Electrical and Automation Engineering
Vol: 4(1), 2025
REST Publisher; ISBN: 978-81-956353-5-1
Website: http://restpublisher.com/book-series/eae/
DOI: https://doi.org/10.46632/eae/4/1/2

A Machine Learning Approach Based On Employee Classification Using the Weighted Composite Method

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Abstract: *Machine learning (ML), a subset of artificial intelligence, centers on developing algorithms and statistical models that allow computers to carry out tasks independently, without the need for explicit programming. This paper presents a comprehensive overview of key ML approaches, including supervised, unsupervised, and reinforcement learning. It also delves into the mathematical principles that underpin these methods, such as optimization techniques and probability theory. Additionally, the study reviews widely used algorithms like decision trees, support vector machines, neural networks, and various clustering techniques... Are examined to highlight the transformative impact of ML. Finally, the paper addresses current challenges in the field, including data quality, interpretability, and ethical concerns, and suggests directions for future research.*

Key Words*:* *Machine Learning, Artificial Intelligence, Supervised Learning, Unsupervised Learning, Statistical Modeling, Neural Networks, Decision Trees, Support Vector Machines Clustering Algorithms*

1. INTRODUCTION

While previous studies have applied machine learning to predict employee churn (EC), they often overlook the fact that not all employees hold the same level of importance to an organization. As a result, they fail to classify employees based on their value and achievements. This limitation is critical, as factors such as the number of projects completed, job engagement, job satisfaction, and tenure can significantly influence an employee's classification. Moreover, the drivers of EC may vary depending on the employee type. Therefore, implementing a one-size-fits-all retention strategy may not be effective. To address this gap, the current study first classifies employees using applies machine learning for EC analysis. . [1] With Focus Company experiencing rapid business growth and a steady rise in customer base and market demand, the existing plant is struggling to keep up with current capacity requirements. To address this issue and prepare for future demand, the management has decided to establish a new plant to offload some of the production burden from the current facility. [2] A decision tree is a useful tool for identifying trends and patterns within a dataset. Each branch of the tree corresponds to a specific decision rule. To enhance the relevance of the tree, algorithms are used to effectively prune unnecessary branches, resulting in a more concise and meaningful set of decision rules. These rules are then integrated into models that can predict outcomes for new data inputs. [3] While numerous comparative studies have been conducted on default classification models, their conclusions often vary. A model that outperforms others on a specific dataset and set of evaluation metrics may not perform as well in different contexts. For instance, Fernandez and Omega found that neural networks generally yielded superior results compared to tree models were more effective than neural networks for predicting mortgage defaults [4] As evident from the preceding analysis, few studies have thoroughly evaluated. Hence, exploring the impact of imbalance-on financial risk prediction and comparing their effectiveness presents an important area of interest. [5] However, with the growing volume of data within organizations, it has become essential to adopt tools that support maintenance management and provide real-time information to aid in decision-making. [6] Combined, these functions offer effective tools to guide and enhance managerial decision-making. While inventory management has not been a primary focus within the wide spectrum of data mining applications potential of integrating to develop more efficient and adaptable inventory classification models.[7] To address this, landslide susceptibility (LS) modeling relies on a variety of conditional factors. These include variables derived from digital elevation models, such as elevation, slope, annual precipitation, and like and proximity; geological elements such as distance to rock formations and fault lines; as well as soil characteristics and land use or landscape features. Additionally, a crucial dataset for both training and validating the models is the landslide inventory map, which documents past landslide occurrences.[8]The goal of this research is to expand the outlined task into a more structured and broadly applicable methodology. This is detailed in the section through a process pipeline designed to optimize and assess. Subsequently, the proposed algorithm is adapted for the specific task of torn image classification. In this context, multi-class linearization techniques and feature selection methods are various machine learning classifiers. [9] This paper selects and assesses several key classification algorithms and. Brief overviews of the significant classifiers and performance metrics are provided below. Supervised learning techniques are commonly employed in systems for credit card fraud detection, financial risk assessment, and healthcare fraud. [10] To address the challenges mentioned, this study introduces a two-stage approach. In the first stage, a soft computing technique is utilized to extract approximate knowledge. In the second stage, a non-additive fuzzy aggregator is employed to combine key attributes, creating a. The anticipated contributions of the proposed approach include: extracting key attributes and approximate financial knowledge (decision rules) for detailed analysis, refining this knowledge by identifying cause-and-effect relationships between key attributes, assessing the synergy between dimensions and criteria to improve financial performance predictions, and supporting systematic planning for the enhancement of insurance companies.[11] A non-essential objective function can also be referred to as redundant, as removing it does not affect the set of all efficient solutions. The literature has defined various groups of non-essential objectives, along with the concept of a minimum-scale objective set. By applying the method of eliminating non-essential objectives, as outlined in the aforementioned literature, computing time can be reduced when determining the efficient set or compromise solution, as it involves working with a smaller set of objectives.[12] In their No Free Lunch Theorem, Wilbert and Macready emphasized that no single algorithm consistently delivers the best performance across all metrics within a given problem domain. As a result, ranking classification algorithms is more beneficial than simply selecting the best-performing one for a specific task. Additionally, user preferences are crucial in the evaluation and selection of algorithms. One approach to incorporate user input in algorithm selection is by allowing them to prioritize performance metrics. Can address both of these needs, they hold significant potential for ranking classification algorithms. [13] Personality plays a crucial role in how individuals respond to work-related stress. It significantly influences behavior and attitudes both in daily life and in the workplace. In this study, personality traits are integrated as a key element in developing a human resource personality model for departments. this compatibility of current employees or new job applicants with specific job positions. [14] While numerous studies have assessed the quality of clustering methods, few have explored this topic. This paper presents an experimental study that evaluates six clustering algorithms, eleven selection criteria,, and three real-world financial datasets to validate the proposed approach. [15] May yield different or conflicting results. This paper aims to highlight to address these discrepancies or contradictions in performance. Furthermore, resolving such differences or conflicts remains a critical issue that has not been thoroughly examined. Additionally, evaluating clustering algorithms typically involves multiple criteria, which must be treated as a complex problem. To address this, the paper proposes a model called "decision support for the evaluation of clustering algorithms," designed to assess and measure while correcting any inconsistencies or contradictions that arise during the evaluation process.[16] In e-learning website design, developers should frequently incorporate graphical animations and audiovisual components. These elements help to break up dense text, maintain user engagement, and enhance the visualization of concise content. More organizations are turning to e-learning solutions over traditional trainers, as they offer several advantages, including cost-effectiveness, improved content delivery, and a reduction in the need for in-person training sessions.[17] It involves multiple stages and is applied to problem-solving across various domains. The initial stage focuses on assigning relative importance values, known as "weights," to both decision alternatives and criteria. These weights represent the significance and priority of each criterion within the set. Due to its simplicity and reliability, the first stage is commonly used across different methods. The importance values derived from this stage are then utilized either in the second stage of AHP or in other related methods to assess the suitability of the alternatives. [18] The primary goal of this paper is to utilize a approach to rank key classifiers that are appropriate for financial risk prediction. Additionally, the paper aims to assess the performance of these classification algorithms and compare the proposed method with other leading. [19] Traditional research in social sciences has primarily utilized statistical methods to explore. Techniques principal component analysis and legit have been extensively employed in earlier studies. Building on Altman's foundational work, discriminant analysis became a common tool for examining institutional financial failure. Subsequently, legit-regression-based scoring models gained recognition in, west applied legit regression alongside factor analysis to evaluate bank performance. Other methods like probity analysis and PCA have also been used individually or in combination to forecast bank performance. A comprehensive review of these approaches was provided by Kumar and Ravi. [20]

2. MATERIAL METHOD

Machine learning (ML) has become a vital asset in the field of materials science, significantly enhancing the speed of discovering, designing, and analyzing new materials. By leveraging data-driven algorithms, ML identifies patterns and correlations within experimental and simulation data to forecast material properties, behavior, and performance under varying conditions. Popular ML techniques include decision and ensemble approaches like random forests and gradient boosting. In materials research, supervised learning is frequently used to predict material characteristics such as mechanical strength, electrical conductivity, and thermal resistance, using labeled data to uncover underlying patterns or group similar materials based on attributes like composition or functionality. Reinforcement learning is also gaining traction, particularly in autonomous experimentation and the optimization of material properties. The process of feature selection and engineering is crucial for boosting predictive accuracy, often involving input features such as atomic radius, electronegativity, and crystal structure. Ultimately, ML enables researchers to make data-informed decisions, cut development costs, and accelerate the pace of innovation in material science.

Weight Sum Method: The process is fully automated to ensure user privacy, and the resulting data is presented in a highly aggregated form. For each restaurant, FINDER estimates the number of visitors during a specific time frame. It then applies the Weighted Sum Model (WSM) to determine the percentage related to foodborne illness after their visit. [1] The company has made significant investments in deploying numerous sensors within the WSM framework. This supports the development of an Iota-based system capable of monitoring and control using computational intelligence. As a result, tasks like monitoring and fault detection, which was previously performed manually, can be carried out with much greater accuracy and near real-time responsiveness, making the process both feasible and intelligent. [2] The findings demonstrate that the proposed optimization algorithm can effectively generate a repository of diverse optimal solutions. Notably, a thorough comparison is presented between the initial Pareto solution and the outcome obtained through the Weighted Sum Model (WSM), which introduces constraints and helps minimize uncertainties typically associated with multi-objective optimization. [3] Online social media platforms now integrate GPS location data, which can be utilized in future, research to enhance WSM-based monitoring systems. Much of the structured content on these platforms can be systematically analyzed and categorized using terms relevant to epidemiology. In addition, this data enables the detection and prediction of disease outbreaks and their geographic spread. [4] To generate a solution within a single convex region of the Pareto front. To address varying front shapes, one researcher introduced a nonlinear secularization approach known as secularization, which can identify Pareto-optimal solutions regardless of the front's geometry. Common secularization techniques include and the goal programming method, met heuristic algorithms often yield superior results for multi-objective optimization (MOO) problems, as they are less influenced by the shape of the Pareto front and are capable of handling concave or discontinuous fronts. Examples of such algorithms include multi-objective evolutionary algorithms and optimization techniques. [5] This study highlights the significance of semi-quantitative estimation. Experiments using ROSIS data were conducted with, and as wavelet kernel functions for the Support Vector the findings demonstrate that the Radial Basis Function (RBF. Among the methods tested, delivers the best performance, showing the highest effectiveness in vanishing transformed scaling functions. [6] The target was and directed to the sample through the used for inducing tissue auto luminescence. pinpointed by an Specifically, the center of each measurement was determined by converting the image to color space, adjusting the hue and saturation channels, and applying a series of morphological operations as previously outlined. To account for tissue movement during data acquisition, volume-matching-based motion tracking was used retrospectively, ensuring that all measurement points remained fixed relative to sequence, which served as the ground truth for the sample. [7] The goal of feature selection is to reduce the, making computation more manageable, while preserving the most relevant features that capture changes in expression. Features are chosen in a fixed step known as Gabor Jet. Little word and Ad boost were applied to iteratively select the features. we introduce a for selecting the most appropriate features for facial expression recognition. And the overall class variance across all training samples. [8] The subsequent sections detail the dataset employed in this research, along with an explanation of the proposed machine learning framework and the metrics used for performance evaluation. This is followed by a presentation of the results and an in-depth assessment of effectiveness. The offer an of the findings and conclude the study with summary and closing remark [9]. Because of East Antarctica's unique geographic position, the majority of temperature forecasting studies and sensor data processing techniques have been concentrated in West Antarctica [10].

4. ANALYSIS AND DISSUCTION

TABLE 1. Data set

Employee ID	Satisfaction Level (A1)	Last evaluation rating (A2)	Projects worked (A3)	Average monthly hours (A4)
E1	0.000	0.000	0.000	0.000
E2	0.000	0.000	0.000	0.000
E3	0.000	0.000	0.000	0.000

The dataset contains employee-specific data with the following attributes: Employee ID: A unique identifier for each employee. Satisfaction Level (A1): Indicates the level of job satisfaction reported by the employee. Last Appraisal Rating (A2): Indicates the most recent performance appraisal score. Projects Worked (A3 the employee was involved the employee worked each month. For entries E1, E2, and E3, all recorded values are zeros, indicating missing data, default entries, or inactive records.

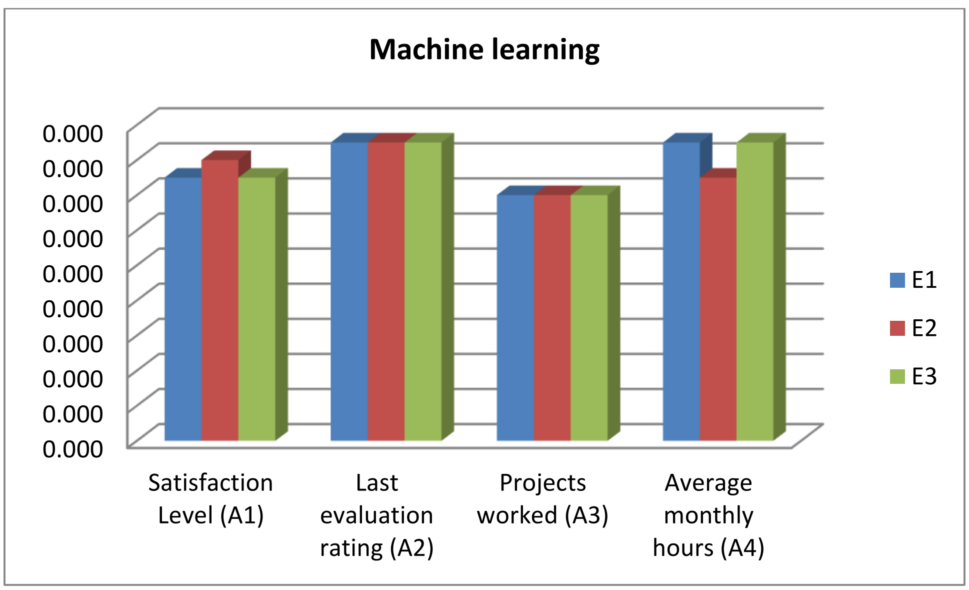

FIGURE 1. Machine learning

The chart illustrates a comparative view of data contributions from three employees (E1, E2, and E3) across a specific dataset. Each bar in the 3D stacked column chart is segmented by employee, with: **Orange** representing employee E1, **Gray** representing Employee E2, **Yellow** representing Employee E3, **Blue** (minimal or not visible) representing the label for Employee ID. Each stacked column displays the aggregated values of employee-related metrics, such as satisfaction level, last evaluation rating, project count, and average monthly hours. The overall scale remains extremely small, with cumulative values not exceeding 0.00060, indicating the input data likely contains either normalized or minimal numerical entries.

TABLE 2. Normalized

Employee ID	Satisfaction Level (A1)	Satisfaction Level (A1)	Projects worked (A3)	Average monthly hours (A4)
E1	0.93750	1.00000	1.00000	0.88235
E2	1.00000	1.00000	1.00000	1.00000
E3	0.93750	1.00000	1.00000	0.88235

The normalized dataset presents standardized performance metrics for three employees (E1, E2, and E3) across four key attributes: Satisfaction Level (A1) Last Evaluation Rating (A2) Projects Worked (A3) Average Monthly hours (A4) Employee E2 scores the highest across all attributes, with normalized values of 1.00000 in every category, indicating optimal performance. Both E1 and E3 share identical scores in most attributes, including full marks in evaluation and project count, but slightly lower values in satisfaction level (0.93750) and average monthly hours (0.88235), suggesting consistent yet slightly lower performance compared to E2.

TABLE 3.weight

Employee ID	Satisfaction Level (A1)	Satisfaction Level (A1)	Projects worked (A3)	Average monthly hours (A4)
E1	0.25	0.25	0.25	0.25
E2	0.25	0.25	0.25	0.25
E3	0.25	0.25	0.25	0.25

In this dataset, equal importance is assigned to each evaluation criterion—Satisfaction Level (A1)**,** Last Evaluation Rating (A2)**,** Projects Worked (A3)**, and** Average Monthly Hours (A4)**.** Each attribute is given a uniform weight of **0.25** across all three employees (E1, E2, and E3). This equal weighting implies that all performance indicators are considered equally significant in the overall assessment of employee performance.

TABLE 4. Weight normalized decision matrix

E1	0.23438	0.25000	0.25000	0.22059
E2	0.25000	0.25000	0.25000	0.25000
E3	0.23438	0.25000	0.25000	0.22059

The table below presents the weighted normalized scores for each employee across four evaluation criteria. These scores are calculated by multiplying the normalized values by their respective weights. Employee E1 has a weighted score of 0.23438 for Satisfaction Level (A1), 0.25000 for Last Evaluation Rating (A2), 0.25000 for Projects Worked (A3), and 0.22059 for Average Monthly Hours (A4). Employee E2 scores 0.25000 uniformly across all criteria, electing maximum performance under equal weighting. Employee E3 has the same scores as E1, indicating similar performance across all measured attributes. These values serve as the basis for further analysis or decision-making.

TABLE 5. Preference score

E1	0.95496
E2	1.00000
E3	0.95496

The preference scores indicate the relative ranking of each employee based on the weighted evaluation criteria: Employee E2 achieved the highest preference score of 1.00000, indicating the top performance among all employees. Employees E1 and E3 both received a slightly lower score of 0.95496, suggesting comparable and strong performance, but marginally less than E2. These scores reflect the final prioritization of employees based on the decision matrix analysis.

TABLE 6. Rank

	Rank
E1	2

E2	1
E3	2

Based on the calculated preference scores: Employee E2 holds the top rank (1st place), indicating the highest overall evaluation. Employees E1 and E3 are both ranked second, showing equal performance in comparison to each other but slightly below E2. This ranking reflects the outcome of the weighted decision-making process.

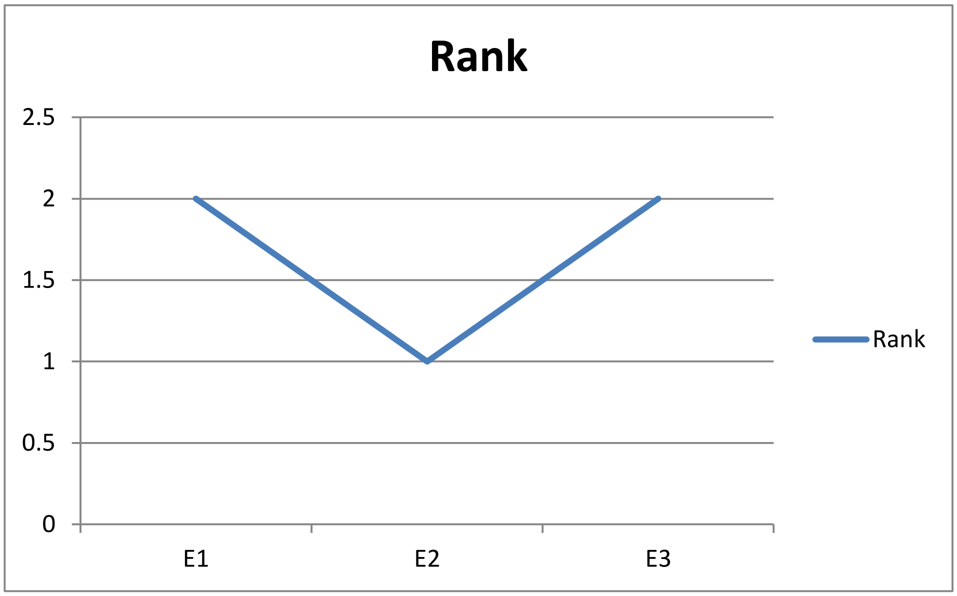

FIGURE2. Rank

The line graph displays the ranking positions of three employees—**E1**, **E2**, and **E3**—based on their evaluated performance. The chart reveals that: **Employee E2** achieves the **highest rank (1st place)**, indicating superior performance. Both **E1** and **E3** share the **second rank**, signifying equal performance, though slightly below that of E2. The chart visually emphasizes E2's lead, forming a "V" shape with E1 and E3 ranked equally on either side.

5. CONCLUSION

This study applied employee performance using normalized data, equal weighting, and a weighted normalized decision matrix. Three employees (E1, E2, and E3) were assessed based on four key attributes and working hours. After computing the weighted normalized values and deriving preference scores, the analysis revealed that Employee E2 achieved the highest overall performance score, thus securing the top rank. Both E1 and E3 received identical preference scores and were consequently ranked second. The use of equal weights ensures fairness in the evaluation by treating all criteria as equally important. The results underscore the value of combining quantitative data and MCDM techniques to support objective and transparent decision-making processes in human resource management. Visual representations such as bar and line charts effectively communicated the performance distribution and ranking outcomes. This methodology can be extended to larger datasets and customized with varying weights or additional performance metrics. Ultimately, the approach offers a systematic and scalable framework for organizations aiming to enhance employee evaluation, support promotions, or make data-driven staffing decisions. It also encourages continuous performance tracking and strategic workforce planning.

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