ISSN: 2633-4828 Vol. 5 No.4, December, 2023

International Journal of Applied Engineering & Technology

PREDICTING JOB PERFORMANCE USING HYBRID DISCRIMINANT NEURAL NETWORKS: AN AI-DRIVEN APPROACH FOR RECRUITMENT

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ABSTRACT
Determining the best candidates for a certain job rapidly has been one of the most interesting subjects for recruiters and companies due to high costs and times that takes the process. The accuracy of the models, particularly, is heavily influenced by the discriminant variables that are chosen for predicting the candidates scores. This study aims to develop an performance job prediction systems based on hybrid neural network and particle swarm optimization which can improve recruitment screening by analyzing historical performances and conditions of employees. The system is built in four stages: data collection, data preprocessing, model building and optimization and finally model evaluation. Additionally, we highlight the significance of Particle Swarm Optimization (PSO) in enhancing the performance of the models created by presenting a training algorithm that uses PSO. We conduct a study to compare the performance of each hybrid model and summarize the results.

Keywords: Artificial Neural Network, Performance job prediction, Particle swarm optimization, Human talent, Variable selection.

INTRODUCTION
The field of human resources (HR) has undergone significant changes over the past few decades, and the rise of artificial intelligence (AI) has had a major impact on how HR functions are performed. From recruitment and employee evaluation to training and career development, the introduction of AI has led to a transformation in the way HR professionals perform their duties. This article will delve into the literature on the impact of AI in HR, analyzing the advantages and drawbacks of utilizing AI in this field, and examining the potential implications for HR professionals and organizations.

Another area where AI is having an impact is in employee evaluation and performance management. AI algorithms can analyze an employee's work history, skills, and achievements to predict their potential for growth and future success within the company. This can help HR professionals make informed decisions about employee development and career advancement. For example, in a study by Deloitte, 92\% of HR professionals reported that AI has improved the accuracy of performance evaluations (Deloitte, 2019).

Performance job prediction has become increasingly popular with the advent of machine learning algorithms such as decision trees, random forests, and support vector machines, which can handle vast quantities of data and discern intricate connections between various variables. These algorithms can be trained on historical performance data to make predictions about the future performance of new hires or current employees. In this study, we will focus on the application of the ANN on the candidate's performance prediction [1].

Designing an ANN with the appropriate parameters can result in a powerful tool. However, selecting the right topology parameters, including the number of input neurons, hidden layers, hidden neurons, and weight values, for a complex problem can pose an optimization challenge. The training process plays a crucial role in determining the ANN topology. Firstly, the most suitable architecture needs to be chosen by assessing the problem at hand, which entails identifying the number of input, hidden, and output neurons. Secondly, the ideal weight values that enable the ANN model to perform at its best must be identified. While the ANN architecture is typically determined by experience, some researchers have started utilizing metaheuristic algorithms such as Particle Swarm Optimization (PSO) to explore various possible architectures and select the optimal one based on a fitness criterion.

The initial stage consists of evaluating variable selection methods by comparing discriminant analysis and logistic regression approaches. Next, the second stage involves determining the best neural network structure by suggesting a training procedure that uses the PSO algorithm to identify the optimal topology.

EXISTING KNOWLEDGE SYNTHESIS

2.1 Performance job prediction

Performance job prediction is the process of using various data points, such as an employee's job performance, education and skill sets, personality traits, and even social media activity, to make predictions about an individual's potential for growth and success within a company [2]. This information can be used by organizations to make informed decisions about employee evaluation, promotion, and training. The goal of performance job prediction is to create a more productive and efficient workforce by identifying high-potential employees and providing them with the resources and support they need to succeed [3].

One of the key advantages of performance job prediction is its ability to provide actionable insights into employee performance. For example, organizations can use these predictions to identify high-performing employees and provide them with the resources and training they need to excel in their roles. In addition, predictions can help managers make informed decisions about promotions, pay increases, and other compensation-related matters.

The accuracy of performance job prediction models is dependent on the quality and quantity of data used in the model. Data sources may include things like past performance evaluations, training data, and demographic information. The use of multiple data sources allows organizations to build a more complete picture of an employee's potential, providing a more accurate prediction.

One of the most used approaches for performance job prediction is regression analysis. This method uses statistical methods to model the relationship between predictor variables (e.g., past performance, training data) and the dependent variable (future performance). Regression analysis can provide valuable insights into the impact of different factors on an employee's performance, allowing organizations to make informed decisions about staffing, development, and compensation.

An alternative method involves utilizing machine learning algorithms, such as decision trees, random forests, and gradient boosting, to construct models that predict employee performance by analyzing data. Machine learning algorithms are highly flexible and can handle large amounts of data, making them well-suited for performance job prediction. [4] [5] [6] [7]

2.2 Classification for Prediction

Intelligent decision-making can be achieved through methods like classification and prediction. Researchers in the fields of machine learning, pattern recognition, and statistics have proposed several techniques for classification and prediction. This study specifically concentrates on classification methods within the machine learning process. These data analysis methods are utilized to extract models that characterize essential data classes or predict upcoming data trends [8] .

The process of classification can be divided into two stages: first, in the learning phase, the classification algorithm examines the training data to create a classifier, which is a set of rules for classification. Second, in the classification phase, the classifier is tested using the test data to determine its accuracy. If the accuracy is acceptable, the model can be applied to new data to make predictions. Numerous techniques for classification exist, including Bayesian methods, decision trees, k-nearest-neighbor, neural networks, and many others.

This study will focus on the application of the artificial neural network and its parameter optimization [9].

2.3 Artificial Neural Network

Artificial neural networks, a subfield of artificial intelligence, takes inspiration from neurobiology and involves creating machines that can learn and complete specific tasks, such as prediction, classification, or grouping. These networks consist of interconnected neurons that learn from the data they are exposed to in order to identify linear and nonlinear patterns in complex data, resulting in reliable predictions for new scenarios [10]. The first neuron model, which was based on biological neurons, was introduced by McCulloch and Pitts in 1943 [11].

In 1943, McCulloch and Pitts introduced the first neuron model, which proved that formal neurons are capable of performing logical functions. Later, in 1949, psychologist Donald Hebb introduced parallel and connected neural network models and proposed many rules for updating weights, including the well-known Hebbian rule [12] . In 1958, psychologist Frank Rosenblatt developed the perceptron model, which could recognize simple forms and perform logical functions [13]. However, in 1969, Minsky and Papert [14] demonstrated the limitations of the perceptron, particularly for nonlinear problems. Interest in artificial neural networks was revived in the 1980s with the publication of Rumelhart's Back-Propagation algorithm [15], which optimizes multilayered neural network parameters based on error propagation towards the hidden layers.

Since then, the use and application of neural networks have expanded into various fields. In fact, studies have demonstrated that a Multilayer Perceptron network with a single hidden layer has the capability to estimate any function of Rn in Rm with high accuracy [15]. The structure and settings of a neural network are crucial factors that determine its effectiveness and efficiency. A widely used structure for neural networks is the multilayer network, which includes an input layer, one or more hidden layers, and an output layer. The hidden layer serves as the link between the input and output neurons, and the relationships between the layers are represented as weights of the connecting links. Generally, the layers in a neural network are linked together in a manner that allows data to flow solely in one direction - this is known as a feed-forward approach. There are no loops or cycles in the network. The data originates from the input layer, traverses through the hidden layers, and finally arrives at the output layer. An example of a neural network with a single hidden layer is shown in **Figure 1** to provide a better understanding of its functioning. In addition, previous research has demonstrated that this architecture is optimal for solving classification problems, which is the focus of this article [15].

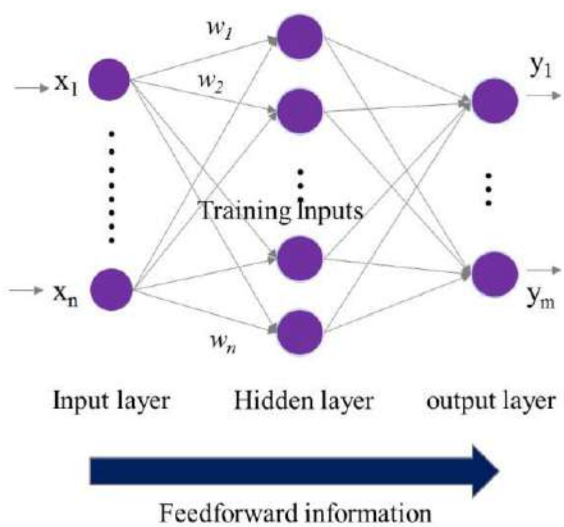

Figure 1: Artificial Neural Network

For a neural network with one hidden layer, each hidden neuron (labeled j = 1, ...,m) takes in an input that is the result of a weighted sum of the inputs to the entire network. This input is then processed by a transfer function f, which transforms the input signal into an output signal.

$$z_j = f\left(w_{j0} + \sum_{i=1}^{n} w_{ji} x_i\right)$$

The variables "n" and "m" represent the number of input and hidden neurons, respectively and w_ij is the weight from the i_th input neuron to the j_th hidden neuron, x_i is input variable i and w_j0 is a bias term.

The hidden neuron signals are subsequently transmitted to the output neurons through weighted connections, similar to the transmission between the input and hidden layers. Consequently, the output neurons obtain the sum of all weighted hidden neurons, which is then passed through a transfer function g, based on the required output range. The output y_o of the network's output neuron o is formulated as:

$$y_o = g\left(b_{z0} + \sum_{i=1}^{m} \beta_{zj}\left(f\left(w_{j0} + \sum_{i=1}^{n} w_{ji}x_i\right)\right)\right)$$

With b_zj is the weight from the J_TH hidden neuron to the O_th

output neuron and b_z0 is a bias term.

As previously stated, the appeal of using neural networks in various fields is its ability to approximate any linear or nonlinear function. However, the difficulty lies in determining the network's topology and weight values that best approach the desired function. This can be viewed as an optimization problem, where the goal is typically to minimize a cost function that is based on the sum of quadratic errors.

2.4 ANN Configuration Optimization

2.4.1 Input variables

Once the artificial neural network is established, the next step is to identify the necessary information required to build the network. This information is provided in the form of input variables that are used to evaluate the potential job performance of candidates. In order for the ANN to accurately classify new observations, the input variables must be carefully selected to ensure the classification model performs well. Therefore, it is crucial to identify the most relevant variables for classification purposes.

2.4.2 Architecture

As mentioned before, the structure of a neural network is an input layer, output layer, and one or more hidden layers. Hence, there are other crucial factors that have an impact on the performance of the artificial neural network, and they need to be considered while designing it. These factors comprise the number of neurons present in each layer and the number of hidden layers that are incorporated into the network. These parameters determine the behavior of the neural network and vary depending on the problem to be solved.

The study employs the neural network architecture with one hidden layer for classification purposes |15] , which is widely acknowledged as the optimal structure for such problems according to existing literature.

Selecting the appropriate number of neurons for the hidden layers of an artificial neural network can be a difficult task. Having too many neurons can lead to an increase in the number of computations required by the algorithm. Conversely, selecting too few nodes in the hidden layer can result in a reduction in the model's ability to learn [16] So, it is crucial to choose the optimal number of neurons to achieve the highest possible performance of the neural network.

2.4.3 Learning Algorithm

The process of finding the optimal weights and biases that maximize the performance of a neural network is known as learning algorithms, which consist of a set of rules. Various techniques have been used in literature to determine the best architectures and topology of weights and biases for the neural network, depending on the learning type. Learning algorithms can be categorized into two main types: supervised learning and unsupervised learning.

Supervised learning refers to the scenario where the dataset used for training is labeled, while unsupervised learning does not have labeled examples to train on or guide the learning process. In unsupervised learning, the weights of the neural network are adjusted based on specific criteria to identify patterns or regularities in the observations.

The main goal of this study is to improve the performance of an artificial neural network (ANN) in predicting job performance of a candidate. This is done using a supervised learning approach where the labels for the classes are already known and provided during the training phase. The learning algorithm adjusts the connection weights between inputs and targets to estimate their dependencies and minimize the error function, such as mean squared error.

The optimization techniques can be classified into two groups:

- The first set of techniques is based on the steepest descent method and includes methods like gradient descent, Levenberg Marquardt, Backpropagation, and their variations. However, some of these algorithms require a significant number of computational resources in terms of time and memory. Out of these, the Backpropagation algorithm is the most widely utilized, as it is a highly effective tool for determining the gradient in neural networks. However, it has its limitations, particularly with regards to the issue of getting stuck in local minima.
- The second group encompasses techniques that are inspired by the evolution of living species, such as genetic algorithms and swarm algorithms among others.

2.4.4 Transfer Function

Before training a neural network, one of the parameters that needs to be determined is the transfer function. The selection of an activation function is dependent on the specific use case. For instance, binary functions are well-suited for organization and distribution problems, whereas continuous and differentiable functions like linear, gradient, and sigmoid functions are utilized to approximate continuous functions. Notably, the sigmoid transfer function is commonly used because it combines nearly linear, curvilinear, and nearly constant behavior based on the input value [16]. The versatility of the sigmoid transfer function allows the artificial neural network to handle both linear and non-linear problems. The sigmoid function can be expressed as: $f(x) = \frac{1}{(1+\exp(-x))}$

The function being used as the transfer function in this study is bounded between zero and one, and it takes a real-valued input and produces an output within that range.

2.5 Particle Swarm Optimization (PSO)

Developed by a social psychologist J. Kennedy and an electrical engineer R. Eberhart in 1995 [17] and described as evolutionary computation method, PSO is one of the swarm intelligence algorithms that are inspired by the natural process of social behavior of organisms as birds flocking and used an technique of optimization in many research fields.

Animals that live in groups, such as swarms, need to travel long distances to migrate or find food. To do this efficiently, they optimize their movements in terms of time and energy spent, and work together to reach their goal. The PSO algorithm is based on this behavior and is used to find solutions for problems by optimizing a continuous function in a data space. Each member of the group, like the animals in the swarm, determines their movement based on their own experience and that of their peers, making the process complex and effective. [17]

The PSO algorithm is designed around a group of individuals called particles. These particles are initially placed randomly in the solution space and move around in search of the best solution to the problem. Each particle's position represents a potential solution to the challenge. The movement of each particle in the search space is governed by specific rules. Each particle has a memory that allows it to remember the best point it has encountered so far and tends to return to that point. Additionally, each particle is informed of the best point found by its neighbors and tends to move towards that point.

```
For each particle i in swarm S
Initialize particle i
End
While stopping condition is false do
For each particle i of the swarm do
Calculate the fitness f(xi(t));
If the fitness value>pbest
Set current value as the new pbest
End
End for
Choose the best fitness value of all the particles as gbest
For each particle i of the swarm do
Update particle velocity according equation (1)
Update particle position according equation (2)
End for
End while
```

Figure 2 PSO algorithm [18]

To use the PSO algorithm, we first define a search space that consists of particles, and a fitness function to optimize. Then, we initialize the system with a population of random solutions (particles) where each particle is assigned a position value representing a possible solution data, a velocity value indicating how much the data can be changed, and a personal best value (pBest) that indicates the best solution reached by the particle so far.

ANALYTICAL FRAMEWORK SETUP

In order to define the solutions, a research framework must first be developed. The research includes four major processes that are included in this research : data collection, preprocessing of data, variable selection, model building and the evaluation of the model.

The proposed framework is shown in the figure below.

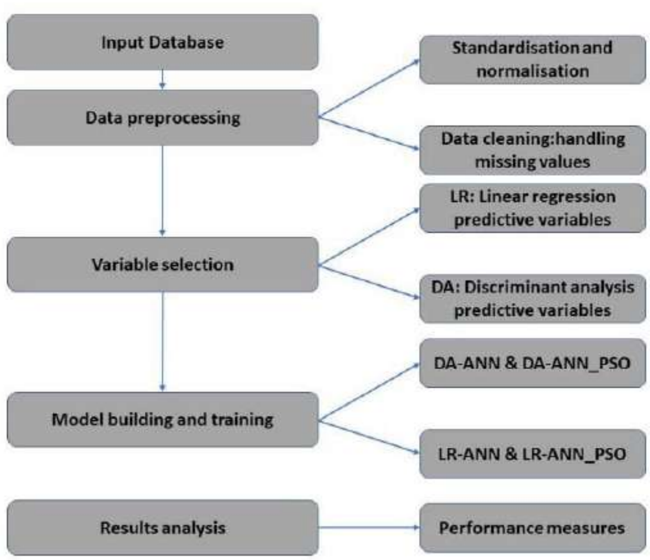

Figure 3. The proposed methodology

Data Collection: This stage involves gathering the necessary data for the study. Depending on the research topic, this data can be collected from various sources such as surveys, databases, experiments, or observations. The aim is to assemble a dataset that will serve as the foundation for the subsequent analyses.

Data Preprocessing: Once the data is collected, it often requires cleaning and formatting to ensure its quality and consistency. This involves tasks like dealing with missing values, handling outliers, and standardizing data formats. Preprocessing ensures that the data is in a suitable state for analysis.

Variable Selection: Variable selection involves identifying and choosing the most relevant and informative variables (features) from the dataset. Not all variables may contribute equally to the research objectives, and some may even introduce noise or redundancy. Selecting the right variables can enhance the accuracy and efficiency of subsequent analyses.

Model Building: This step entails constructing a model or algorithm that can extract meaningful insights from the data. Depending on the nature of the research, this could involve developing statistical models, machine learning algorithms, or other computational methods. The model should be designed to address the research objectives and make accurate predictions or classifications.

Model Evaluation: Once the model is built, it needs to be rigorously evaluated to determine its performance and effectiveness. This involves using appropriate evaluation metrics to assess how well the model performs on new, unseen data. If the model doesn't perform as expected, this stage might also involve fine-tuning or refining the model to improve its results.

The overall research framework outlines a systematic approach to conducting the study, ensuring that each stage is well-defined and contributes to achieving the research goals. This process provides structure and clarity to the research endeavor, guiding researchers in making informed decisions at each step and ultimately producing reliable and meaningful results.

3.1 Discriminant variables

In the pursuit of determining the most effective architecture for an Artificial Neural Network (ANN), the initial and pivotal stride involves the meticulous identification of input variables. These variables serve as the bedrock upon which mathematical models are constructed, functioning as the conduits through which predictions about job performance are formulated. However, the selection of these variables isn't a trivial matter—it's a decision that inherently carries a profound impact on the accuracy and reliability of the resultant model's outcomes.

The process of selecting these variables is anything but straightforward. It involves navigating the intricate landscape of potential factors that could influence job performance. The selection process necessitates a comprehensive understanding of the domain under investigation and an astute judgment to discern the variables that genuinely contribute significant insights.

Within the context of this study, the approach taken was to enlist 15 specific variables, as outlined in Table 2. These variables were chosen based on the data that was accessible and available for analysis. This pragmatic approach acknowledges the reality of working with the data at hand while ensuring that the selected variables possess a degree of relevance to the task at hand—forecasting job performance.

This selection process extends beyond mere availability ; it's a careful curation that seeks to strike a balance between data richness and the practicality of collection. The chosen variables constitute a blend of tangible attributes that can be quantified and statistically examined. They encapsulate dimensions that, when fused together, are anticipated to holistically encapsulate the essence of job performance prediction.

3.2 Data preprocessing

Studies and research have demonstrated that several artificial intelligence algorithms may exhibit poor performance due to the inferior quality of data and variables. Therefore, two critical steps are required to enhance the feasibility of the variables for constructing a predictive model : variable selection modeling for reducing dimensionality and data preprocessing. This process involves data preparation and normalization to accomplish reduction or classification tasks. The presence of outliers in the learning dataset can have an adverse impact on the performance of any model, including neural networks, and can be mitigated by normalizing variables.

Dataset

Table 1. Dataset description

Variables	Description	Value
ID	Employee's id	integer
Age	Employee's Age	Integer
Gender	Employee's gender	M or F
Marital status	Employee's status	S or M
Diploma	Employee Education Degree	Bachelor, High Diploma Master, Phd
Experience years	Employee year of experience	Integer
Salary	Employee salary	Integer
Communication Level	Employee level in communication	1 to 5
Motivation enthusiasm	Employee motivation for work	Yes or No
Language score	Employee language level	1 to 5
Specialization	Employee general Specialization	IT, Economics, HR, Network, business
Effectiveness in a remote environment	Employee ability in remote	Yes or No
Seniority	Employee seniority in the company	Junior, Senior, Manager
Physical abilities	Employee ability to work	Yes or No
Additional Certificate	Employee additional Certificate	Yes or No
Employee performance	Employee performance	BA, Good

3.3 Feature Selection Approaches

In classification studies, it is crucial to ascertain the variables of utmost importance for distinguishing between different categories. Obtaining reliable and meaningful data can be challenging, underscoring the need to pinpoint significant variables that can provide insights for predicting candidate performance. This effort aims to reduce the burden of data gathering and verification.

One approach to consider when establishing a prediction model involves reducing dimensionality. This not only decreases computational complexity but also enhances the performance of classification algorithms, including neural networks. Additionally, the task involves identifying a concise yet impactful set of variables capable of effectively distinguishing between candidates' performances. To accomplish this and to select the most suitable variable selection model for optimizing ANN performance, a dual classification technique is adopted, encompassing both statistical methods and artificial intelligence techniques.

In this study, the focus primarily centers on statistical methods. The chosen statistical methods, specifically Discriminant Analysis (DA) and logistic regression, are preferred due to their common usage in variable selection. Discriminant analysis, in particular, is renowned for deriving a linear combination of attributes that effectively separates multiple classes, resulting in dimensionality reduction prior to subsequent classification stages.

3.4 Architecture of ANN

This study utilizes an ANN model for predicting the job performance of candidates chosen at random. As previously stated, the architecture of the ANN is critical to its functionality and effectiveness. Therefore, this section focuses on determining the optimal topology that can differentiate between a good candidate and a poor one based on the selected variables.

To define the architecture of an ANN, certain parameters must be determined such as the number of input neurons, hidden layers, and hidden neurons. According to the literature, ANNs with one hidden layer are considered the optimal structure for classification problems. [15].

CROSS VALIDATION

Any biases or data-related shortcomings present in the dataset could potentially exert a significant influence on the determination of the artificial neural network and its associated parameters. In this context, the utilization of the cross-validation technique is aimed at mitigating such issues.

In this study, a 3-fold cross-validation methodology is employed to train and evaluate the hybrid ANN, with the primary goal of mitigating the occurrence of overfitting (**Overfitting** refers to an unfavorable behavior in machine learning wherein the model demonstrates accurate predictions on training data but falters when presented with new data.). \par

Concretely, the dataset is divided into three equal-sized subsets. This division entails training and evaluating the model on three separate occasions. The comprehensive accuracy of the model is gauged by calculating the mean of the three distinct accuracy metrics.

EFFECTIVENESS MEASUREMENT

To evaluate the performance of our model, we use this list of evaluation metrics : Overall accuracy : it is defined as the percentage of records well classified by the model. According to confusion matrix in Table 2 the formula is:

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Overall accuracy: it is defined as the percentage of records well classified by the model. According to confusion matrix in Table 2 the formula is:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{TP + TN + FP + FN}$$

Precision: it is defined as the ratio of the number of True Positive (correctly predicted cases) to the sum of the True Positive and the False Positive.

Recall: It is defined as the ratio of the True Positive (the number of correctly predicted cases) to the sum of the True Positive and the False Negative.

Specificity: The True Negative Rate is calculated as the number of True Negative.

Predicted		
Actual	**BA candidates**	**Good candidates**
BA candidates	True negative	False Positive
Good candidates	False Negative	True Positive

F-Measure: F-measures take the harmonic mean of the precision and Recall Performance measures. [19]

$$F\_Measure = \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recal}}$$

Data Driven Examination

As previously stated, the primary objective of this research is to use a hybrid neural network, primarily based on Particle Swarm Optimization, to predict the job performance of a random candidate. The first step in this process, as outlined in the research methodology, is to select the appropriate set of variables that can be utilized to construct our model to achieve high model performance**.**

6.1 Dataset and Attributes

The dataset used in this study issued from a Moroccan firm contains the most variables used on the manual recruitment process based on the survey made inside each department of this firm. Data collected contains more than 1000 individuals. A variable class is created with two values (BA if the candidate is below the average, Good is the candidate have a good qualification). The individuals was selected randomly from a different department: IT department, finance department, HR department, Data department...

Before using our Data as input for our model, a normalizing **function (3)** was applied to bound data values to -1 and +1 with X is the input matrix,

Y is the normalized matrix, x_min and x_max are respectively the maximal and the minimum values of a variable. [20]

$$Y = \frac{0.9-0.1}{\text{xmax} - \text{xmin}} X + \left(0{,}9 - \frac{0.9-0.1}{\text{xmax}-\text{xmin}} \text{xmax}\right)$$

6.2 Study results

The primary phase of data processing and administration encompasses addressing absent information, reducing variable count, and assessing the most pivotal ones an indispensable undertaking. Hence, the inception of constructing a job performance prediction model involves addressing the absent values. Given that our dataset harbors numerous gaps, we resort to KNN imputation as a remedy. Essentially, this technique involves imputing a fresh data point by identifying akin instances within the training dataset and computing an average based on the values of these proximate data points to substitute the absent value.[4] Next, it becomes imperative to assess the impact of individual variables on a candidate's job performance through the application of variable selection methodologies. We will juxtapose prevalent models like Discriminant Analysis and Logistic Regression, subsequently compiling the variables chosen by each model in a tabular format for concise representation.

Table 2. Variables selection models results

Variables selection techniques	Number of selected variables	Selected variables
Discriminant Analysis DA	8	Gender, Marital status, Seniority ,Salary, Communication level, Employee ethics Specialization, Physical abilities
Logistic Regression	12	Age, Gender, Marital status, Seniority, Salary, Diploma, Experience years; Language score, Communication score Specialization, Additional Certificate, Effectiveness in a remote environment

The table above shows that each model has chosen its own set of variables based on their ability to discriminate. We've separated the features sets into two groups; one with 8 variables chosen by DA and another with 12 variables chosen by LR.

The input layer of the ANN model will be based on the set of variables chosen by the variable selection models. Thus, two hybrid neural network models named MDA-ANN and LR-ANN are formed accordingly.

After defining the best variables that will have a big impact on our target variable, it's time now to define the best architecture for our model, for this reason we compare the following learning algorithm based on PSO, and the hybrid artificial neural network trained separately.

Now, we have reached the step of designing the topology of our hybrid neural network. for this step, we used the following parameters:

Table 3 PSO parameters

Parameters	Architecture Optimization	Weights Optimization
Swarm Size	20	20
Stop criteria	100 iterations	100 iterations
Search space limit	[3, 20]	[-2.0, 2.0]
Inertia factors	$(wn = 0.9 * wn-1)$ $w0 = 0.8$	$(wn = 0.9*wn-1)$ $w0 = 0.8$

The PSO algorithm was used to train the hybrid ANN mentioned earlier, and the architecture that produced the highest performance accuracy was determined to be 12-18-1 (12 input neurons, 18 hidden neurons, and one output neuron). The 12 input neurons in this case correspond to the number of variables selected by the logistic regression algorithm, indicating that these variables have strong discriminatory power when it comes to predicting candidate performance.

We can see also that the application of our Hybrid artificial neural network separately decreases the performance of the two models DA-ANN and LR-ANN compared to its application with the PSO.

The results will be presented and analyzed in the **table 4.**

Note that the evaluation of the evaluation metrics alone does not give a good judgment on the quality of the prediction and the classification. In this performance comparison, we will also focus on the performance attribute to each class which gives important information about a model specially to select the variables which discriminate the performance of the candidates.

This appears clearly in the application of the hybrid algorithm: DA-ANN and DA-ANN_PSO. In fact, even with its big accuracy, they present the less rate of good classification of good candidates (47.5%, 48.3%) contrary to below average candidates (between 83.3% and 83.4%). The LR-ANN_PSO model gives the best classification rate. These findings suggest that the variables identified by the LR statistical models provide more insights into a candidate's job performance.

Table 4 Classification results of Hybrid Neural network

Model	LR-ANN	LR-ANN-PSO	DA-ANN	DA-ANN-PSO
Accuracy	72,5%	75,0%	65,0%	65,4%
Precision	70,1%	72,9%	47,5%	48,3%
Sensitivity	73,1%	75,6%	74,9%	75,1%
Specificity	72,0%	74,5%	60,3%	60,6%
F-measure	71,6%	74,2%	58,1%	58,8%
BA	74,9%	77,0%	83,4%	83,3%
Good	70,1%	72,9%	47,5%	48,3%

CONCLUSION

In this study, a hybrid discriminant neural network is devised by combining particle swarm optimization and statistical variable selection techniques. The developed models incorporate variables commonly used in manual performance job prediction. To address missing values, the K-nearest neighbor algorithm is employed.

The proposed variable selection methodology assesses the impact of different models by comparing Multivariate Discriminant Analysis and Logistic Regression. The results highlight the exceptional suitability of logistic regression as a variable selection model for enhancing the performance of Artificial Neural Networks (ANN) in distinguishing candidates' job performance. Utilizing variables chosen through this technique yields optimal predictive performance for candidate job performance.

The hybrid neural network, when paired with the PSO learning algorithm, yields superior optimization results and efficient identification of local minima. This combination significantly enhances the accuracy of job performance prediction. Consequently, this model holds considerable promise for recruiters in evaluating and forecasting the performance of prospective candidates.

REFERENCES

[1] A. Mohan and S. Suresh, "Support Vector Machines for Job Performance Prediction : A Comparative Study," 2021.

[2] J. Zhang and Y. Liu, "The Use of Big Data Analytics in Job Performance Prediction : A Literature Review," 2020.

[3] S. Kaur and M. Singh., "A Review of Machine Learning Algorithms for Job Performance Prediction," 2019.

[4] "machinelearningmastery.com/knnimputation- for-missing-values-in-machinelearning/ : :text=One%20 popular%20technique%20 for%20imputation,to%20fill%20in%20the%20value.,"

[5] S. Krishnan, "Predictive employee analytics : A new frontier in HR. Forbes.," 2020.

[6] R. C. J. Stone, D. L., "Employee analytics : How to improve business performance by measuring and managing your workforce. John Wiley Sons.," 2015.

[7] Z. Y. Wang, H., "A review of predictive analytics in human resources management.," 2018.

[8] J. Han and M. Kamber, "Data Mining : Concepts and Techniques," 2006.

[9] G. K. F. Tso and K. K. W. Yau, ""Predicting electricity energy consumption : A comparison of regression analysis, decision tree and neural networks"," 2007.

[10] D. W. L. Liang, "An application of pattern recognition on scoring chinese corporations financial conditions based on backpropagation neural network,," , 2005.

[11] W. M. et W. Pitts, "A Logical Calculus of the Ideas Immanent in Nervous Activity,"

[12] E. D. et P. Naïm, "Des réseaux de Neurones," 1992.

[13] F. Rosenblatt, "The Perceptron : a probabilistic model for information storage and organization in the brain, Psychological Review," 1958.

[14] J. L. M. e. C. P. R. G. D. E. Rumelhart, "Parallel distributed processing : explorations in the microstructure of cognition, vol. 1 : foundations," 1986.

[15] J. H. M. et Y.-C. Lee, "Bankruptcy prediction using support vector machine," 2005.

[16] D. T. L. et C. D. Laros, "Discovering knowledge in data : an introduction to data mining," 2014.

[17] R. C. a. K. J. Eberhart, “A new optimizer using particle swarm theory,” 1995.

[18] “arxiv.org,”

[19] “hal.archives-ouvertes.fr,”

[20] “cyberleninka.org,”