used to find suitable employees who are geographically close to the organization, which can help job seekers reach their destination at no cost. This system also reveals how much important data is lost in the recruitment process that is done incorrectly by traditional methods. It lays a clear and effective scientific foundation for reaching a suitable recommendation for both hiring parties.

Keywords: Job Recommendation System, Recruitment Optimization, Machine Learning, Artificial Intelligence in HR, Misurata Free Zone.

الملخص
مع تزايد التطور التكنولوجي، أصبحت معظم الوظائف تمتلك مزايا ومواصفات خاصة، مما أدى إلى زيادة حجم الفرص المتاحة وعدد الأشخاص الراغبين في التوظيف بشكل كبير. كما تسارعت وتيرة زيادة عدد أصحاب العمل في سبيل

الحصول على موظف مميز جاهز لشغل الوظيفة المطلوبة. يركز هذا البحث على بناء نظام توظيف يهدف إلى خدمة كلا الطرفين، حيث يخدم الباحث عن العمل ويساعد صاحب العمل في العثور على الموظف المناسب. يتمحور البحث حول بناء نظام توصيات وظيفية يعتمد على المهارات المكتوبة في السيرة الذاتية للموظف، ومن ثم يقوم النظام بتقديم اقتراحات للوظائف الشاغرة التي يمكن للموظف التقدم لها. يقدم هذا البحث أيضًا عرضًا مختصرًا للإطار التقليدي السائد داخل مؤسسة هامة، وهي المنطقة الحرة بمصراتة. في البداية، يعمل النظام على تنظيف المعلومات من خلال استبعاد البيانات غير المكتملة أو التي تحتوي على أجزاء مفقودة أو مكررة. بعد ذلك، يتم تقديم توصيات وظيفية للمتقدمين المستهدفين بناءً على تفضيلاتهم الشخصية أو بناءً على ما تحدده إدارة الموارد البشرية في المنطقة الحرة بمصراتة. يستخدم النظام إجراءات مختلفة للتعلم الآلي، وتظهر النتائج أن أنظمة الذكاء الاصطناعي تحقق أعلى مستويات الدقة في التنبؤ، خاصة عند مقارنتها بالأنظمة التقليدية. يعتمد نظام التوصيات على سمات متعددة، بما في ذلك الموقع الجغرافي، لتحديد الموظفين المناسبين القريبين جغرافيًا من المؤسسة، مما يساعد الباحثين عن العمل في الوصول إلى وجهاتهم دون أي تكلفة. يكشف هذا النظام أيضًا عن حجم البيانات المهمة التي يتم فقدانها في عملية التوظيف عندما تتم بطرق تقليدية. ويضع البحث أساسًا علميًا واضحًا وفعالًا لتحقيق توصيات مناسبة للطرفين في عملية التوظيف.

الكلمات المفتاحية: نظام توصيات الوظائف، أتمتة عملية التوظيف، التعلم الآلي في الموارد البشرية، تطبيقات الذكاء الاصطناعي، المنطقة الحرة مصراتة.

Introduction

The use of the internet for job sourcing and candidate referral is gradually becoming increasingly popular and significant today. The HR disagrees with acknowledging all of the referrals concurrently due to the large influx in referrals. This research paper contains an approach to job sourcing and candidate recommendation systems. The job sourcing and hiring recommendations are constructed using an MLPC classifier in this proposal. Additionally, this suggestion comprises a performance enhancement method called proposals scaling. This approach rescales the lower valued suggestions into the bigger scale of the counseling score. This approach has an advantage over other approaches to building a counseling suggestion. The method of weighting is simply in relation to the HR's desires. The general performance of the MLPC classifier is utilized in the experiments to demonstrate the work's validity.

The total experiment of the job sourcing and hires recommendation performance demonstrates that the construction of the MLPC classifier has a big prognosis bandwidth that could be employed as a construction engine for various suggestion modalities of job sourcing and hires. On the other hand, this paper has several limitations worth discussing. This discussion aims to become the early stepping stone to comprehend the job sourcing and hiring recommendation suggestion problems. The job sourcing here refers to obtaining information from potential candidates' references, while the hiring recommendation refers to the hiring final decision. The reason for conducting the job sourcing is that the HR needs more information about the potential candidates, while the reason for conducting the hiring recommendations is to present the best candidates from the list of interviewees to hire.

1. Background and Rationale:

The demand for high-tech skills continues to expand. As a result, there is frequent competition for this talent in an ever-increasing complex job market. As we continue to live in these digital passages, it is more important for job seekers to locate the right employer as the employer to locate the right employee [1][2].

This research is being conducted for a new business user who is seeking talent and is looking for employees that are interested in the job. At first glance, it shows jobs to job seekers according to their own criteria. The users may apply for a job position and if the employer is impressed, he may be invited for an interview. After an interview, the user can be hired or rejected, and the employer has the right to save the user profile. Relevant keywords play a fundamental role in job sourcing; this fact has been reinforced by the results of the job categorization [3].

Job listings are messy and often short, composed of figures or headlines that recipient, for several reasons, tend to only read. A job description that is easy and interesting attracts candidates who apply. If the potential employee's résumé is not appealing, the recruiter deletes it. Personnel officers filter the résumé and contact several selected candidates, simultaneously estimating the general impression a résumé has on paper. For the personnel officer, the task is slow and riddled with private mistakes. If several candidates have been allotted for initial interviews, the time to carry out the process is multiplied.

The personnel officer may have difficulties due to limitations of local area and travel expenses. Some of these time-consuming duties can be automated with the base of online staffing system services. Note, not all résumé information is reliable. Patentable participants may put fallacious information into résumé thinking that it may give a good impression. Otherwise, not-so-expectable applicants may put valuable information [4][5].

2. Research Objectives

The aim of this postgraduate study is the development of a job sourcing and hiring recommendation system using machine learning classification algorithms called multilayer perceptron (MLP) classifier. The study's main objective is to process an online job placement matching web application to predict where potential jobs and candidates might be paired with each other. By identifying the specific capabilities of both the job and the candidate side and comparing them within the available vacancy data, it not only targets the job-sourcing website to help job seekers or talent hunters, but also places them and their abilities in maximizing job satisfaction, leveraging the gaps and capabilities at both ends. This additional filtering of finding the best candidate will not only save time and employment costs in the hiring process, but is a step closer to assessing the personality and ability of applicants as part of a conceptual hiring process beyond the typical matrix we already know.

The hierarchical algorithm of job outsourcing and hiring, called the multilayer perceptron (MLP), was used in the hidden layer to capture and relate the capabilities, skills or characteristics of self-attributed job performance. It was tested to determine if performance appears to be impracticable, relevant in getting the job as an association in an attempt to capture the performance of each employee, changing the level of achievement, including the maturity of the participants and the level of experience in the job market.

3. Scope and Limitations

The job recommendation and recruitment system using a multi-layer classifier will focus on the needs of the Libyan labor market in different job sectors, with a focus on the Misurata Free Zone, where the Libyan labor market is currently facing a series of challenges related to the ability to hire well, and suffers from a serious loss of skills, and the digital gap. This research will follow a data- and research-driven approach to understand the needs and challenges imposed by the Libyan labor market, in addition to the specific soft and professional skills required by different companies and institutions in the Libyan country. This research will also explore candidate profiles in order to identify their educational, professional, technical, human and personal background, in addition to their skill approach to work and positions. Furthermore, this research will explore companies' preferences, identifying the required experience, technical skills, soft and human skills (professional skills). The results will support a multi-layer neural network constellation, in addition to supervised training with already well-classified inputs. Within the scope of this research, it may be useful to integrate the outputs of this research into the job search and recruitment process by recommending potential employees.

Literature Review

The proposed 'Job sourcing and hiring recommendation system utilizing a multilayer perceptron (MLP) classifier' aims to improve the efficiency of the overall job sourcing and recruitment processes. In this section, the literature on job sourcing and recruitment, recommendation systems, and machine learning classification models in general, and the multilayer perceptron classifier, in particular, is discussed.

As the proposed recommender system has two parts, the literature on both job sourcing and recruitment is reviewed. Job sourcing is the task of finding qualified job candidates. Attracting qualified and interested job candidates is essential for a recruiter or employer, and activities incorporating the marketing of job openings, the employer brand and culture, and engaging current employees are often associated with this activity. Job recommendations have not been extensively studied in the job sourcing literature. However, a few studies have combined concepts related to job sourcing and job recommendation. For example, using machine learning to find similar jobs having the same title and description, and matching explicit job requirements of a similar job to candidate profiles from resumes.

In contrast, recruitment refers to the overall process of attracting, selecting, and appointing suitable candidates for job openings. Literature in this domain is extensive and covers various aspects of the recruitment process, including the creation of realistic job overviews, the assessment of candidate affects, and the utility of social media. However, relatively little is known about the actual recruitment activities and how to approach such personalized recommendations systematically.

Machine learning has been widely used for classification and prediction tasks. An extension of logistic regression to be used in classification is the multilayer perceptron (MLP) classifier. The processed data is gradually reduced and fused multiple times through hidden layers, leading to phenotype-like structures.

1. Job Sourcing and Recruitment

Job sourcing is considered as a new industrial development in the process of demand and supply of jobs. The main concern in this commercial world is to bring the right candidate at the right time. Literature review of job sourcing states that both corporate and organization lay emphasis on more job sourcing practices than recruitment only. This is due to the fact that this process has many advantages of offering jobs to worthy candidates as well as ways of poaching and then helping it. Moreover, job sourcing gives information to recruits about meeting long and short-term objectives. The goal of HR policy is to achieve the objectives of hiring. The recruitment and employment process in an organization involve and increase the effectiveness of the existing sourcing processes [6][1].

released a survey report that 89 percent of hiring managers and 84 percent of job seekers believe. also evaluated major job sourcing dominated websites. Website differentials focus towards getting relevant "job postings" published on behalf of companies. Serving humans and getting right to specify the point of user need is the key role of job recommender systems. Job recommender systems are a derivative of traditional recommendation systems, where the item in the current domain is a job or a combination of job and company-based jobs respectively. Recommender systems in general are used by companies or groups of companies to help the user make better decisions from a carefully filtered subset of items. Applications, for strategic purposes, are published by connected users on job suggestions. It is designed to accept sets of jobs and a company to publish those jobs. There are two design principles mentioned in the system [7][8].

2. Recommendation Systems

As mentioned, the field of recommendation systems has proliferated over the past two decades. This section explores the different fields in which these systems have been applied, the algorithms that exist, and the types of recommendation systems available [9][10].

Recommendation systems have increasingly become a popular research field in the past twenty years. One key application of recommendation systems is e-commerce, where product recommendation systems have a considerable role to play. However, recommendation systems also receive substantial attention from other domains such as travel, music, news, books, and scholarly papers. Recommendation systems (RSs) are utilized to discover single users or groups of users who share similar interests or behavior. Moreover, they make predictions and generate personalized recommendations as to what opportunities or products the consumer will most likely be interested in [11][12].

Some of the existing recommendation algorithms include content-based filtering, collaborative filtering (CF), and hybrid recommendation systems which often combine content-based filtering and collaborative filtering. More recently, a novel approach such as the tag repository-based recommendation system was introduced and widely used by scholars to provide matching services for the rental housing market. Content-based filtering recommends the products or content based on user preferences. Collaborative filtering uses the past behavior and user behavior in order to recommend those products that users have not yet picked. Finally, CF calculates the matrix factorization techniques to learn user and product embeddings simultaneously. Although RS is applied to different fields such as e-commerce, travel, music, news, books, and scholarly papers, only a few articles have integrated a recommendation system and employment domain to address the needs of job seekers. The proposed work targets the global problem of linking candidates and employers based on hyper personalized job recommendations using a multilayer perceptron classifier for accurate matching skill gaps within a specific career stream [13][14].

3. Multilayer Perceptron Classifier

3.1. Theoretical Exploration

The multilayer perceptron (MLP) classifier has evolved in numerous forms. This particular classifier has proven to be very practical and efficient for many purposes, garnering substantial attention in the research world. It belongs to the class of numerous applications based on the latest feedforward (FF) neural networks used to solve and explore supervised problems. Many of its extended versions and modifications can be quite beneficial for multiple applications, such as occasional-delayed FF neural networks with recurrent connections and reduced-stability neural networks. The MLP is thought to be one of the best-documented neural networks, having collaborated with several researchers in different areas of computations, such as engineering, science, finance, remote sensing, industry, and optimization [15][16].

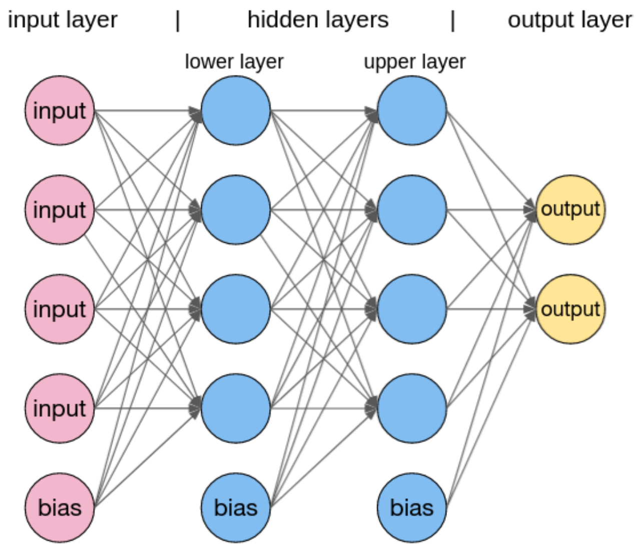

Figure 1: Structure of a Multilayer Perceptron (MLP).

3.2. Application Exploration

The experimental data used to demonstrate the efficiency of the mixture of experts along with the MLPs are given in various domains, such as mechanical, polymer production, and bacterial growth. Nevertheless, this classifier has some relevant features that make it suitable for certain applications and fields. The MLP is widely employed as an operator that maps a set of given input/output patterns via the application of the backpropagation algorithm to adjust weights so as to mimic the desired output and make useful predictions about new data. The strong points of the overall MLP architecture for interest classifier design can be reported as follows: the MLP can be trained directly from the available discrete input features and structure, and thus MLP inputs need not be firsthand submitted to domain discretization and feature extraction procedures. Reducing feature size leads to more efficient classification [15].

Methodology

There are several steps in the making of this research according to the flowchart shown in Figure 2. The process started with data collection and continued to data preprocessing, feature engineering, and model building. It continued with a series of evaluations, such as parameter evaluations and feature engineering. After obtaining a satisfactory model, operationalization was carried out.

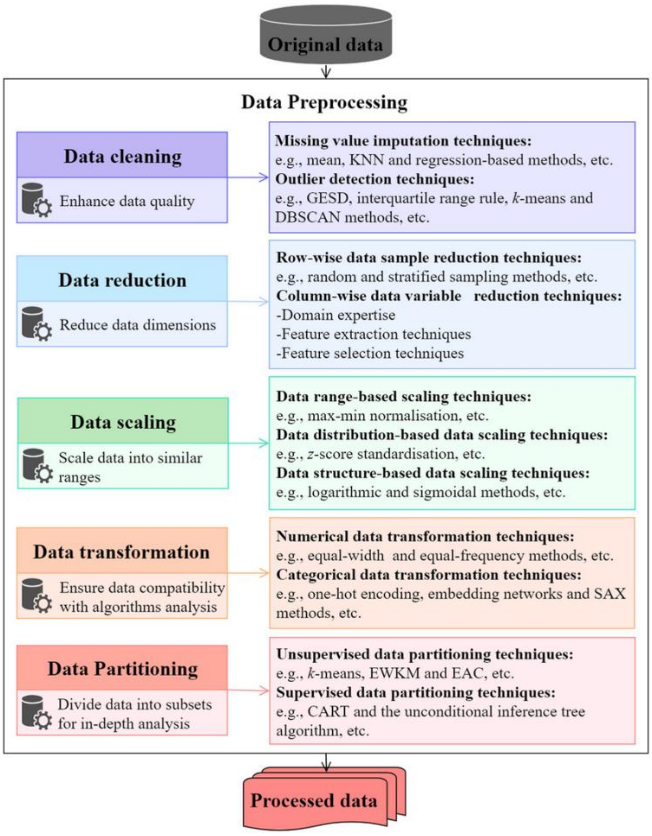

Figure 2: Steps in Data Preprocessing for Enhanced Data Quality and Analysis**.**

Data Collection: the data was collected from the Misurata Free Zone database, Human Resources Management Department, for the year 2023, and was cleaned and pre-processed. The data is in "csv" format and contains 745 rows representing employees, and 34 columns representing the most important job data. The data used from these columns is 7 characteristics or attributes, represented in the vector of features as Date of Birth, Learning Level, City, Country, Job, Salary, and Experience, this vector supported by another one contains the value of each feature as shown in table 1.

Table 1: The desired form of features vector and its value that processed from obtained data of HR office free area zone Misurata.

Vector feature	Date of Birth	Learning Level	City	Country	Job	Salary	Experience
Vector value							

In addition to several other columns, which can be included in other more extensive future studies, and the data in these columns varies from several types, such as string, integer, and float, as shown in Table 2.

Table 2: The desired form of features vector and its value that processed from obtained data of HR office free area zone Misurata.

n	**age,**	**ll,**	**city,**	**country,**	**job,**	**sa,**	**ex**	**Selected features**	**Vector frame values input**
1	24	2	1	1	20	2	7	age,ll,city,country,job,sa,ex	24,2,1,1,20,2,7
2	53	4	1	1	37	5	25	age,ll,city,country,job,sa,ex	53,4,1,1,37,5,25
3	32	2	1	1	21	3	3	age,ll,city,country,job,sa,ex	32,2,1,1,21,3,3
4	45	3	1	1	34	1	4	age,ll,city,country,job,sa,ex	45,3,1,1,34,1,4
5	26	5	1	1	33	2	17	age,ll,city,country,job,sa,ex	26,5,1,1,33,2,17
6	57	2	1	1	48	1	4	age,ll,city,country,job,sa,ex	57,2,1,1,48,1,4

7	29	2	1	1	33	5	17	age,ll,city,country,job,sa,ex	29,2,1,1,33,5,17
8	37	3	1	1	34	5	17	age,ll,city,country,job,sa,ex	37,3,1,1,34,5,17
9	53	4	1	1	14	5	24	age,ll,city,country,job,sa,ex	53,4,1,1,14,5,24
10	49	1	1	1	23	5	16	age,ll,city,country,job,sa,ex	49,1,1,1,23,5,16
11	34	2	1	1	13	3	5	age,ll,city,country,job,sa,ex	34,2,1,1,13,3,5
12	21	5	1	1	36	1	16	age,ll,city,country,job,sa,ex	21,5,1,1,36,1,16
13	37	3	1	1	13	4	24	age,ll,city,country,job,sa,ex	37,3,1,1,13,4,24

Data Preprocessing: the data is preprocessed and loaded into the database where we load and explore the data. In the data loading phase, we load the target dataset after ensuring that it is complete according to the proposed tool's working method, then, this is done by checking the columns to see if they contain empty values and replacing them if there are any with different data types that better fit the data. In contrast, in the data exploration phase, the following exploratory data analysis steps are performed, including distributing the data in each column, checking for skipped applicants and duplicate counts, checking which columns can be further processed, and possibly checking which columns are relevant to the proposed system's working method, as shown in table 3.

Table 3: Selected real data valid and complete, and eliminate the invalid or missing data records.

Number of collected and valid data		
745	record	
Number of collected and eliminated data		
1392	record	

Feature engineering: feature engineering is used to fit the business contexts. This involves transforming the eight defined and relevant columns based on the business or application context. Additionally, we add new columns (features) that support the business context. Furthermore, we select and prioritize features in the search. Feature selection is used to take relevant columns and filter out unimportant or irrelevant columns. This is based on a combination of field knowledge/experience and correlation matrix evaluation techniques or other machine learning libraries (e.g., frequent feature selection), and the prioritization of these features can be based on being dynamically selected by employers.

Model Building: we have enabled the "selection" feature for the hiring priority dynamically from the employer, by specifying the columns that represent the characteristics required for hiring, and 7 columns will be used as the main characteristics in hiring by the employer, and the available data has already been divided into 80 percent as a training set, and 50 percent as a test set, the (MLP) algorithm has been used as a classification and filtering model in the job recommendation and hiring system by leveraging a multi-layer classifier in this data to predict the job that will be selected.

One of the most powerful parts of machine learning is discovering how to learn from data and make accurate predictions.

1. Data Collection

The first step to complete the practical part of this research was to clean and collect the available data from the database in Misurata Free Zone. After the data was converted into a web form, the data was collected again directly from the application programming. The data consists of different job vacancies containing relevant content, such as job titles, job specifications, and job descriptions. A large number of job need data was collected within the zone, especially during the middle of 2023 until June 2024, which totaled 745 employment cases, based on specific specifications clearly defined by the Human Resources Office of the Free Zone, and compared to what the employees submitted in terms of CV, educational level, work experience, and other evaluation factors that help in nominating for the job.

The basic cleaning process includes removing incomplete records or data that is not relevant to the objectives of the proposed system. Since this process can significantly affect the final results of this study, the study was limited to only including the eight most effective data in employment that is mainly defined by the Free Zone. The dataset consists of text and classification attributes only. Each record has attributes dedicated to creating the system. Some cases of employees who were hired for other reasons not relevant to the study were excluded. A consistent vocabulary was introduced to make the classification more manageable and thus simplified. The text was then sorted by job type, as will be discussed in the next section. The job record resulting from the text cleaning is organized by the features and attributes identified during the cleaning process. The size of the lexicon and the number of examples varied accordingly. The dataset was then divided by type in line with the first stage.

Finally, the text data was cleaned to remove any unwanted parts of the description. Each description has a specific type according to the source and includes additional information, such as "Employer_Name" which contains the names of jobs that require special and more precise descriptions.

2. Data Preprocessing

The collected job information was created in the form of a data frame and stored as a comma-separated value file using the panda's data frame to csv function. The data was collected and cannot be directly ingested by the neural network because it is full of noise and unwanted data. Therefore, we start working on cleaning the collected data in this step.

The second step involved transforming the text and structured numeric columns into sets of features that can be easily ingested by the deep neural network. To identify the majority of information in the text data about the job, we ran our model using only the text data found in the previously mentioned lists in the Misurata Free Zone.

As permitted by our implementation, all text data is transformed by replacing all numbers, special characters, unaccented characters, spaces, and stop words in the job advertisements with some corresponding characters specified by the implementation. Then, the transformation to a generalized form transforms the words to their most general form or to their lexical form so that queries return all instances of the relevant words. We used transformation to a generalized form instead of branching in order to force search engines to return more documents specific to the job seeker's CV for matching purposes.

3. Feature Engineering

Although a large amount of missing data was found, most of the structures or features agreed to be included in the expert validation framework. The process of finding and generating relevant features with the desired output, while at the same time, eliminating those features that are irrelevant or filled with irrelevant information, is a very important aspect because irrelevant features may introduce noise into the model and may have a negative impact on the neural network training process. In fact, the output label is not affected by this set of features. For the result range and candidate workplace feature. In this model, the missing values in the data were also analyzed. Real-world applications sometimes work with missing data, and in this scenario, the missing values are valuable and potentially meaningful information. We do not apply any data imputation technique afterwards, because missing values indicate no value.

4. Model Building

This study built a job and recruitment recommendation system using a multi-layer classifier by following several procedures, from data collection, pre-processing, representation, transformation, model building, and model evaluation. This section will discuss the procedures required to build the model and the algorithms used to build the models. A multi-layer classifier will be used through a model to predict the interest of job seekers in the organization.

The model was built based on the algorithm and data generated from the pre-processed data transformation section. The model was built using Python tools and libraries, such as scikit-learn, which contains many tools for statistical modeling, such as classification, regression, clustering, etc. The multi-layer condition was used through scikit-learn to find out the accuracy based on the given random condition and parameter tuning. Moreover, the network architecture is shown in Figure 1, which contains four layers. The input layer consists of 8 features, and for the first two hidden layers (hidden layer 1 and hidden layer 2), each consists of 48 neurons, which are mitigated by the ReLU function. Finally, in the output layer, we used a softmax function with three neurons, aiming to capture the job seeker's interest y where 1 represents “not interested/neutral”, 2 means “interested”, and 3 means “very interested”. This is done by using a cross-entropy function that can determine how good or wrong the model is with respect to the given label or interest. Additionally, during the training phase, the momentum optimizer will update the network parameters to minimize the values of the loss function based on the gradients. Based on the data from the previous phase, we estimate hyperparameters such as learning rate and batch size. For the random case, we used a value of 78 as it provided the highest accuracy up to the fourth digit after the decimal point. After that, experiment sessions were conducted to optimize and fine-tune the learning rate of the hyperparameters and batch size, resulting in 0.01 and 50, respectively. Furthermore, the cross-entropy loss of Softmax measures the correctness of the outcome distribution between 0 and 1.

Experimental Design

The data used in this study are actual records of employees hired in the free zone during the period from mid-2023 to mid-2024 based on the data provided by the Human Resources Department of this organization. Each job offer was collected from a publicly available summary of a few months and stored as a single document with the date and time of publication. The job offers were collected from multiple categories representing the type of job, region, and employment level associated with each job. This research subsequently contains statistics on the data sizes in different categories. Data in groups is usually unbalanced by nature, as there are usually more qualified employees for a job than available vacancies.

1. Data Description

This section details our experimental design. We employed publicly available datasets from the recruitment websites to equate our job candidate sourcing and hiring system with existing market counterparts. In this subsection, we detail the number of participants, class attribute distribution, feature space dimension and type, and class label description.

In table 1 shows the detailed descriptions of the studied employment datasets. A number of employees were not provided due to insufficient data. The frequency rate represents two entities (candidates or job offer descriptions) with a similarity rate of 60% to 65% based on the available description and what was written in the CV received from the database. The job seeker’s attributes were identified from the employment dataset available in the database in the HR department, and these available attributes were tested and compared with the available job attributes in order to quickly reach the closest available job correlation based on the degree of convergence between the vectors used in the learning and comparison process. The proposed system updates dozens of new job offers regularly based on what is determined by the HR office. From there, the job seeker can view the vacancies according to the health determined by the Free Zone Employment Office, where job seekers can be allowed to filter while searching for available jobs and what is the required job description to get that job? The job rank was filtered, such as the employee being a fresh graduate or having experience for a certain period of time ... and so on. This allows data to be classified and tabulated based on several types of categorical variables that can be increased or decreased according to the circumstances of each organization in which the system is installed.

2. Model Evaluation Vector

This study aimed to address the limitations of job vacancy and employee recommendation models. We achieved this by developing a job sourcing and employment recommendation system using a multi-layered model (MLP). This section describes the specific measures and criteria that were used to evaluate the performance of the developed job sourcing and employment recommendation system.

The quantitative measure is the weight and value of each measure to produce the recommended job results for the job seeker. In general, the setting generates an F1 score for the first recommendation system with a match rate between the job candidate and the job description based on the job seeker’s resume and initial data that achieves 85% suitability for filling that job, a rate that can be dynamically controlled by the HR office, as the match rate in some jobs reaches 60% or more to fill that job.

These rates are very important and play a major role in sorting the available jobs and the suitable ones for filling them from the job seekers, and provide an almost immediate response at the time of searching. Accordingly, the accuracy of nomination and recommendation for employment screening and job suitability using the recommendation system reaches 0.77 and 0.82, respectively. These results help to illustrate the efficiency of the recommendation systems developed in this study and the success achieved by the system's results. The system requires only 0.3% recall to achieve an initial accuracy of more than 40%.

Results and Discussion

1. Performance Comparison

In this study, we compared our AI-based system with the actual or traditional reality of recruitment within the organization, and whether the recruitment process was carried out taking into account the CV and skills acquired by the employee and linking them to the job requirements mentioned in the job description or not? In order for this research not to go beyond the targeted scope according to the available time frame, the results of AI applications were not compared to each other, but rather a system developed using MultiLayer Perceptron (MLP) was adopted.

From the collected results as shown in table 4 show a comparison of the performance of the proposed system compared to the performance of the traditional system used in the recruitment process. Since we have only used seven features in the comparison and linking process between the two trends in the recruitment process, it appears that there is a large discrepancy between the two criteria used as a result of the loss of stability and consistency in the recruitment method followed according to the institution's policy in adopting the current method, which is the traditional one.

Table 4: Comparison between the two traditional recruitment methods currently in use and what is recommended by the proposed system.

Report Items	Current Traditional System	Automated Recommendation System
Number of job titles	48	48
Number of job needs	745	745
Number of available employees	745	334
Number of job compatibility	745	334
Number of job compatibility ratio	100%	64%
Number of jobs without employees	0	12
Number of employees without jobs	0	411

In many cases, we find that there is a large discrepancy in some jobs, as employees who are not suitable for performing those jobs were hired, with a compatibility rate of no more than 30% between what is stated in the job description. This matter led to an increase in the demand for training for those employees after their appointment, which made the allocated training budgets relatively large than expected, in an attempt to make up for the cognitive loss between the employee's skills that he possesses and what the job requires in terms of a description of him.

The system also shows some functional surplus, as sometimes some jobs appear for which the employees with their current data do not have what qualifies them to fill that job, and also on the other hand some employees appear without jobs to perform due to the lack of anything that matches their CV as well, and the most likely reason here may be due to a large extent to the number of features used in the vector on which the system was trained, as it is expected that if the number of features extracted from the data for the employee vector and the job vector were increased, there would be more reconciliation and accuracy in linking between them.

Among the interesting results is that there are job titles that the organization does not have employees who can fill them, and their number in this table is 12 job titles, in addition to the fact that there is a large number of employees who will be without a job, and the reason for this may be due to the small number of extracted characteristics included in the employee vector and the job vector.

From the same table, the traditional system shows us that things are normal and that the number of employees is ideal and that they occupy their jobs in proportion to their skills, and this is not true if we follow up on job performance reports that constantly complain about the existence of a defect in the performance of roles and jobs, as is the case with most Libyan institutions. This matter contributes to conveying a completely false image of the reality of the situation in terms of filling jobs and those who perform them, and it is one of the very important benefits that appeared during the implementation of this paper and which will open the doors to other subsequent studies at various university levels for the purpose of study and development, in various technical, administrative and other fields, leading to improving the employment system in an effective and practical manner.

2. Insights and Implications

Updating the machine learning model in the recruitment field is crucial in the changing market situation. The main contribution of this research to the literature is to present a job and recruitment recommendation system using an advanced MLP classifier for the Libyan labor market. The system is particularly interesting due to its great benefits in the Libyan market. However, its most significant limitation is the extent of the targeted accuracy when compared to the current recruitment method that relies on a mixture of social, demographic, cultural and geographical factors. Therefore, the current research enables a better interpretation and comprehensive understanding of the effects of the job and recruitment recommendation system using a new multi-layer classifier that can cover many other added features that may contribute to representing some other factors in the recruitment process. Moreover, the results of the study provide direct criticism of the current recruitment method prevailing in most Libyan institutions, which are mostly not based on the competency criterion. This leads to conducting several researches in a sequential and gradual manner that aims primarily to put the interest of the institutions above all other considerations. In addition to providing many suggestions for future studies that address adding other important additional features that contribute to a successful nomination and recruitment process. In addition, using feature extraction techniques from data on job candidates and the target job, we can systematically and reliably organize large amounts of data across a variety of sectors, organizations and departments.

Conclusion and Future Work

In this study, we presented a new job recommendation and recruitment system that includes a multi-layer classifier (MLP) within the Libyan market. We discussed our methodology consisting of the stages described above, starting from the process of obtaining data produced by traditional recruitment systems, pre-processing techniques, and evaluation metrics, with the activation of performance measurement. This paper contributes to helping human resources managers in institutions to determine the appropriate recruitment criteria and characteristics to search for employees according to what is specified by the job description within them. Instead of the prevailing traditional method, which many institutions still suffer from in terms of poor professional performance and critical shortcomings in performing the tasks expected of them. Several different methods can be used in the artificial intelligence environment, which is witnessing great development in this field, and used as recommendation systems.

The recommendation system proposed in this paper is one of the basic studies that recommend the necessity of using these platforms and programs by human resources managers or job seekers and monitoring their performance. The results demonstrated the strength of the approach and clarity with which artificial intelligence systems deal and their accuracy in describing data for both sides, the job seeker and the job, and excluding noise and deleting data that does not affect the hiring or nomination decision. It was recognized that there may be limitations in terms of data, its accuracy and completeness in the required form, which will greatly contribute to a highly accurate recommendation process that increases the likelihood of obtaining the best options in employees to fill a specific job, and the best job suitable for the job seeker. One of the most important recommendations that I conclude this paper with is to develop studies of the same type on this institution in an attempt to provide the best tool to provide a method that contributes to employment in a professional and effective manner. Which will certainly contribute to adding improvements in the characteristics of the data and controlling the features used as inputs to the machine learning system.

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