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Optimizing Human Resources' Selection Criteria and Classification Algorithms' Parameters in Greek Public Sector. A Meta-analysis

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ABSTRACT

Background- Successful human resources selection is considered the main step for every organization. Previous research has identified many challenges and innovations concerning the application of Artificial Intelligence/Machine Learning in Human Resources Management.
Purpose- The purpose of this study was to apply machine learning algorithms in order to match human qualifications to position's standards and finally to establish a rapid and more reliable procedure either for initial selection or for authority positions and additionally, to optimize the selection coefficients of properly chosen variables that describe qualifications and, in parallel, to optimize the best fit algorithms' parameters in order to achieve the greatest accuracy. Finally, this procedure may support automatic mobility.
Approach- This study was based on civil section data in order to match human qualifications to position's standards using machine learning algorithms and finally to establish a rapid and more reliable procedure mainly for initial selection but also for authority positions. Supervised machine learning algorithms were applied. Optimization of selection coefficients of properly chosen variables was performed, followed by algorithms' parameters optimization in order to achieve the greatest accuracy.
Findings- Metrics of algorithms were improved at about 3% for accuracy and F-Measure, especially for J48, which found to be the best algorithm for matching with accuracy close to 97% and pruning simplified the final tree and thus visual classification. This procedure may also be useful in order to support a system of automatic mobility (internal and external) of highly qualified executives

KEY WORDS

Personnel, Machine Learning, Supervised Methods

JEL Code: J24, M14

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1 INTRODUCTION

Previous research has identified many challenges and innovations concerning the application of Artificial Intelligence/Machine Learning (AI/ML) in Human Resources Management (Pampouktsi et al., 2021a,b,c; 2022). Gélinas et al. (2022) adopted the Human Resource Life Cycle to describe the varied nature of Human Resources functions, which is divided in six distinct functions: 1) Strategic Planning, 2) Recruitment and Deployment, 3) Training and Development, 4) Performance Management, 5) Compensation Management, and 6) Human Relations Management. According to Pampouktsi et al. (2021a,b,c; 2022), machine learning and artificial intelligence can be used to support staff recruitment and deployment. They can analyze large data sets to find suitable candidates, evaluate resumes, and help predict a candidate's suitability forparticular position. Human Resources Analytics (HRA) was first described in the 70's and 80'sbut with little academic attention (Marler & Boudreau, 2017).

However, professionals and consultants from around the world are urging their companies to invest more in sophisticated HR information systems to collect and analyze employee data. Nowadays 69% of organizations are building integrated systems to analyze employee-related data, 17% have already implemented real-time systems in new and innovative ways, and 84% of professionals consider HRA management as very important (Kaushal et al., 2023). HRA (data) is connected to Human Resource Management (HRM) because of its strategic ability as a main decision-making process on human capital (Minbaeva, 2018).

Modern techniques like machine learning and artificial intelligence can support recruitment in the following ways (Pampouktsi et al., 2021a,b,c; 2022; Ansari, 2023): 1. CV Analysis: Algorithms can analyze CVs automatically, extracting information related to education, work experience and skills. 2. Skills Assessment: Systems can analyze data to assess candidate skills, including the use of text analysis tools. 3. Interview Management: Support applications can assess candidate behavior and responses in interviews. 4. Provision of Eligibility: Algorithms can predict a candidate's suitability for a particular position based on historical data. The combination of these processes can help in the effective and efficient recruitment process. A Human Resources Information System includes hardware and software, but also includes human resources, big data, policies and proper procedures. Artificial intelligence (AI) is defined as the ability of systems to acquire and handle successfully external data, to learn from such data and resulting in achievement of certain goals or tasks (Kaplan and Haenlein, 2019).

AI and machine learning resume analysis techniques include: 1. Automatic Text Understanding (Known as NLP): Used to recognize and understand resume structure, extracting information such as education, work experience and skills. 2. Skills and Experience Categorization: Machine learning can identify and group skills and work experience, helping to assess candidate suitability. 3. Sentiment Analysis: Can be used to identify emotional elements in the text, offering additional insight into the candidate's personality. 4. Compatibility Assessment: Analyzes resume against job requirements, helping to pre-screen candidates. 5. Suggestions for Customization: Provides suggestions for improving the final results (resumes), based on the analyses performed. The above techniques allow the efficient processing of a large volume of resumes and the optimization of the candidate search and simultaneously the selection process (Gélinas et al., 2022).

HR metrics and organizational people-related data are an invaluable source of information from which to identify trends and patterns in order to make effective business decisions (Dulebohn and Johnson, 2013). But HR practitioners often lack the statistical and analytical know-how to fully harness the potential of these data. Predictive HR Analytics provides a clear, accessible framework for understanding and working with people analytics and advanced statistical techniques. Using the statistical package SPSS (with R syntax included), it takes readers step by step through worked examples, showing them how to carry out and interpret analyses of HR data in areas such as employee engagement, performance and turnover. The research results enable managers to develop effective evidence-based HR strategies, especially when analyzing big data (García-Arroyo and Osca-Segovia, 2019).

Decision rules based on decision trees have been used previously by many researchers (Pampouktsi et al., 2021a,b,c; 2022). Mainly algorithm CHAID, C4.5 was used to make predictions about work behavior including performance, as well as stay in the company, using as input data, available data at the selection stage, such as age, gender, marital status, educational background, work experience and recruitment channels. Analyzing such data, employees with higher qualifications, higher educational level, such as postgraduate or doctoral and employees with one or more years of work experience, always performed better than other employees Also, employees hired by internal channels is possible to perform better than those hired by external channels (Chien & Chen, 2008). The lack of a proper framework while recruiting new employees, lead Thakur et al. (2015) to propose machine learning techniques based on rules produced by the use of Random Forest algorithm classifications on three main results (Good, Average, Poor), by using candidates' skills as inputs to define the suitable results on performance as output. Data mining is usually defined as the process of discovering logical patterns in various data for classification purposes (Witten et al., 2011). According to the previous researchers, data mining process must involve special mechanisms and revealed patterns must lead to a final advantage. Data mining solves problems from a large number of data (big data). Machine learning allows the system to learn by example and can be useful in reducing labor efforts. Thus, machine learning assists organizations as decision support systems in order to achieve their final goals set by executive officers (Witten et al., 2011).

Optimization refers to a procedure for finding the input parameters or arguments to a function that result in the minimum or maximum output of the function. The most common type of optimization problems encountered in machine learning are continuous function optimization, where the input arguments to the function are real-valued numeric values, e.g. floating point values. The output from the function is also a real-valued evaluation of the input values. Generally, the more information that is available about the target function, the easier the function is to optimize in case of information that can effectively be used (Pampouktsi, 2022). Usually optimizing of algorithms involves the following stages:

Understand the problem >> Choose the right data structure. Be the first >>
Analyze the complexity >> Apply optimization techniques and algorithms >>
Test and debug >> Learn from external source >>Rest issues for optimal application

In Greek public sector's selection procedure, civil servants are selected via a time-consuming procedure, which usually lasts for two years. Specific criteria are used by ASEP (Greek Higher Council for Employees Selection) in order to select the proper personnel. The purpose of this study was to apply machine learning algorithms in order to match human qualifications to position's standards and finally to establish a rapid and more reliable procedure either for initial selection or for authority positions. The second thing in mind, is to optimize the selection coefficients of properly chosen variables that describe qualifications and, in parallel, to optimize the best fit algorithms' parameters in order to achieve the greatest accuracy. Also, this procedure may support automatic mobility (internal and external) of highly qualified executives (General Directors and Directors of Units).

In the present study we followed a 4-step optimization that includes: 1. Choosing the proper attributes, 2. The modification of the weights of the decision parameters, based on ASEP (Greek Civil Servant Selection Authority) main selection parameters, 3. The selection of the proper algorithm (best-fit on data), and 4. The modification of the internal algorithm's parameters, resulting in higher accuracy.

2 METHODOLOGY

Proper criteria were chosen carefully according to literature and are included in description for the job position qualifications in Table 1. We used selection criteria as performance factors, related to learning ability and subsequently to cognitive ability. A preliminary questionnaire was conducted to the employees of a public organization to ask their opinion about the relative weight of each criterion (Pampouktsi et al., 2021a; Pampouktsi, 2022). The final investigation covered personnel data from two public organizations in the Greek public sector (one main: 80% of data and one additional: 20% of data/records) and data of over a thousand employees were collected according to GDPR to form an Excel file (Microsoft Excel, 2007).

Table 1. Attributes/Features of Employees' Qualifications and Job Specification

Employees Qualifications & Job specification	
University degree level (number & what-text)	Appraisal mean score (degree in number)
Degree value (numeric)	Experience in years (numeric)
Master (MSc)-relevance (yes, no, number)	Experience in authority positions (numeric)
PhD-relevance (yes, no, number)	Interview value (degree in number)
National School for Public Administration (NSPA)	Group work and committees (yes, no, number)
Seminars (yes, no, number)	Research work (yes, no, number)
Languages (number and level)	Character remarks of employees' files (numeric)
Computer certification (yes, no)	Specialty based on academic title (text)

Source: Authors' own elaboration

The weight and contribution of each criterion was the relative mean of all the answers in the questionnaire. Coefficient of variation was between 10 and 20%, showing a different approach of the sample employees in different questions. A linear model was chosen to calculate the qualifications of each candidate.

$$Yn = \sum_{i=0}^{n} CiPi$$

Where:
C= the specific weight of each criterion
P= each criterion score
n= total criteria used (up to 15)

The criteria/qualifications finally selected are: University degree level, the degree value, Master (MSc), PhD, National School for Public Administration (NSPA), seminars, language (number and level), computer certification, appraisal, experience in years, authority position in years, interview score, group work and committees, research work and character remarks (on punctuality) in the personal employees' files (Pampouktsi et al., 2022; Pampouktsi, 2022).

Machine learning algorithms will learn from our training dataset (that contains predictors, used to determine the suitable class) to assign a class label to given examples in order to predict later the suitability of a candidate of a testing dataset (that will contain new data to be classified by the model that has been built, from our experiments). The final result is to classify candidates in three main classes of authority positions: General Director (GenDir), Director (Dir), Head of Department (HDep), as long as employees A (Low Level) & B (High level). Total methodology is summarized in the following graph (Figure 1).

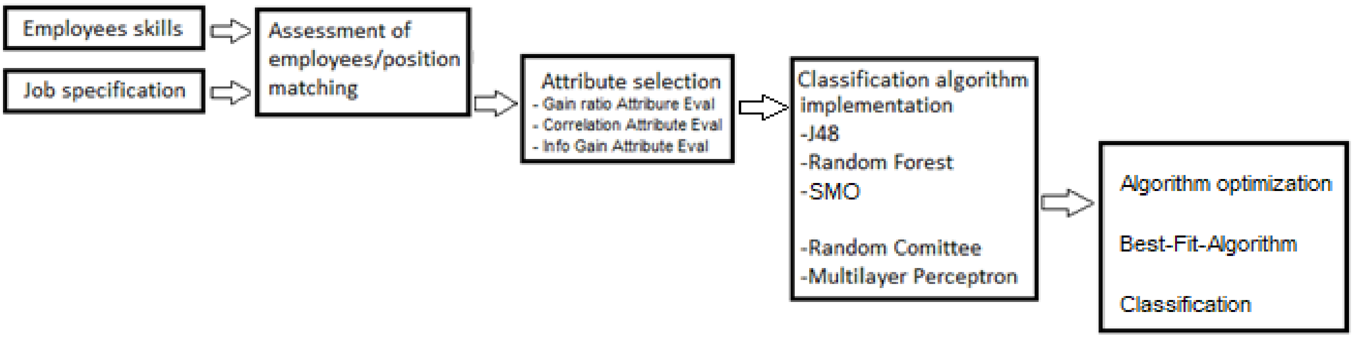

Fig 1. The Final Methodology Scheme

Source: Authors' own elaboration

A number of classification algorithms exist that are suitable for the purposes of experimentation on the theme of this work. As classification approaches for selection and positioning of HR prediction are limited in the literature, the choice of classification algorithms is a great and innovative extension. WEKA (Waikato Environment for Knowledge Analysis) software machine learning workbench was used for running our classification experiments. Six classification algorithms have been tested in this study, which are widely-known among the machine learning community, as follows (Pampouktsi et al. 2021a,b; 2022; Pampouktsi, 2022):

- J48, a decision tree induction algorithm (Witten et al., 2011).
- Random Forest, a meta-learning classification algorithm that runs iteratively (Breiman, 2001).
- Random Committee, a meta-learning algorithm using randomizable classifiers (Witten et al., 2011).
- Multilayer Perceptron, an artificial neural network (Rosenblatt, 1961).
- Naïve Bayes, is a simple classification algorithm.
- SMO is a standard machine assisted classification algorithm.

In order to select (reduce) the used features/attributes in our experiments, we took into account the evaluation results of three rankers, proposed by WEKA (using the default parameters). The rankers are presented as follows:

- Gain Ratio Attribute Eval, evaluates the worth of an attribute by measuring the gain ratio with respect to the class.

- Correlation Attribute Eval, evaluates the worth of an attribute by measuring the correlation (Pearson's) between it and the class.
- Info Gain Attribute Eval, evaluates the worth of an attribute by measuring the information gain with respect to the class.

The feature evaluation led to the selection of the following attributes: degree level, master degree, languages knowledge, experience years, experience years in authority positions, participation in working groups or committees, interview score, appraisal mean score, total score of employees, employees' suitability and present employees' position. The above attributes were used as the inputs in our classification experiment. Parameter adjustment followed and was applied in order to improve metrics and mainly accuracy and precision of prediction. The WEKA software (Waikato University, ver. 3) ran all six algorithms of our final dataset which exceeded 1000 cases (Pampouktsi et al. 2021a,b; 2022).

3 RESULTS

Application of Multilayer Perceptron and Random Committee algorithms on our dataset was proved improper and insufficient, because metrics were found too low to predict the four classes (Accuracy just over 50%, and the rest metrics near 0.6) and thus they will not be mentioned any further. Table 2, presents the actual weights of attributes used by ASEP (The Greek Selection Authority for personnel in the public sector) and our new proposal (standardized weights) for classification and selection of candidates in three main classes of authority: General Director, Director and Head of Department according to Sum of Coefficients. It is obvious that hard skills like Degree (including the final result in degree, Pampouktsi, 2022) MSc and PhD titles now are more important according the level of authority, even though differences are small. We took in account that selection and promotion procedure must be unified and number of degrees must have a limit of two (for basic title and post-graduated titles).

Table 2. Actual Weights of all attributes Used by ASEP (Left) and Our Proposal (Right) for Classification and Selection of Candidates in three Main Classes of Authority: General Director (GenDir), Director (Dir) and Head of Department (HDep), according to Sum of Coefficients (SumCoef)

Weight	Attribute	SumCoef	HDpt	Dir	GenDir	HDpt	Dir	GenDir
100	Degree	0.07874	0.027559	0.019685	0.019685	0.125	0.125	0.125
30	b-degree	0.023622	0.008268	0.005906	0.005906	0.0125	0.0125	0.0125
200	MSc	0.15748	0.055118	0.03937	0.03937	0.05	0.05	0.05
70	Mscnon	0.055118	0.019291	0.01378	0.01378	0.005	0.005	0.005
50	MScInt	0.03937	0.01378	0.009843	0.009843	0.05	0.05	0.05
250	NSPA	0.19685	0.068898	0.049213	0.049213	0.04	0.08	0.08
350	PhD	0.275591	0.096457	0.068898	0.068898	0.0625	0.1262	0.1262
100	Phdnon	0.07874	0.027559	0.019685	0.019685	0.005	0.01	0.01
100	Lang	0.07874	0.027559	0.019685	0.019685	0.0375	0.0563	0.0563
20	Seminar	0.015748	0.005512	0.003937	0.003937	0.1125	0.1125	0.1125
1270	SUM	1	0.35	0.25	0.25	0.5	0.6275	0.6275

Source: Authors' own elaboration

Table 3. Parameters for J48 (Old/optimized)

Binary Splits	False	False
Confidence Factor	0.25	0.1
Minimum instances per leaf	2	3 / 5
Reduced Error Pruning	False	False
Subtree Raising	True	True
Pruned	False	True
Laplace Smoothing	False	False
meta/CVParameter Selection	none	on
Confidence Interval		0.5
Minimum number of objects		1-10
Step		10
Attribute selection	No	Yes

Prunning

Source: Authors' own elaboration

Table 4. Parameters for Random Forest (Old/optimized)

Maximum Depth	Unlimited	Unlimited
Number of attributes	0	0
Number of trees to be generated	100	110
Seed	1	1
Attribute selection	No	Yes

Source: Authors' own elaboration

Table 5. Parameters for Naïve Bayes (Old/optimized)

Use kernel estimator	No	No
Use supervised discretization	No	No
Threshold optimization	No	No
Attribute selection	No	Yes

Source: Authors' own elaboration

Table 6. Parameters for SMO (Old/optimized)

Complexity parameter	1.0	1.0
Round-off error	1.0E-12	1.0E-12
Filter Type	Normalize training data	Normalize training data
Kernel	PolyKernel	PolyKernel
Random seed for cross validation	1	1
Tolerance parameter	0.001	0.001
Attribute selection	No	Yes

Source: Authors' own elaboration

Table 7. Optimization of Algorithm Parameters and Results on Max Precision, Max Recall, Mean Accuracy (%) and F-Measure

Main metrics:	Max Precision	Max Recall	Mean % Accuracy	F-Measure
J48				
Initial			93.12	0.935
Final	0.99	1.0	96.99	0.969
Random Forest				
Initial			94.02	0.949
Final	0.966	0.978	95.04	0.950
Naïve Bayes				
Initial				0.933
Final	0.982	1.0	93.16	0.933
SMO				
Initial				0.921
Final	0.935	0.978	02.47	0.921

Source: Authors' own elaboration

Tables 3 to 6 present the initial (old) parameters proposed by WEKA and the optimized parameters proposed by our research team in this study, for algorithms: J48, Random Forest, Naïve Bayes and SMO. In many cases the parameters were not changed because there was not any effect on final metrics.

Table 7 presents the results on Max Precision, Max Recall, Mean Accuracy (%) and F-Measure after performing optimization of algorithm parameters. As it is clearly seen values of J48 algorithm were improved. J48, also exhibited the highest values in all metrics. Especially for F-measure, J48 was the best performing algorithm (Fig. 2) exhibiting the highest value (0.969) followed by Random Forest (0.95).

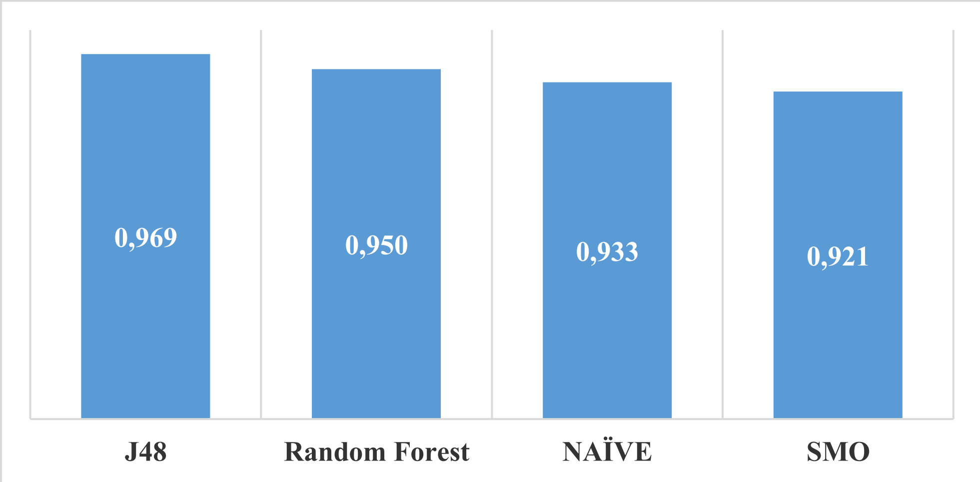

Fig 2. Algorithms' score for F-Measure metrics

Source: Authors' own elaboration

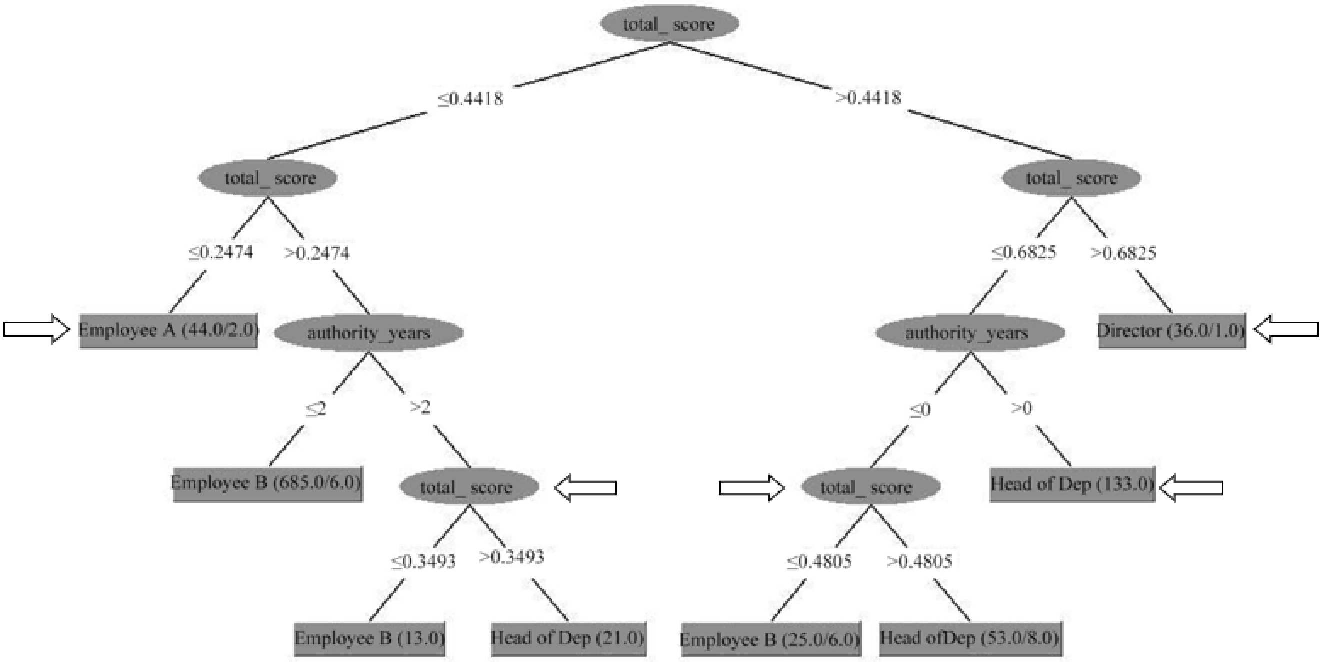

Fig 3. The Classification Tree for Best Performing (Best-Fit-To-Data) Algorithm J48 (With Main Points of Classification Depicted by Arrows)

Source: Authors' own elaboration

In Figure 3, is presented the classification tree for best performing (best-fit-to-data) algorithm J48. Using only two attributes: total score (as a result of all skills according to their weights) and years in previous authority positions, J48 managed to classify two kind of employees (A and B level), as well as Head of Departments (Dep) and Directors (from which will arise finally the General Directors).

4 DISCUSSION

In Greek public sector civil servants are selected by ASEP (Greek Higher Council for Employees Selection), but the selection criteria have been never optimized to fit in newer skills and newer technology. Our attributes are combination of two ASEP distinguished procedures. We unified these procedures and also improved weights of attributes (hard and soft skills), for both initial selection and promotion of employees. Many (decision) areas being the responsibility of managers (including HR managers), like employment relations, hiring, performance management, and remuneration are now replaced by algorithmic management (Sienkiewicz, 2021; Kim et al. 2024). Meijerink et al. (2021) also showed that algorithmic HR management is a useful tool for HR managers. Mann and O'Neil (2016) reported that newer technological advances allow organizations to utilize artificial intelligence by machine learning training and solve problems in increasingly complicated issues. Gal et al. (2020) stated that despite algorithmic management is often considered as supportive to evidence-based, bias-free, and objective decisions it might lead to ethical challenges that must be taken into account. Duggan et al. (2020) define algorithmic management (known as machine learning) as a system of control where self-learning algorithms are given the responsibility for making and executing decisions affecting labour (HR management), thereby limiting human involvement.

Chien and Chen (2008) using machine learning showed that employee selection may be depended mainly on experience years, but being independent from their academic level. Later research proved that employee selection must include other skills (attributes) like working resilience (Bakker and Demerouti, 2024). We showed that attribute selection is useful for better visualization and faster analysis during algorithm process and is the first step of optimization. Our results indicated that J48 (based on authority years and total score) gives more accurate classification and thus computes the proper work positions better, followed by Random Forest. The parameters of the rest algorithms were similar and also satisfactory (but with lower pairing accuracy). Accuracy and F-Measure were found 97%, indicating high level of classification and pairing. The main metric F-Measure provides an overall estimate of all models combining two other metrics, recall and accuracy, being the harmonic mean of recall and accuracy (Gaber et al., 2007). Varshney et al. (2014), during their research on IBM salesmen' data reported accuracy around 80% using HR information and job title (the main attributes). Azar et al. (2013) reported relatively low accuracy (between 60% and 80%) for HR selection, due to the performance of the chosen algorithm and the main parameters used: province of employment, education level, exam score, interview score and work experience.

Our approach showed that machine learning procedure may also be useful in order to support a system of automatic mobility (internal and external) of highly qualified executives. In total, optimization was successful in: 1. Choosing the proper attributes for faster procedure and better learning for matching purposes, 2. The modification of the weights of the decision parameters, based on ASEP's main selection parameters, 3. The selection of the proper algorithm (best-fit on data), and 4. The modification of the internal algorithm's parameters, resulting in higher accuracy. Development of a PC software for human resources management is the final stage of this procedure, according to the indicative software interface in Fig. 4 and scheme (in Python code) in Fig. 5. Also, new applications in neuroscience may use such kind of algorithms, recognizing the best people for a certain job, according to job analysis (De la Nuez et al., 2023; Konstantinidis et al., 2025). Another aspect is to improve the whole learning procedure by using a large number of possible candidates (Pampouktsi, 2022).

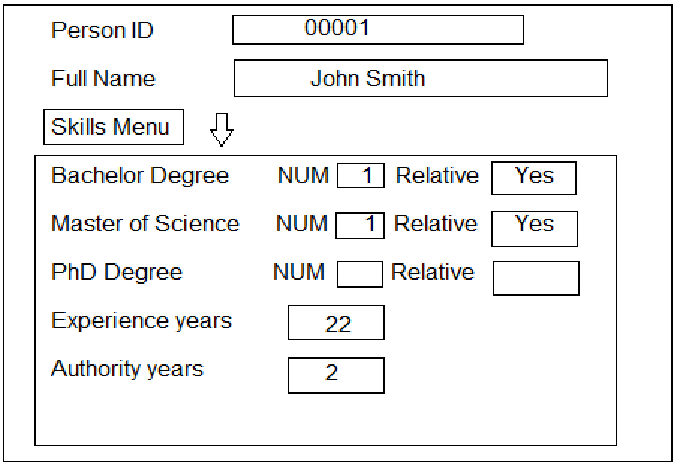

Fig 4. Indicative Software Interface

Source: Authors' own elaboration

```
# Human Resource Selection Script

class Candidate:
    def __init__(self, name, experience_years, education_level, skills):
        self.name = name
        self.experience_years = experience_years
        self.education_level = education_level
        self.skills = skills

    def __str__(self):
        return f"{self.name} | Experience: {self.experience_years} |
Education: {self.education_level} | Skills: {', '.join(self.skills)}"

def select_candidates(candidates, min_experience, required_education,
required_skills):
    selected = []
    for candidate in candidates:
        if candidate.experience_years < min_experience:
            continue
        if candidate.education_level not in required_education:
            continue
        if not all(skill in candidate.skills for skill in required_skills):
            continue
        selected.append(candidate)
    return selected

# Sample data
candidates = [
    Candidate("John Smith", 5, "Bachelor", ["Python", "Teamwork",
"Communication"]),
    Candidate("Anna Johnson", 2, "Master", ["Python", "Leadership"]),
    Candidate("Maria Davis", 4, "PhD", ["Python", "Machine Learning",
"Teamwork"]),
    Candidate("James Brown", 3, "Bachelor", ["Java", "Teamwork"]),
]
```


```
# Sample data
candidates = [
    Candidate("John Smith", 5, "Bachelor", ["Python", "Teamwork",
"Communication"]),
    Candidate("Anna Johnson", 2, "Master", ["Python", "Leadership"]),
    Candidate("Maria Davis", 4, "PhD", ["Python", "Machine Learning",
"Teamwork"]),
    Candidate("James Brown", 3, "Bachelor", ["Java", "Teamwork"]),
]
```


```
# Selection criteria
min_experience = 3
required_education = ["Bachelor", "Master", "PhD"]
required_skills = ["Python", "Teamwork"]

# Select suitable candidates
selected = select_candidates(candidates, min_experience,
required_education, required_skills)

# Output selected candidates
print("Selected Candidates:")
for c in selected:
    print(c)
```

Fig 5. Indicative Python Code for Developing Software, According to Certain Parameters (skills)

Source: Authors' own elaboration

5 CONCLUSIONS

Human resources optimization selection is essential for implementing ML and AI techniques.

In the level of optimizing coefficients of selection we proposed new values which proved to be more suitable for selecting the right people and fit to algorithmic performance and precision.

In the level of optimizing the algorithm parameters, after choosing the proper algorithm, we managed to increase accuracy and F-Measure up to 97% by handling parameters.

A rapid and automated system could be established in order to select the proper candidates for a certain position, especially in high executive positions. Also, this method may contribute to acceleration and automation of both internal and external mobility of high class executives, like General Directors or Directors of Units.

Future applications: 1) PC software development for human resources management (HRM) and 2) applications in neuroscience using proper algorithms.

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