International Journal of Data Science and Analytics (2025) 20:1461–1483
https://doi.org/10.1007/s41060-024-00545-6

REGULAR PAPER

# Enhancing author assessment: an advanced modified recursive elimination technique (MRET) for ranking key parameters and conducting statistical analysis of top-ranked parameter

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Received: 14 November 2023 / Accepted: 26 March 2024 / Published online: 22 April 2024


**Abstract**
Assessing the impact of authors in scientific research is crucial for evaluating scholarly contributions. Various parameters exist in the literature to quantify researchers' productivity, such as publication count, citation count, and the h index. However, prioritizing the most effective metrics among the plethora available is essential. In this paper, we employ a powerful deep learning technique, the multi-layer perceptron (MLP), for classification and ranking. We propose the MRET technique to assign importance scores to each parameter, aiding MLP in its task. Through comprehensive statistical analysis, we evaluate the top 10 parameters out of 64 distinct metrics using seven well-known statistical methods. Our study utilizes a dataset from the Civil Engineering domain, comprising 590 non-awardees and 590 awardees over the last three decades. Results reveal the normalized h index as the most important parameter among the 64, and the Trigonometric Mean as the superior statistical model. Furthermore, combining parameters such as M-Quotient and FG index with others consistently yields promising results across various statistical models.

**Keywords** Author assessment parameters · Parameter ranking · Multi-layer perceptron (MLP) · Variants of h index · Mathematics domain datasets

## 1 Introduction

In the contemporary research landscape, the production of scholarly articles is prolific, with researchers generating a substantial volume of work daily [1]. The qualitative evaluation of researchers' output plays a pivotal role in addressing various crucial aspects within the academic community. These aspects encompass determining eligibility for scholarship awards, recognizing individuals who have made influential contributions to research, selecting editors and reviewers for scientific publications and conferences, and evaluating the competency of potential fellows or members of scientific societies [2]. Furthermore, such assessments also assist students in identifying suitable supervisors for their research endeavors [3]. However, the techniques employed for evaluating research work vary considerably based on the specific criteria and merits of the relevant scientific community. There exists no universally standardized approach for measuring a researcher's potential [4]. To tackle these challenges, a plethora of quantitative research assessment parameters have been proposed to pinpoint researchers who produce innovative and impactful contributions to the scientific domain [5]. Each technique outlined in the literature is tailored to its unique criteria for gauging the significance of a researcher's work.

Traditionally, researchers' productivity has been quantified primarily through publication count, serving as a fundamental parameter for assessing their impact [6]. However, concerns have been raised within the scientific community regarding the sole reliance on total publications to gauge researchers' impact [6]. To exemplify this concern, Cameron

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compared the profiles of two researchers in the database field: E.F. Codd and Hector Garcia-Molina. Despite Codd having fewer total publications (49) compared to Garcia's 248, Codd was still perceived as more renowned, having won the Turing award twice (in 1981 and 1994). This case underscores the importance of prioritizing quality over quantity in evaluating researchers [7]. To address this issue, the scientific community introduced a new metric: citation count, reflecting the number of times a researcher's work is cited by peers. A higher citation count signifies greater recognition within the research community. However, relying solely on citation count has its limitations, including potential biases such as self-citation, the incorporation of negative citations, and the tendency for survey papers to garner more citations, potentially skewing the true impact of a study.

In response to the challenges posed by traditional metrics, there has been a concerted effort in research to develop indices that account for both the quantity and quality aspects of scholarly output. Among these, the h index, introduced by Hirsch [8], stands out as one of the most prominent parameters for assessing researchers' impact. The h index evaluates the quality dimension of a researcher's work and has garnered widespread acceptance due to its computational simplicity and effectiveness. Notably, Hirsch highlighted that the h index not only reflects current performance but also serves as a predictor of future impact. The concept of the h index has been extensively discussed and explored by numerous researchers, contributing to its global adoption. However, criticisms have been raised, particularly by scholars like Dienes, who have pointed out certain limitations. Dienes argued that additional citations to already indexed papers do not enhance researchers' impact. Additionally, it has been noted that different authors can achieve the same h index despite having varying numbers of published papers and citations, and vice versa [9].

To address the limitations of the h index, the scientific community has proposed over 70 alternative parameters in the literature [10], including the g index, k index, w index, x index, Maxprod, f index, and so on [11–13]. However, the evaluation of these new techniques often occurs within hypothetical or fictional case scenarios, making it challenging to ascertain their significance across different datasets. Recognizing this challenge, efforts have been directed toward developing efficient methods for swiftly ranking researchers [14]. Recent studies have conducted empirical evaluations of the h index and its variants to assess their efficacy in determining the achievements of award winners in fields such as Mathematics and Neuroscience [5, 15]. These evaluations aim to provide insights into the performance of these indices in real-world settings, specifically within these disciplines. By analyzing the practical effectiveness of these indices, researchers aim to improve understanding of their applicability and offer valuable insights for research evaluation in these specialized fields.

Based on our review of existing literature, we have identified two significant gaps in current research methodology. Firstly, there is a notable absence of studies that utilize deep learning and machine learning techniques to rank a large number of parameters for evaluating researchers' impact. By leveraging these advanced computational methods, researchers could gain insights into the most effective parameters for assessing scholarly contributions. Secondly, there is a lack of research that combines multiple parameters using various statistical methods to observe the resulting outcomes. Such analyses could provide valuable insights into how different parameters interact and contribute to the overall assessment of researchers. Addressing these gaps through empirical research could lead to more comprehensive and accurate methodologies for evaluating researchers' contributions in academia.

This study aimed to address these issues. To address the raking problem, we used well-known deep learning multilayer perceptron classifiers. With this classifier, to determine the importance of each feature, we require a feature selection technique. For this, we employ a modified recursive elimination technique in machine learning to extract the importance score for each feature, which constitutes another contribution to our work. By applying this modified recursive elimination technique, we obtained important scores for each parameter. These scores allowed us to rank the parameters based on their relative importance, which is a valuable contribution to the field of author assessment. Furthermore, we address the second point by analyzing the results of the top-ranked parameters using statistical methods. In this task, we combined the top-ranked individual parameters and performed a comprehensive statistical analysis to derive meaningful insights. The integration of statistical methods with ranked parameters constitutes a unique and valuable contribution to the field.

For evaluation purposes, we assembled a dataset comprising 1180 authors from the Civil Engineering domain, including 590 non-awardees sourced from a provided dataset [15]. To ensure balance, we supplemented the dataset with data from 590 awardees spanning the last three decades, drawn from the civil engineering societies. Moreover, this study aimed to address two key questions: firstly, which index exhibits a stronger relationship with award winners in civil engineering compared to others? And secondly, which statistical methods contribute the most by retrieving the highest number of awardees compared to others?

The remainder of this paper is organized as follows: First, we offer a concise review of the ranking parameters in the "Literature" section. Following this, the "Methodology" section outlines our proposed approach for ranking the indices and conducting statistical analysis. Subsequently, the study

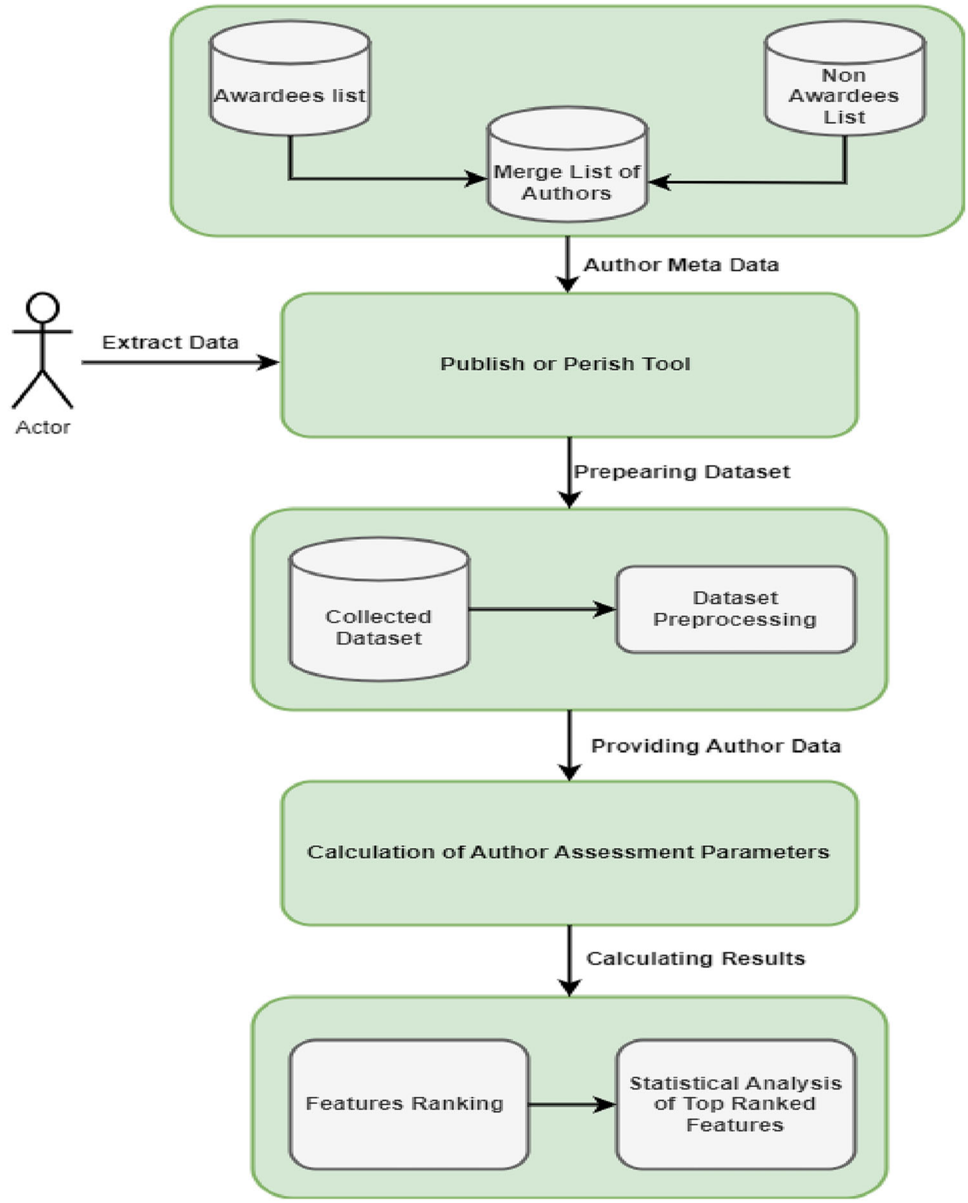



**Fig. 1** Illustration of the proposed methodology

results are discussed in the “Results and discussion” section. Finally, the “Conclusion” section wraps up the paper with concluding remarks.

## 2 Literature

In the current domain of scientific research, the necessity for a universal criterion to impartially evaluate and rank researchers’ scientific performance is paramount. Numerous parameters are involved in assessing and ranking the scientific performance of a researcher, encompassing publication count, citation count, the h index, and its various derivatives. Traditional methods employed by the scientific community often involve subjective evaluations to nominate scholars for academic accolades and professional advancements [16–18]. Nonetheless, these conventional strategies predominantly lean on quantitative metrics such as publication and citation counts, which have faced considerable criticism due to their inherent limitations.

Merely having a high publication count does not guarantee the quality of work, as authors might choose to publish in journals with low impact factors or present their findings at local conferences [19, 20]. Likewise, relying solely on citation counts fails to accurately assess research influence, as they can be easily manipulated. Authors may resort to self-citation or cite articles from a negative perspective, artificially inflating their citation counts without truly reflecting the impact of their work [21–24].

To overcome the limitations of conventional metrics, Hirsch introduced the h index, which has garnered widespread acceptance among researchers due to its simplicity [8]. Nevertheless, Dienes identified several shortcomings of the h index, including its inability to reflect increased citations of indexed papers in authors' impact assessments [9]. Moreover, the h index may not effectively evaluate the performance of early-career researchers, as it necessitates time for their publications to accumulate citations and their h index to rise. Additionally, the h index may inadvertently favor inactive researchers [25–28]. Consequently, researchers have proposed over 70 alternative parameters, such as the g index, k index, t index, and f index, among others, to address these limitations.

Furthermore, Antinous et al. [29] makes significant contributions to the refinement and extension of the original h index, aiming to uncover latent yet influential insights within citation networks while maintaining the simplicity and elegance of the original metric. Introducing two novel generalizations, namely the contemporary h index and the trend h index, the paper offers tailored approaches for scientist ranking, capable of identifying brilliant young scientists and trendsetters. These generalizations also prove applicable to conference and journal ranking scenarios. Additionally, the paper introduces a normalized h index for scientist ranking and two variants, the yearly h index and the normalized yearly h index, suited for ranking journal and conference publications. Through extensive experimentation utilizing real data from the DBLP bibliographic database, the efficacy of these proposed citation indices is thoroughly evaluated. While the paper focuses on empirical validation, it also acknowledges the potential for future work involving mathematical modeling and theoretical analysis to further elucidate the properties of these indices.

Ayaz and Afzal [30] conducted a study to assess the effectiveness of the complete h index, g index, and h index, focusing on awardees from mathematical scientific societies [30]. Their findings revealed that the complete h index outperformed both the g index and h index. Similarly, another study by Ayaz et al. (Year) explored the h index and its variants in the context of ranking award winners, concluding that the h index was superior to other alternatives [3]. Ameer and Afzal [5] evaluated quantitative parameters for neuroscience societies and found that the hg index and R index effectively elevated awardees to top positions among researchers [5]. Likewise, Ain et al. [15] examined scientific quantitative parameters for mathematicians, establishing correlations between selected parameters and the rankings of award-winning researchers [15]. However, it's important to note that these studies attempted to establish associations between the h index or its variants and pre-existing award winners, potentially leading to coincidental findings. To address this limitation, Usman et al. [4] proposed a technique for evaluating the h index and its variants using data from the civil engineering domain, focusing on researchers who received awards after 2005 [4]. Despite their efforts, the dataset's comprehensiveness may not yet suffice to definitively determine crucial parameters for award winners. Additionally, Alshdadi et al. [31] introduced rules using deep learning as minimum thresholds for qualifying subjective evaluations, employing a dataset from a different domain for evaluation. Moreover, Mustafa et al. [1] evaluated publication and citation count-based parameters using a mathematics domain dataset, finding that the normalized h index outperformed all other indices in this category [2].

The literature extensively discusses numerous parameters employed in determining and evaluating the worth of publications and identifying outstanding scholars. While publications and citations have been the primary metrics for assessing researchers over the past decade, the introduction of variants of the h index has occurred without adequate consideration of limitations or contextual backgrounds. Often, these methodologies have been developed in unconventional ways or based on disparate datasets, complicating the assessment of their individual significance. Moreover, to our knowledge, there are no existing studies in the literature that have ranked such a large number of parameters using deep learning and machine learning techniques. Additionally, we have observed a dearth of studies that perform statistical analyses by combining these parameters. Therefore, this study aims to address these identified gaps.

## 3 Methodology

The scientific community has put forward numerous research evaluation metrics for ranking researchers. In this study, our goal was to evaluate and rank these metrics using a deep learning classifier coupled with a modified recursive elimination method. The proposed methodology is depicted in Fig. 1.

### 3.1 Field selection

To tackle the aforementioned research inquiries, a comprehensive dataset within a specific scientific discipline is imperative for implementing this methodology. We've opted for the realm of Civil Engineering for evaluating variants of the h index due to its rich history and extensive research. Civil Engineering stands as one of humanity's oldest fields, boasting significant scholarly contributions, making it an apt choice for our evaluation framework. Despite annual accolades bestowed upon distinguished researchers within this domain, their collective expertise remains underutilized in h index ranking and evaluation. By prioritizing the ranking of research assessment parameters, we aim to empower the Civil

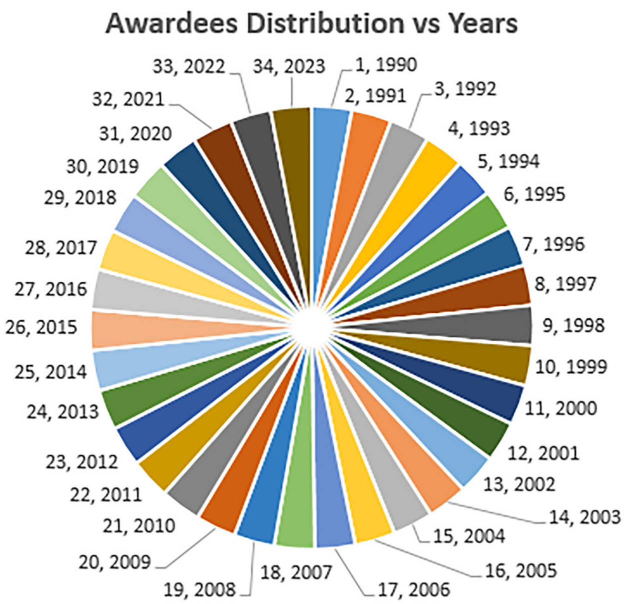



**Fig. 2** Awardees distribution

**Table 1** Dataset before preprocessing

| Features | Total count |
|---|---|
| Total authors | 1180 |
| Total awardees | 590 |
| Total non-awardees | 590 |
| Total citation | 24,061,210 |
| Total publication | 214,897 |

**Table 2** Dataset statistics after preprocessing

| Researchers metadata | Count |
|---|---|
| Total authors | 1180 |
| Total awardees | 590 |
| Total non-awardees | 590 |
| Total citation | 24,061,210 |
| Total publication | 214,672 |

Engineering community to identify trailblazing researchers and foster further advancement in this vital field.

### 3.2 Dataset collection

For our experimental endeavors, we've amassed a thorough and diverse dataset to appraise the proposed methodology. This dataset comprises 1180 records, capturing information from both recipients and non-recipients of awards. Specifically, it encompasses data from 590 non-recipients and 590 recipients. The data for non-recipients were drawn from the datasets utilized by Alshdadi et al. [31]. However, given that the original datasets utilized by Gadde et al. [22] contained only a limited number of entries for awardees, spanning until 2020, we expanded our dataset by gathering updated information on awardees up to 2023. To achieve this, we scoured various civil engineering society websites, compiling the names and corresponding recognition years of researchers over the past three decades. The distribution of awards across different years is depicted in Fig. 2.

To gather data on awardees, we employed the Publish or Perish tool, employing a hold-on strategy to capture records of researchers even prior to their receiving awards. This tool utilizes a sophisticated algorithm to extract author metadata from Google Scholar (GS). Google Scholar was chosen for data extraction due to several factors. Firstly, it offers extensive coverage of academic publications across various disciplines. Secondly, it is accessible worldwide and can retrieve both open-access and paid publications. Additionally, numerous studies have compared Google Scholar with Web of Science, indicating a 13% higher average growth rate for the former. Moreover, citations on Google Scholar have shown an average monthly increase of 1.5% over the past year. Google Scholar's dynamic nature ensures regular updates, maintaining the relevance and timeliness of the information it provides [21]. To balance the dataset, we collected data on non-awardees in the same proportion as the number of awardees for each specific year. For instance, if there were 19 awardees in 2008, we gathered data from 19 non-awardees prior to 2008, utilizing the same techniques. The statistics regarding the datasets are detailed in Table 1.

### 3.3 Data preprocessing

Before initiating any analysis or evaluation, it's imperative to meticulously clean the data collected from sources like Google Scholar. This process aims to weed out irrelevant or erroneous information, commonly referred to as noise, which could undermine the integrity of the findings. The data cleansing process entails several steps, including validating the accuracy of the data and removing duplicate entries. In our extensive research dataset, two pivotal processes were undertaken to enhance data quality and relevance. Firstly, a filter was applied to ensure that each publication pertained to the civil engineering field, thus eliminating irrelevant or non-civil content and refining the dataset's focus to the pertinent domain. Subsequently, an author disambiguation process was executed to identify and eliminate duplicate entries stemming from authors publishing under different names. Following the completion of these steps and the validation of the aforementioned processes, the characteristics and properties of the final dataset were documented for evaluation. The resultant dataset and corresponding evaluation outcomes are itemized in Table 2.

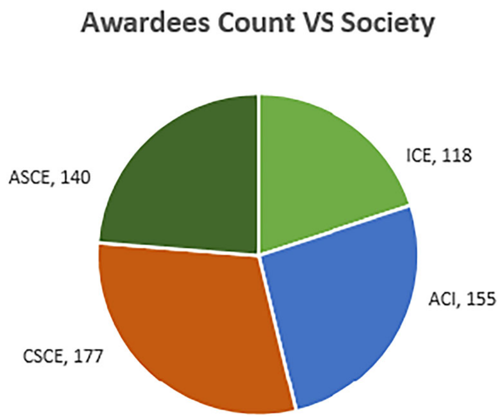



**Fig. 3** Awardees count against societies

### 3.4 Benchmark data set

The dataset comprises lists of both awardees and non-awardee researchers from the civil engineering domain, sourced from the dataset retrieved by Raheel et al. [3] and Usman et al. [4]. They have collected the list of researchers using accredited civil engineering database (CEDB) terms, an initiative of the American Society of Civil Engineering (ASCE), a renowned scientific society in civil engineering. To ensure the impartiality of our proposed methodology, we filtered the dataset to include 590 non-awardees representing a spectrum of high, average, and low impactful researchers based on their publication and citation counts. Similarly, the list of awardees was also extracted from these dataset and also added the recent awardees. However, we specifically considered awardees who had received recognition for their work before the proposal of the novel h index. The objective of this research is to ascertain the association of awardees with parameters now utilized to gauge the impact of researchers in the scientific community. Thus, we filtered the award winners to cover the period between 1990 and 2023. All of these award winners belong to several scientific societies, including ASCE, CSCE, ACI, and ICE. Figure 3 visually presents the total number of awardees associated with each society.

### 3.5 Calculation of indices

In this section, the research study is centered on calculating 63 indices using the collected data. These indices have been categorized into multiple categories by Bihari et al. [10]. The list of categories along with their respective indices is presented below. (The calculation of these indices is provided in Appendix A.)

- *Primitive Parameters*
  The parameters belonging to primitive parameters are Total Publication, Total Citation, Total years, Cites/Year, Cites/Paper, Author/Paper, Cites/author, and Papers/author.
- *Publication and Citation count-based parameters*
  The parameters belonging to this category are H index, G index, E index, H core citation, A index, R index, P index, M index, F index, T index, Q2 index, Tappered h index, Maxprod, Wu index, Pi index, Weighted h index, H(2) index, Wogienger index, Gh index, Rm index, X index, Hg index, H2 upper index, H2 center index, H2 lower index, K dash index, Rational h index, Real h index, I10 index, Normalized h index, K index, W index, and H dash index.
- *Author-based Parameters*
  The parameters belonging to author-based parameter are HI index, HI norm, Hm index, Gm index, Hf index, Gf index, GF index, K norm index, W norm index, Pure h index, Fractional g index, Fractional h index, and Normalized hi index.
- *Age-based Parameters*
  The parameters belonging to age-based parameters are Platinum h index, M quotient index, AW index, AR index, V index, Ha index, Hc index (Contemporary h index), and AWCR (Age-weighted citation rate).

### 3.6 Modified recursive elimination techniques (MRET) with MLP

In machine learning, the task of feature-ranking holds paramount importance as it aids in identifying the most influential feature for various purposes such as prediction [32], model interpretability [33], and dimensionality reduction [34]. To address the first research question, we introduce a technique termed the modified recursive elimination technique (MERT). This approach is a tailored version of the well-established feature selection technique known as the recursive elimination technique (RET). RET is widely utilized to pinpoint relevant features that substantially contribute to a model's performance [35]. Moreover, this technique diminishes the dataset's dimensionality and enhances the model's interpretability, efficiency, and generalization ability [36]. RET systematically eliminates irrelevant or redundant features, focusing on a subset of features that exert the most significant impact on the model's performance. Figure 4 illustrates the methodology of our modified recursive elimination technique (MRET).

The proposed algorithm begins by splitting the dataset into a training set and a validation set using a 80:20 ratio. The training dataset is employed to train a multilayer perceptron classifier (outlined in the subsequent section) for classification purposes. Subsequently, the trained model is provided with a validation sample, and it predicts the class label for each sample. The accuracy achieved during this prediction

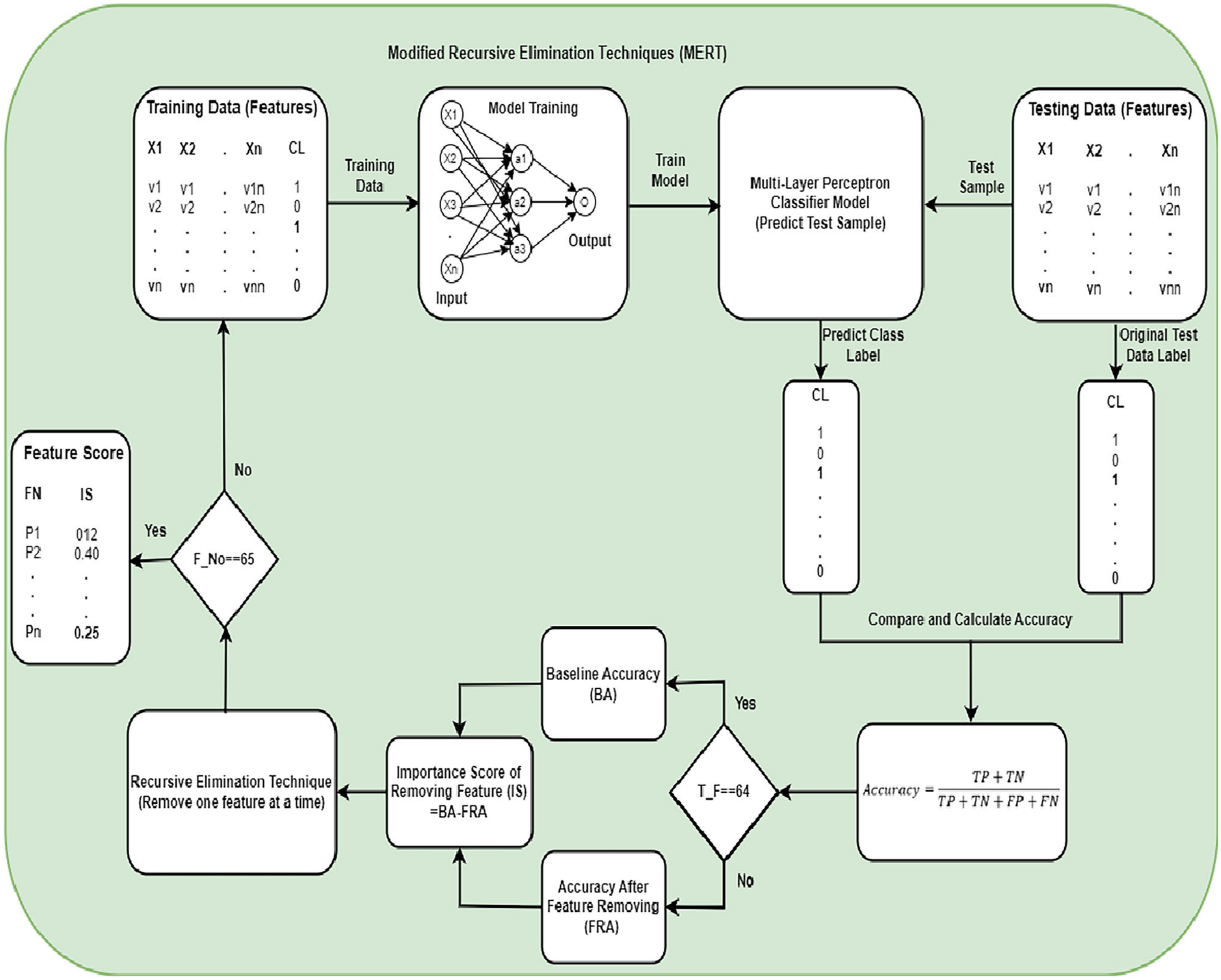



**Fig. 4** MRET proposed technique

stage is regarded as the baseline accuracy when all features are included. The subsequent phase of the algorithm revolves around feature elimination. One parameter is removed from the feature list, and the dataset is once again divided into training and validation sets. The multilayer perceptron classifier is then trained using the updated feature set. After training, a test sample is utilized to predict the class label, and the accuracy is recorded. The new accuracy obtained is subtracted from the baseline accuracy, resulting in a subtraction value that serves as the importance score for the removed feature. This process is iterated for each parameter across at least five different epoch phases, generating an importance score for each. Equation 1 illustrates the calculation for the importance score.

$$\text{Importance Score} = \frac{1}{5}\sum_{i=20}^{100}(\text{BLA}_i - \text{WOPA}_i) \tag{1}$$

Where i represents the number of epochs, $\text{BLA}_i$ represents the baseline accuracy against the $i$th phase, and $\text{WOPA}_i$ represents the without-parameter accuracy of the $i$th phase. After iterating through all features in the dataset, the algorithm produces two lists. The first list comprises the names of the features, while the second list contains the corresponding importance scores. Algorithm 1 outlines the proposed approach.

### 3.7 Multilayer perceptron classifier (MLP)

The MLP classifier served as the foundation of the proposed technique. MLP, a feed-forward artificial neural network, comprises multiple hidden layers [37] (refer to Fig. 5). In classification problems, the total number of features corresponds to the number of neurons in the input layer, while the total number of classes into which the data are categorized corresponds to the number of neurons in the output layer.

**Algorithm 1:** Modified Recursive Elimination Techniques with MLP

```
Input: Dataset (Features with Class label) ;  // Features and its Class Label
Output: Parameter list with Importance Score against each Parameter
while i ≤ len(Features) do
    if i == 0 then
        X ← All Parameters Data ;  // Load parameters data except class label
        y ← Class Label ;  // Load class label of all records
        Xtrain, Xtest, ytrain, ytest ← Split(X, y, 0.20) ;  // Split the data
        mlp ← BuildMLPClassifier() ;  // Build Multilayer Perceptron
        mlp.fit(Xtrain, ytrain) ;  // Model fit on data
        ypred ← mlp.predict(Xtest) ;  // Class Label prediction
        baseAccuracy ← accuracyScore(ytest, ypred) ;  // Accuracy with all parameters
    else
        X ← X ;  // Assign data after removal of parameter
        y ← Class Label ;  // Load class label of all records
        Xtrain, Xtest, ytrain, ytest ← Split(X, y, 0.20) ;  // Split the data
        mlp ← BuildMLPClassifier() ;  // Build Multilayer Perceptron
        mlp.fit(Xtrain, ytrain) ;  // Model fit on data
        accuracy ← accuracyScore(ytest, ypred) ;  // Predict Accuracy after removal of parameter
        parameterName.append(X[i].name) ;  // Append the Name of Parameters Which can Eliminate from Parameter List
        importanceScore.append(baseAccuracy-accuracy) ;  // Importance Score of Parameters Which are Eliminating in iteration List
    end
    X ← All Parameters Data ;  // Load all data before removing index parameter in each iteration
    X.remove(i) ;  // Removing Index parameter
end
return parameterNameList ;  // Return Parameter Name List
return ImportanceScoreList ;  // Return Importance Score List
```

The intermediary layers situated between the input and output layers constitute fully connected layers trained using a backpropagation algorithm. During the forward propagation phase, the network computes the output for each layer using an activation function based on the output of the previous layer, alongside the corresponding weight and bias values, as delineated in Eq. 2.

$$Z = \mathrm{WA} + b \tag{2}$$

Where $Z$ denotes the output matrix, $W$ denotes the weight matrix, and b denotes the bias vector.

To confine the output of the MLP within a predefined range, an activation function was employed. This function normalizes the output of each layer, ensuring its adherence to the desired range. By utilizing the activation function, the output of a layer can be effectively transformed into the desired range, as illustrated in Eq. 3.

$$A = g(Z) \tag{3}$$

Where $A$ denotes the activated output matrix.

In our proposed method, we employed a rectified linear unit (ReLU) as the activation function for the hidden layer and Softmax for the final output layer. The ReLU activation function, defined in Eq. 4, sets values less than zero to zero while leaving positive values unchanged. This activation function effectively introduces nonlinearity into the network. On the other hand, Softmax, defined by Eq. 5, is commonly utilized in multi-classification tasks. It addresses the limitations of the sigmoid function and ensures that the probabilities of the output layer sum to one. By applying Softmax, we can determine the most probable prediction for the given inputs.

$$a_{\text{relu}} = \max(0, z) \tag{4}$$

$$a_{\text{soft}} = \frac{a^{z_i}}{\sum_{j=1}^{j} e^{z_j}} \tag{5}$$

Where J denotes class number while $z^i$ denotes $i$th output value. Equation 6 depicts the loss function utilized to quantify the error between predicted and actual values in the MLP. This function serves as a metric for evaluating the model's performance. By computing the loss, we can assess the disparity between predicted and target values. Subsequently, a backpropagation algorithm is employed to adjust the weights (w) and biases (b) in the network. This iterative process aims to optimize the model's performance by minimizing the loss and fine-tuning the network's parameters.

$$L(y, \hat{y}) = \frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2 \tag{6}$$

Where $m$ denotes number of samples, $y$ denotes predicted value and $\hat{y}$ denotes actual value. Furthermore, in deep learning models, it's crucial to mitigate overfitting. Excessively deep layers in a deep neural network can lead to issues like gradient vanishing or explosion, which detrimentally impact the model's performance and contribute to overfitting. To address these challenges, Loffe and Szegedy introduced a method called batch normalization in 2015 [38]. The objective of batch normalization, as described in Eq. 7, is to

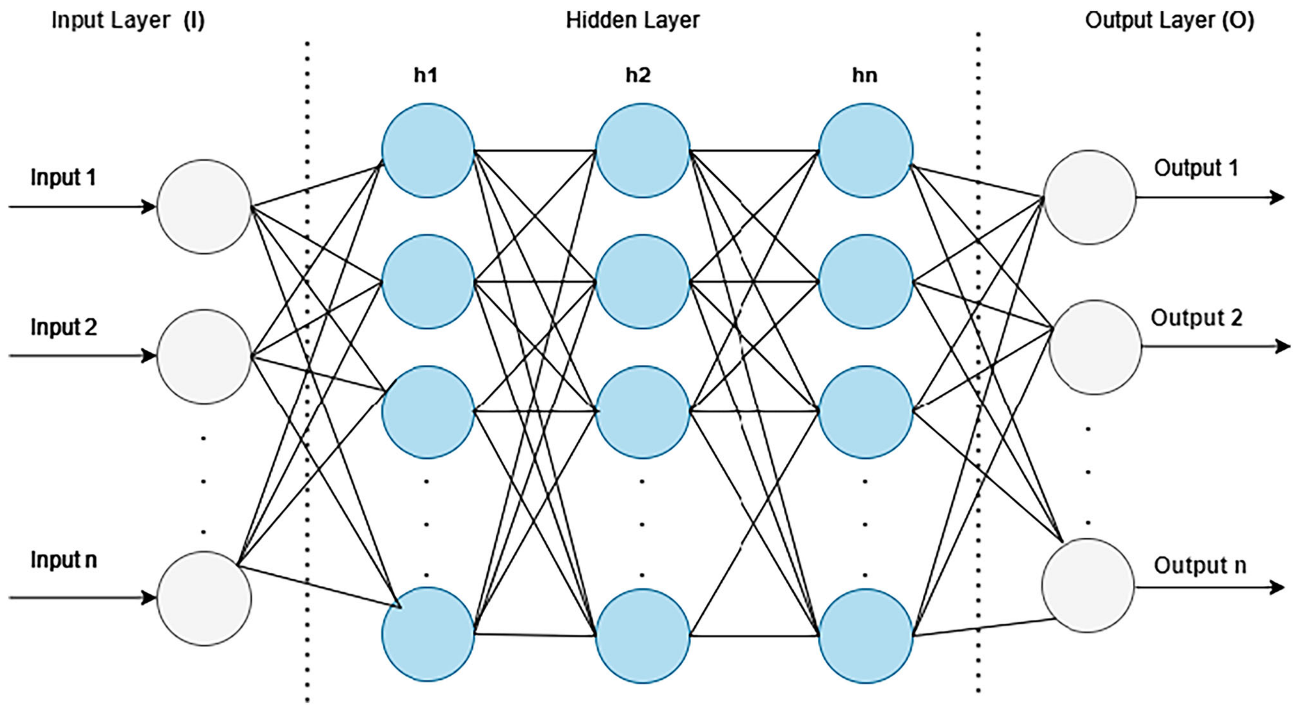



**Fig. 5** Basic MLP model

**Table 3** Statistical methods

| Method names | Formulas |
|---|---|
| Arithmetic mean | Arithmetic $= \frac{X_1+X_2+\cdots+X_n}{n}$ |
| Harmonic mean | Harmonic Mean $= \frac{n}{\sum_{i=1}^{n} \frac{1}{X_i}}$ |
| Contra-harmonic mean | Contra-Harmonic Mean $= \frac{(X_1^2)+(X_2^2)+\cdots+(X_n^2)}{(X_1+X_2+X_3+\cdots+X_n)}$ |
| Geometric mean | Geometric Mean $= (X_1 * X_2 * X_3 * \cdots * X_n)^{\frac{1}{n}}$ |
| Logarithmic mean | Logarithmic Mean $= (\frac{1}{n}) * (\sum_{i=1}^{n} log(X_i)))$ |
| Root mean square | Root Mean Square $= \sqrt{\frac{x_1^2+x_2^2+\cdots+x_n^2}{n}}$ square |
| Trigonometric mean | Trigonometric Mean $= \frac{\prod_{i=1}^{n} sin(x_i)}{\prod_{i=1}^{n} x_i}$ |

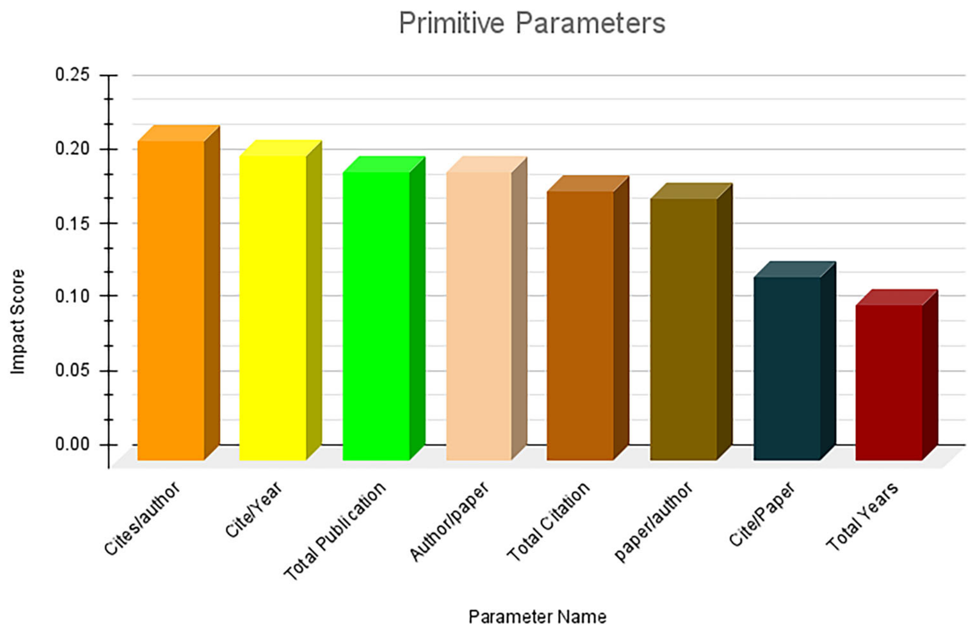
counteract gradient explosions or vanishing. This is accomplished by normalizing the output values after each hidden layer, ensuring they do not become excessively large or small. The process involves subtracting each output from the vector's mean value and then dividing it by a standard deviation. In our MLP model, batch normalization was implemented after each hidden layer to effectively mitigate overfitting.

$$X_i = \frac{X_i - \text{Mean}_i}{\text{Standard Deviation}_i} \tag{7}$$

Where $X^i$ denotes $i$th hidden layer's output matrix, $\text{Mean}_i$ is the mean value of $X^i$, and Standard $\text{Deviation}_i$ is the standard deviation of $X^i$. In this study, we utilized a multilayer perceptron (MLP) as a classifier with 10 hidden layers. Each hidden layer consisted of 10 neurons, and the rectified linear unit (ReLU) activation function was employed in each of these layers. The selection of the sizes of the hidden layers and neurons was determined through multiple experiments. To regularize the network and prevent overfitting, batch normalization was applied after each hidden layer. The selected features and preprocessed data were fed into the neural network through the input layer. The model was trained using forward and backward propagation techniques, with the output layer employing the Softmax activation function to generate class probabilities. During the prediction phase, a class probability vector is produced, and the argmax function (as shown in Eq. 8) was utilized to identify the highest probability value and return its corresponding index.

$$\text{Result} = \max(\text{Predicted Vector Space}) \tag{8}$$

**Fig. 6** Primitive parameters ranking



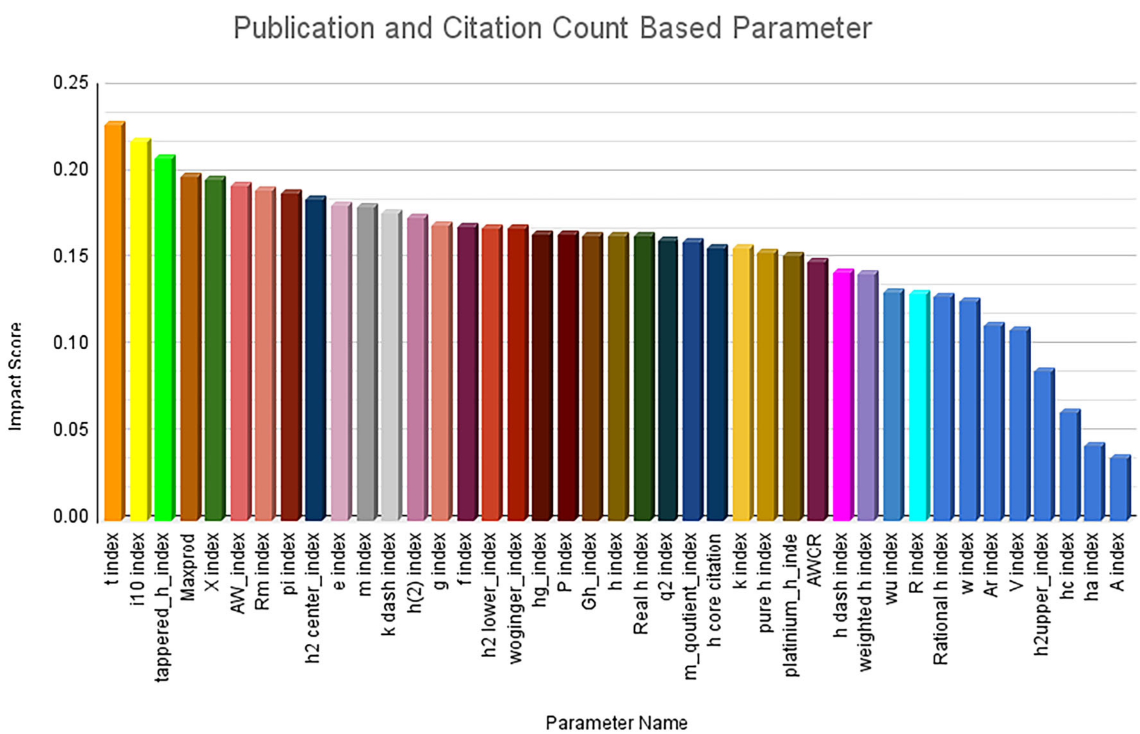




**Fig. 7** Publication and citation ranking

To train our model, we employed the Adam optimization algorithm, which dynamically adjusts the learning rate based on recent weight gradients. Specifically, we utilized a learning rate of 0.0003, a batch size of 64, and conducted training for 100 epochs. To mitigate overfitting, we implemented the early stopping technique. This technique halts the training process when signs of overfitting become apparent and restores the best model parameters. The early stopping parameter was set to 40, meaning that if the loss of the validation set did not decrease for more than 40 consecutive epochs, it was determined that the model had overfit. At that point, the training was stopped, and any changes made during the epochs were reversed.

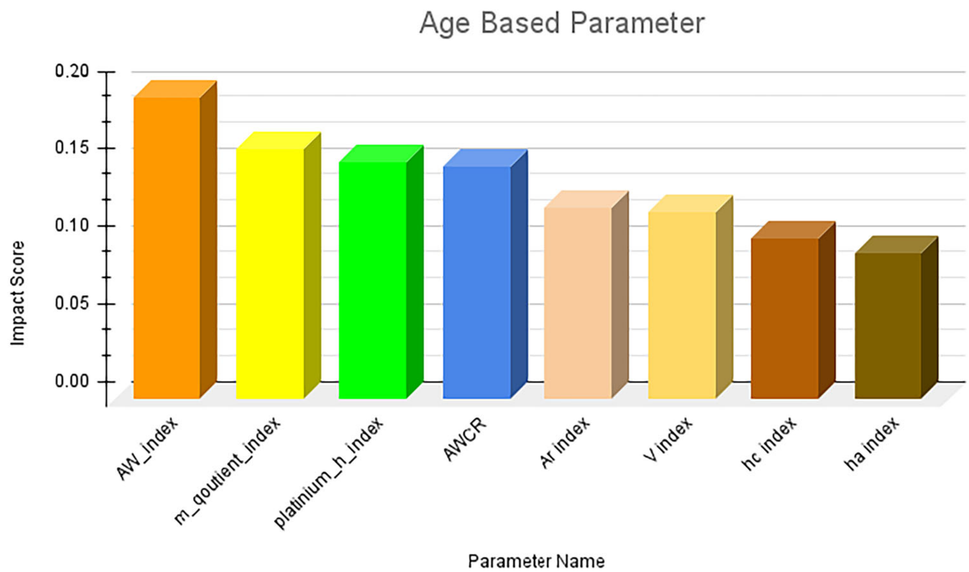



**Fig. 8** Age-based parameter

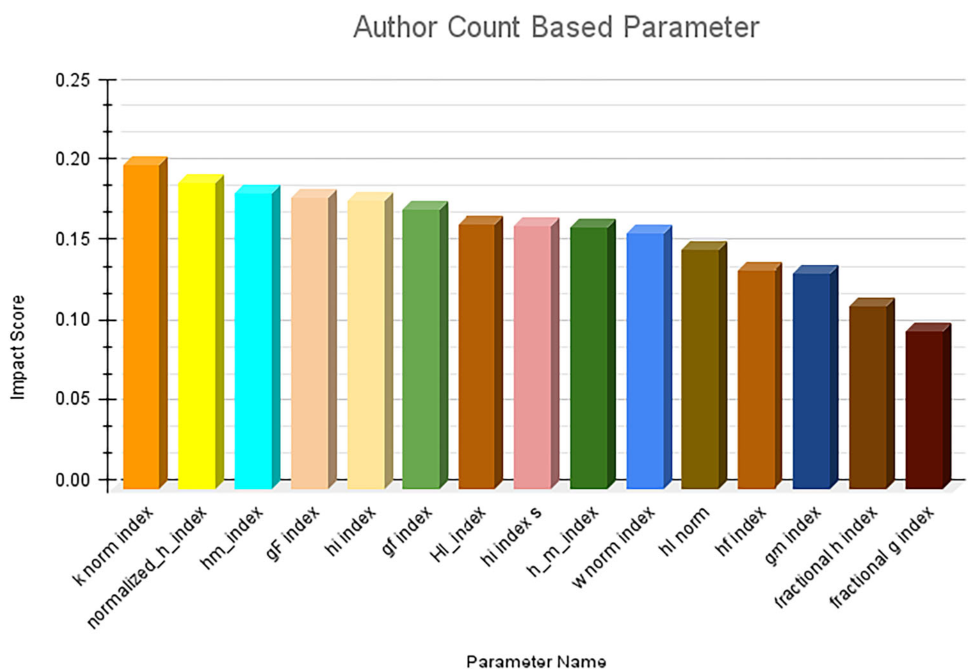



**Fig. 9** Author count-based parameter ranking

## 3.8 Ranking of parameter

Following the acquisition of importance scores for each parameter using the MERT algorithm, the parameters underwent sorting based on their respective scores. This sorting procedure yielded a parameter ranking.

## 3.9 Statistical analysis

Statistical methods are pivotal in the analysis of data across various research domains [39]. In this study, we utilized a spectrum of statistical techniques to delve deeper into our research question and draw meaningful conclusions. Leveraging the power of statistical analysis enabled us to methodically scrutinize the data, detect patterns, quantify relationships, and draw informed inferences. Our objective was to amalgamate top-ranking parameters using diverse statistical analysis methods. These methods encompass the arithmetic mean, contra-harmonic mean, geometric mean, harmonic mean, Lehmer mean, logarithmic mean, root mean square (RMS), and trigonometric mean. Employing these methods facilitates a comprehensive understanding of author rankings and enables us to evaluate their significance within the dataset. The calculations for these methods are outlined in Table 3.

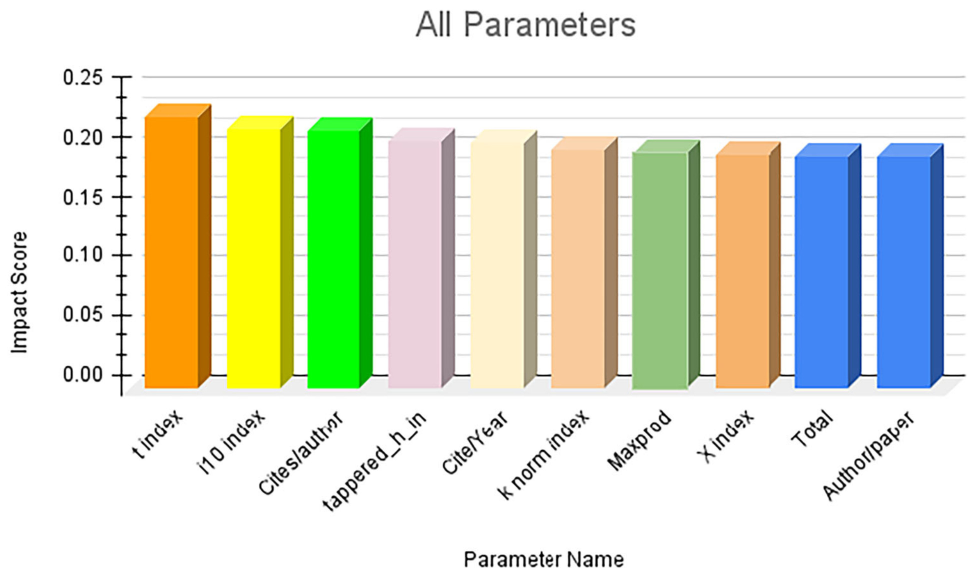



**Fig. 10** Top 10 highest impact score parameters

In this study, we utilized the array of statistical methods presented in Table 3 to analyze the top-ranked parameters in pairs. Employing this list of statistical methods, we computed the respective statistical values for each parameter pair. Subsequently, we generated eight distinct lists for each pair, corresponding to each statistical method. Furthermore, we conducted comparisons among these lists to determine the most influential statistical method for each pair. This analysis enabled us to identify potential pairings of parameters showcasing noteworthy patterns or relationships. The findings of this study offer valuable insights into the selection of statistical methods and parameter combinations for further analysis and investigation.

# 4 Results and discussion

The following section outlines the findings obtained in response to the research questions.

## 4.1 Ranking of parameters

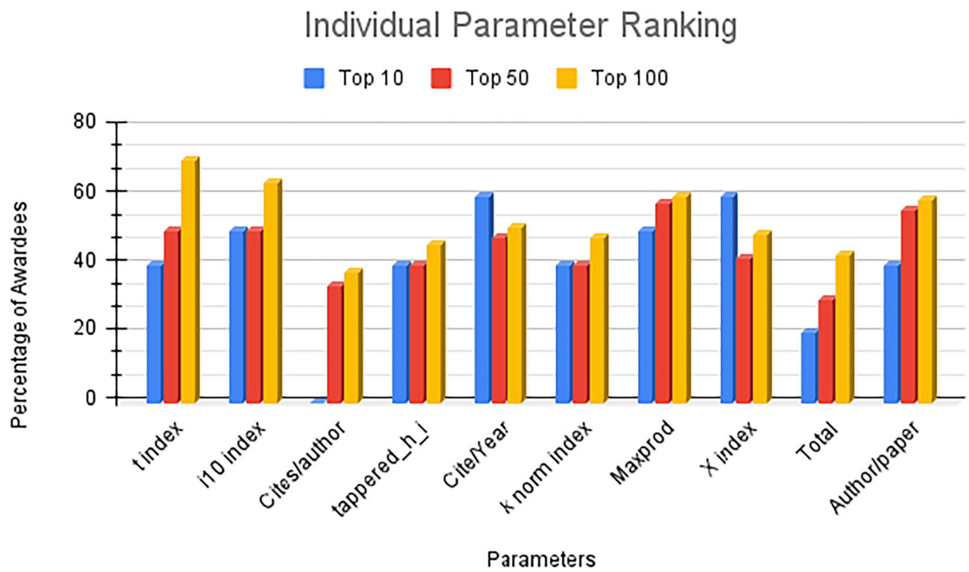
This section presents the findings of the first research question. Due to the extensive number of parameters involved, presenting them in a single figure is impractical. Thus, we initially categorized the parameters and then consolidated the top 10 parameters across all categories. The results categorized by parameter type are depicted in Figs. 6, 7, 8 and 9. Analysis reveals that among primitive parameters, "cites per author" had the highest impact score, approaching 0.21. Regarding publication- and citation-based parameters, the "t index" exhibited the highest impact score at 0.22. In the age-based category, the "AW index" demonstrated the highest impact score of 0.19. Lastly, within the author count-based category, the "k-norm index" achieved the highest score of 0.20. Figure 10 illustrates the amalgamation of parameters across categories, presenting the top 10 parameters with the highest impact scores. Notably, the "t index" emerges as the most influential parameter among the 64 parameters examined. Following closely, the "i10 index" claims the second position, while "cites per author" ranks third.

## 4.2 Statistical evaluation

Prior to conducting a statistical evaluation, it is crucial to individually assess the top ten ranked parameters. This preliminary examination offers insights into the significance of each parameter. Subsequently, various statistical methods can be utilized to amalgamate these parameters and conduct a comprehensive analysis of the results. To comprehend the impact of these parameters, we can analyze the occurrence of awardees within the top 10, 50, and 100 records associated with these parameters. For this analysis, we initially sorted the index data and then determined the number of awardees represented by these indices in the top 10, 50, and 100 records, respectively. Figure 11 illustrates the individual parameter rankings. As depicted in the figure, the "t index" outperformed all other parameters, accounting for 40%, 50%, and 70% of award recipients within the ranges of 10, 50, and 100 records, respectively. The "i10 index" brought forth 50%, 50% and 64% of the awardees in the top 10, 50, and 100 records, respectively. Conversely, the "total publication" parameter exhibited the lowest performance, representing 20%, 30%, and 43% of awardees within the ranges of 10, 50, and 100 records, respectively.

Following an analysis of the individual performance of the top 10 highest-ranked parameters, the subsequent critical step involved amalgamating these parameters with their

**Fig. 11** Individual parameter ranking




various possible combinations across eight distinct statistical models. This procedural approach is designed to delve into and assess the cumulative impact of these parameters on the overall performance of top-ranking awardees. Through the implementation of this comprehensive methodology, we aim to glean valuable insights into the intricate interplay between different parameters and statistical models, thereby enriching our comprehension of their combined effects. To initiate this process, we commence by generating all conceivable combinations of the top 10 indices and pairing them accordingly. Subsequently, our focus shifts toward computing the values of eight distinct statistical methods for each pair of parameters. Following the acquisition of these values, we proceed to sort the list of values generated by each method. This sorting facilitates a deeper examination of the performance of these statistical methods. Further elucidating our analysis, we conduct an assessment of the top 10, 50, and 100 records to ascertain the efficacy of the statistical methods in identifying awardees. This evaluation involves scrutinizing the number of awardees returned by each statistical method within these subsets of data. By discerning the outcomes of this analysis, we can effectively gauge the efficiency of the statistical methods. Tables 4, 5 and 6 present the top 10, 50, and 100 records of the analysis results, respectively. In these tables, the following abbreviations are utilized: First Parameter of Pair (FP), Second Parameter of Pair (SP), Arithmetic Mean (AM), Harmonic Mean (HM), Contra-Harmonic Mean (CHM), Geometric Mean (GM), Logarithmic Mean (LOM), Lehmer Mean (LM), Root Mean Square (RMS), Trigonometric Mean (TM), Total Publication (TP), T index (TI), I10 Index (I10), Cite/Author (C/A), Tapered h index (TH), Cite/Year (C/Y), K norm index (KN), Maxprod (MA), X index (X), and Author/Paper (A/P).

Tables 4, 5, and 6 provide a detailed breakdown of the percentage scores achieved by awardees concerning individual parameters and their combinations, employing different statistical models for the top 10, 50, and 100 records. In the subsequent paragraphs, we delve into a comprehensive analysis of various statistical models concerning different parameter combinations.

### 4.2.1 Arithmetic mean (AM)

In the top 10 records, the AM demonstrated moderate percentage scores ranging from 0 to 40% across all parameter combinations, generally lower than individual parameter scores. The highest AM score recorded was 40%, achieved through various parameter combinations, notably including “Cite/Author” and “K norm index”, as well as “I10 index’ and “K norm index”. Transitioning to the top 50 records, AM behavior mirrored that of the previous analysis, with the highest percentage score reaching 34%, notably through the combination of “Cite/Year” and “Cite/Author”, while the lowest score recorded was 0%, seen in combinations such as “Total Publication” and “Cite/Year”. Extending the analysis to the top 100 records, the trend with AM persisted, albeit with a slight decrease in percentage scores, dropping to a maximum of 30%, particularly notable in combinations like “Cite/Year” and “Tapered H index”. Conversely, the lowest accuracy score for this subset remained at 0%, achieved through the combination of “Total Publication” and “Tapered H index” parameters.

### 4.2.2 Harmonic mean (HM)

Upon analyzing the top 10 records, it becomes evident that the performance of the HM closely mirrors that of the

**Table 4** Top 10 records analysis results

| Parameters pair | FP | SP | AM | HM | CHM | GM | LOM | RMS | TM |
|---|---|---|---|---|---|---|---|---|---|
| TP & C/Y | 20 | 60 | 5 | 0 | 0 | 10 | 0 | 5 | 60 |
| TP & TI | 20 | 40 | 20 | 0 | 20 | 0 | 0 | 20 | 80 |
| TP & TH | 20 | 40 | 0 | 10 | 0 | 0 | 0 | 10 | 50 |
| TP & MA | 20 | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 60 |
| TP & X | 20 | 60 | 0 | 30 | 0 | 20 | 0 | 0 | 80 |
| TP & I10 | 20 | 50 | 0 | 20 | 0 | 0 | 0 | 0 | 40 |
| TP & KN | 20 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 20 |
| TP & A/P | 20 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 80 |
| TP & C/A | 20 | 0 | 0 | 10 | 0 | 0 | 0 | 0 | 80 |
| C/Y & TI | 60 | 40 | 20 | 40 | 20 | 30 | 30 | 20 | 60 |
| C/Y & TH | 60 | 40 | 30 | 10 | 30 | 20 | 20 | 30 | 50 |
| C/Y & MA | 60 | 50 | 40 | 20 | 30 | 30 | 30 | 30 | 40 |
| C/Y & X | 60 | 60 | 0 | 30 | 0 | 20 | 20 | 0 | 20 |
| C/Y & I10 | 60 | 50 | 40 | 40 | 30 | 40 | 40 | 30 | 50 |
| C/Y & KN | 60 | 40 | 40 | 40 | 40 | 40 | 50 | 50 | 90 |
| C/Y & A/P | 60 | 40 | 20 | 10 | 30 | 10 | 10 | 30 | 60 |
| C/Y & C/A | 60 | 0 | 30 | 20 | 30 | 30 | 30 | 30 | 60 |
| TI & TH | 40 | 40 | 20 | 0 | 20 | 20 | 20 | 20 | 40 |
| TI & MA | 40 | 50 | 20 | 20 | 20 | 20 | 20 | 20 | 70 |
| TI & X | 40 | 60 | 0 | 20 | 0 | 0 | 0 | 0 | 30 |
| TI & I10 | 40 | 50 | 20 | 40 | 20 | 20 | 20 | 20 | 60 |
| TI & KN | 40 | 40 | 20 | 40 | 20 | 30 | 40 | 20 | 40 |
| TI & A/P | 40 | 40 | 20 | 0 | 20 | 10 | 10 | 20 | 40 |
| TI & C/A | 40 | 0 | 20 | 10 | 20 | 20 | 20 | 20 | 70 |
| TH & MA | 40 | 50 | 10 | 10 | 10 | 10 | 10 | 0 | 10 |
| TH & X | 40 | 60 | 0 | 0 | 0 | 0 | 0 | 0 | 20 |
| TH & I10 | 40 | 50 | 10 | 40 | 0 | 20 | 20 | 0 | 40 |
| TH & KN | 40 | 40 | 30 | 10 | 40 | 20 | 30 | 60 | 60 |
| TH & A/P | 40 | 40 | 0 | 10 | 0 | 10 | 10 | 0 | 50 |
| TH & C/A | 40 | 0 | 0 | 10 | 0 | 10 | 10 | 0 | 40 |
| MA & X | 50 | 60 | 0 | 20 | 0 | 10 | 10 | 0 | 30 |
| MA & I10 | 50 | 50 | 20 | 40 | 10 | 20 | 20 | 10 | 40 |
| MA & KN | 50 | 40 | 40 | 20 | 60 | 30 | 40 | 60 | 60 |
| MA & A/P | 50 | 40 | 10 | 10 | 10 | 0 | 0 | 30 | 50 |
| MA & C/A | 50 | 0 | 20 | 20 | 10 | 10 | 10 | 10 | 80 |
| X & I10 | 60 | 50 | 0 | 40 | 0 | 20 | 20 | 0 | 60 |
| X & KN | 60 | 40 | 0 | 40 | 0 | 20 | 30 | 0 | 30 |
| X & A/P | 60 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 60 |
| X & C/A | 60 | 0 | 0 | 10 | 0 | 0 | 0 | 0 | 60 |
| I10 & KN | 50 | 40 | 40 | 40 | 40 | 40 | 50 | 40 | 30 |
| I10 & A/P | 50 | 40 | 0 | 30 | 0 | 10 | 10 | 0 | 60 |
| I10 & C/A | 50 | 0 | 40 | 40 | 40 | 40 | 40 | 30 | 50 |
| KN & A/P | 40 | 40 | 30 | 10 | 60 | 10 | 20 | 60 | 50 |
| KN & C/A | 40 | 0 | 40 | 20 | 40 | 30 | 40 | 40 | 40 |
| A/P & C/A | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 |

**Table 5** Top 50 records analysis results

| Parameters pair | FP | SP | AM | HM | CHM | GM | LOM | RMS | TM |
|---|---|---|---|---|---|---|---|---|---|
| TP & C/Y | 30 | 48 | 0 | 0 | 0 | 0 | 0 | 0 | 40 |
| TP & TI | 30 | 50 | 12 | 0 | 12 | 2 | 2 | 16 | 60 |
| TP & TH | 30 | 40 | 0 | 0 | 0 | 20 | 0 | 0 | 50 |
| TP & MA | 30 | 58 | 0 | 6 | 0 | 0 | 30 | 0 | 77 |
| TP & X | 30 | 42 | 14 | 0 | 14 | 20 | 0 | 16 | 56 |
| TP & I10 | 30 | 50 | 0 | 20 | 0 | 0 | 0 | 0 | 54 |
| TP & KN | 30 | 40 | 2 | 0 | 0 | 0 | 8 | 0 | 40 |
| TP & A/P | 30 | 56 | 0 | 4 | 20 | 0 | 0 | 0 | 48 |
| TP & C/A | 30 | 34 | 0 | 24 | 0 | 0 | 0 | 0 | 80 |
| C/Y & TI | 48 | 50 | 12 | 54 | 12 | 20 | 22 | 12 | 52 |
| C/Y & TH | 48 | 40 | 28 | 44 | 38 | 22 | 22 | 44 | 64 |
| C/Y & MA | 48 | 58 | 30 | 20 | 40 | 22 | 22 | 42 | 66 |
| C/Y & X | 48 | 42 | 14 | 32 | 14 | 18 | 18 | 14 | 38 |
| C/Y & I10 | 48 | 50 | 32 | 24 | 34 | 26 | 26 | 34 | 70 |
| C/Y & KN | 48 | 40 | 24 | 33 | 26 | 24 | 32 | 26 | 80 |
| C/Y & A/P | 48 | 56 | 32 | 54 | 38 | 24 | 24 | 38 | 50 |
| C/Y & C/A | 48 | 34 | 34 | 28 | 34 | 26 | 26 | 34 | 48 |
| TI & TH | 50 | 40 | 12 | 16 | 35 | 14 | 16 | 12 | 50 |
| TI & MA | 50 | 58 | 12 | 20 | 12 | 16 | 18 | 12 | 48 |
| TI & X | 50 | 42 | 14 | 12 | 14 | 14 | 14 | 14 | 42 |
| TI & I10 | 50 | 50 | 12 | 24 | 44 | 16 | 18 | 12 | 52 |
| TI & KN | 50 | 40 | 12 | 26 | 55 | 20 | 28 | 12 | 77 |
| TI & A/P | 50 | 56 | 12 | 14 | 12 | 16 | 16 | 12 | 52 |
| TI & C/A | 50 | 34 | 12 | 24 | 12 | 14 | 14 | 12 | 48 |
| TH & MA | 40 | 58 | 18 | 20 | 18 | 20 | 20 | 12 | 66 |
| TH & X | 40 | 42 | 14 | 18 | 14 | 14 | 14 | 14 | 46 |
| TH & I10 | 40 | 50 | 18 | 20 | 18 | 20 | 20 | 18 | 54 |
| TH & KN | 40 | 40 | 24 | 33 | 24 | 24 | 34 | 30 | 42 |
| TH & A/P | 40 | 56 | 14 | 14 | 18 | 16 | 16 | 16 | 56 |
| TH & C/A | 40 | 34 | 18 | 24 | 18 | 18 | 18 | 18 | 44 |
| MA & X | 58 | 42 | 14 | 20 | 14 | 16 | 16 | 14 | 32 |
| MA & I10 | 58 | 50 | 20 | 22 | 20 | 22 | 24 | 20 | 54 |
| MA & KN | 58 | 40 | 22 | 20 | 26 | 24 | 32 | 24 | 52 |
| MA & A/P | 58 | 56 | 18 | 20 | 20 | 20 | 20 | 22 | 62 |
| MA & C/A | 58 | 34 | 20 | 26 | 20 | 20 | 20 | 20 | 42 |
| X & I10 | 42 | 50 | 14 | 22 | 14 | 18 | 18 | 14 | 54 |
| X & KN | 42 | 40 | 14 | 26 | 14 | 18 | 28 | 14 | 62 |
| X & A/P | 42 | 56 | 14 | 12 | 14 | 14 | 14 | 14 | 52 |
| X & C/A | 42 | 34 | 14 | 26 | 14 | 12 | 12 | 14 | 58 |
| I10 & KN | 50 | 40 | 26 | 22 | 26 | 24 | 32 | 26 | 48 |
| I10 & A/P | 50 | 56 | 16 | 22 | 14 | 22 | 24 | 14 | 50 |
| I10 & C/A | 50 | 34 | 24 | 24 | 24 | 24 | 24 | 24 | 72 |
| KN & A/P | 40 | 56 | 24 | 20 | 26 | 24 | 34 | 26 | 52 |
| KN & c/A | 40 | 34 | 26 | 26 | 26 | 24 | 32 | 26 | 40 |
| A/P & C/A | 56 | 34 | 14 | 22 | 14 | 14 | 14 | 14 | 54 |

**Table 6** Top 100 records analysis results

| Parameters pair | FP | SP | AM | HM | CHM | GM | LOM | RMS | TM |
|---|---|---|---|---|---|---|---|---|---|
| TP & TI | 43 | 70 | 12 | 1 | 15 | 6 | 7 | 16 | 49 |
| TP & TH | 43 | 46 | 0 | 8 | 0 | 0 | 0 | 0 | 53 |
| TP & MA | 43 | 60 | 0 | 12 | 0 | 0 | 1 | 0 | 47 |
| TP & X | 43 | 49 | 14 | 0 | 14 | 3 | 3 | 14 | 48 |
| TP & I10 | 43 | 64 | 0 | 21 | 0 | 2 | 3 | 0 | 55 |
| TP & KN | 43 | 48 | 3 | 9 | 0 | 6 | 13 | 0 | 42 |
| TP & A/P | 43 | 59 | 0 | 9 | 0 | 0 | 0 | 0 | 47 |
| TP & C/A | 43 | 38 | 0 | 22 | 0 | 0 | 0 | 0 | 65 |
| C/Y & TI | 51 | 70 | 17 | 24 | 17 | 21 | 22 | 17 | 56 |
| C/Y & TH | 51 | 46 | 30 | 24 | 28 | 27 | 27 | 28 | 52 |
| C/Y & MA | 51 | 60 | 29 | 25 | 28 | 28 | 29 | 28 | 60 |
| C/Y & X | 51 | 49 | 14 | 29 | 14 | 21 | 22 | 14 | 65 |
| C/Y & I10 | 51 | 64 | 27 | 25 | 27 | 28 | 28 | 27 | 55 |
| C/Y & KN | 51 | 48 | 31 | 27 | 29 | 30 | 39 | 30 | 75 |
| C/Y & A/P | 51 | 59 | 27 | 20 | 28 | 27 | 27 | 28 | 44 |
| C/Y & C/A | 51 | 38 | 27 | 23 | 27 | 26 | 26 | 27 | 65 |
| TI & TH | 70 | 46 | 16 | 19 | 17 | 18 | 19 | 16 | 51 |
| TI & MA | 70 | 60 | 17 | 22 | 17 | 18 | 19 | 17 | 49 |
| TI & X | 70 | 49 | 14 | 16 | 14 | 17 | 18 | 14 | 53 |
| TI & I10 | 70 | 64 | 17 | 23 | 17 | 21 | 22 | 17 | 60 |
| TI & KN | 70 | 48 | 17 | 23 | 16 | 20 | 30 | 17 | 44 |
| TI & A/P | 70 | 59 | 17 | 18 | 17 | 16 | 17 | 17 | 51 |
| TI & C/A | 70 | 38 | 17 | 18 | 17 | 19 | 20 | 17 | 46 |
| TH & MA | 46 | 60 | 20 | 22 | 19 | 21 | 22 | 14 | 55 |
| TH & X | 46 | 49 | 14 | 19 | 14 | 16 | 17 | 14 | 44 |
| TH & I10 | 46 | 64 | 19 | 24 | 19 | 23 | 23 | 19 | 53 |
| TH & KN | 46 | 48 | 26 | 23 | 27 | 25 | 36 | 29 | 54 |
| TH & A/P | 46 | 59 | 18 | 17 | 19 | 18 | 19 | 20 | 51 |
| TH & C/A | 46 | 38 | 19 | 20 | 19 | 20 | 20 | 19 | 66 |
| MA & X | 60 | 49 | 14 | 22 | 14 | 17 | 18 | 14 | 55 |
| MA & I10 | 60 | 64 | 23 | 24 | 22 | 23 | 24 | 22 | 49 |
| MA & KN | 60 | 48 | 27 | 24 | 25 | 26 | 36 | 27 | 55 |
| MA & A/P | 60 | 59 | 21 | 20 | 20 | 20 | 21 | 23 | 52 |
| MA & C/A | 60 | 38 | 23 | 21 | 23 | 21 | 22 | 23 | 66 |
| X & I10 | 49 | 64 | 14 | 24 | 14 | 19 | 20 | 14 | 52 |
| X & KN | 49 | 48 | 14 | 26 | 14 | 21 | 32 | 14 | 45 |
| X & A/P | 49 | 59 | 14 | 17 | 14 | 16 | 17 | 14 | 51 |
| X & C/A | 49 | 38 | 14 | 21 | 14 | 13 | 14 | 14 | 58 |
| I10 & KN | 64 | 48 | 26 | 24 | 26 | 25 | 35 | 26 | 51 |
| I10 & A/P | 64 | 59 | 17 | 21 | 16 | 19 | 20 | 13 | 49 |
| I10 & C/A | 64 | 38 | 21 | 19 | 25 | 21 | 21 | 24 | 53 |
| KN & A/P | 48 | 59 | 28 | 21 | 25 | 23 | 34 | 25 | 52 |
| KN & c/A | 48 | 38 | 26 | 20 | 26 | 22 | 33 | 26 | 45 |
| A/P & C/A | 59 | 38 | 17 | 17 | 16 | 16 | 17 | 16 | 51 |

AM concerning award percentage scores. However, the HM demonstrates superior results compared to the AM, albeit with occasional instances where the HM score drops to zero when certain indices are combined, contrasting with their individual scores. Notably, when pairing the Cite/Year index with any other index using the HM, the resulting accuracy score consistently hovers around 30–40%. Moreover, most indices returned a 0% result, except when combined with the Cite/Year index. Expanding the analysis to encompass the top 50 records, the HM exhibited slightly higher performance compared to the previous subset. Nevertheless, the behavior of the Cite/Year index when combined with other indices remains consistent, achieving higher percentage scores, with the highest reaching up to 54%, achieved by pairing "Cite/Year" with "T index". The lowest percentage score recorded in this subset was 0%, noted in combinations such as the Tappered index and the T index. Extending the analysis to include the top 100 records, the observed trend concerning the Cite/Year parameter in conjunction with the HM persisted. However, there was a slight decrease in percentage scores, likely due to the increase in the number of records. Within this expanded subset, the highest accuracy score achieved using the HM was 29%. This notable score was attained by pairing the Cite/Year parameter with the X index. Conversely, the lowest accuracy score recorded for this subset remained at 0%, achieved by combining the Tappered index and the T index parameters.

#### 4.2.3 Contraharmonic mean (CHM)

In the top 10 records, the CHM displayed behavior similar to the AM, with percentage scores spanning from 0 to 60% across all parameter combinations. Notably, the highest percentage score achieved using the CHM within this subset was 60%, observed in the combination of "Maxprod" and "K norm index", indicating a relatively higher level of accuracy with this specific pairing. Conversely, the lowest percentage score recorded in this subset was 0%, observed across numerous combinations. Expanding the analysis to include the top 50 records, the CHM continued to exhibit slightly lower performance compared to the previous subset, with percentage scores ranging from 0 to 55% across various parameter combinations. Noteworthy within this subset was the highest percentage score achieved using the CHM, reaching 55% through the combination of "T index" and "I10 index". Conversely, the lowest percentage score recorded for this subset remained at 0%, achieved by combining "Total publication" and "Citation/Author" index. Extending the analysis to encompass the top 100 records, a trend of percentage scores lower than the previous dataset was observed, ranging between 0 and 29%, reflecting the performance of the CHM across different parameter combinations. Notably, within this extended subset, the highest accuracy score achieved using the CHM was 29%, observed in the combination of the "Cite/Year" parameter with the "K norm index". Conversely, the lowest accuracy score recorded in this subset remained at 0%, achieved by combining "Total Publication" and "Tapper h index".

#### 4.2.4 Geometric mean (GM)

Upon examination of the top 10 records, it is evident that the GM exhibits a performance similar to the harmonic mean, with accuracy ranging from 0 to 40%. Interestingly, when combining the Cite/Year with any other index using GM, the resulting accuracy consistently falls within the range of 10–40%. Conversely, most other indices, when combined with any other index and assessed using GM, tend to return accuracy scores of 0–10%. Expanding the analysis to the top 50 records, the GM continued to demonstrate slightly lower performance compared to the previous subset. However, the behavior of the Cite/Year index when combined with other indices remains consistent and achieves higher percentage scores, reaching up to 29%. The lowest percentage score recorded in this subset is 0%, achieved by "Total Publication" and "Cite/Year". Extending the analysis to the top 100 records, the observed trend concerning the Cite/Year parameter in conjunction with GM remains consistent. However, there is a slight decrease in percentage scores, likely due to the increase in the number of records. Within this extended subset, the highest accuracy score achieved using GM was 30%. This notable score is obtained by combining the Cite/Year parameter with the "K norm index". Conversely, the lowest accuracy score recorded for this subset remains at 0%. This score is achieved by combining the parameters "Total Publication" and "Tapered h index".

#### 4.2.5 Logarithmic mean (LOM)

Upon examining the top 10 records, it is evident that the behavior of the Cite/Year index aligns consistently with the LM. Combinations involving the Cite/Year index generally result in a percentage of awardees ranging from 0 to 39%. The highest percentage was achieved by pairing Cite/Year with the K norm index. Conversely, when most other indices were combined with any other index and assessed using the LM, they tended to return percentage scores of 0%. Expanding the analysis to the top 50 records, the dominance of the Cite/Year combination becomes apparent over other combinations. The highest percentage was obtained by pairing Cite/Year with the K norm index, resulting in a score of 32. The lowest percentage score recorded in this subset was 0%, observed across many combinations. Extending the analysis to the top 100 records, the observed trend with the Cite/Year parameter in conjunction with the LM remains consistent. However, there is a slight decrease in the percentage scores. Within this extended subset, the highest accuracy score achieved using the LM was 39%. This notable score was obtained by pairing the "Quotient" parameter with the Cite/Year index. Conversely, the lowest accuracy score recorded for this subset remains at 0%, observed across multiple combinations.

#### 4.2.6 Root mean square (RMS)

Upon examination of the top 10 records, it is evident that the combination involving "Cite/Year" demonstrates dominance over other combinations, achieving a perfect score of 50%. Additionally, the "K norm index" also returns results up to 60% when combined with itself. Conversely, when some of the other indices are combined with each other and assessed using the RMS, they tend to return percentage scores of 0%. Expanding the analysis to the top 50 records, the dominance of the "Cite/Year" combination persists, achieving a percentage of 44%. The lowest percentage score recorded in this subset is 0%, observed across many combinations. Extending the analysis to the top 100 records, the observed trend with the "Cite/Year" parameter in conjunction with the RMS remains consistent. However, there is a slight decrease in the percentage scores, likely due to the increase in the number of records. Within this extended subset, the highest accuracy score achieved using the RMS was 30%. This notable score was obtained by combining the "Cite/Year" parameter with the "K norm index". Conversely, the lowest accuracy score recorded for this subset remains at 0%, observed across many combinations.

#### 4.2.7 Trigonometric mean (TM)

Upon examining the top ten records, the utilization of the TM yielded remarkable results. Unlike other statistical methods, no single combination returned a 0% accuracy score. This suggests that the TM mean consistently performs well across different parameter combinations. The lowest accuracy score recorded in this subset was 10%, achieved by combining the "Tappered h index" and "Maxprod". Conversely, the highest accuracy score of 90 percent was attained by combining "Cite/Year" and "K norm index". Expanding the analysis to the top 50 records, it becomes evident that the TM continues to display consistent results across different combinations. Regardless of the parameter combination, the TM mean maintained stable performance. In this subset, the highest accuracy score achieved using the TM mean was 80%, obtained by combining "Cite/Year" with "K norm index". In contrast, the lowest accuracy score recorded in this subset is 38%, achieved by combining "Cite/Year" and "X index". Extending the analysis to the top 100 records, the observed trend with the TM remains consistent. TM continues to demonstrate stable performance across various combinations within this extended subset. In this subset, the highest accuracy score achieved using the TM was 75%, obtained by combining "Cite/Year" with "K norm index". The lowest percentage score recorded for this subset was 44%, achieved by combining "T index" and "K norm index". After conducting a thorough analysis of the statistical methods applied to parameter combinations, it is clear that the TM surpasses the other six statistical models. TM consistently delivers outstanding results when assessing the percentage of different parameter combinations. Throughout the analysis, TM consistently demonstrates its effectiveness in capturing percentage scores across various combinations, maintaining stable performance and providing notable accuracy scores compared to other models. These exceptional results imply that TM is a robust statistical method for evaluating accuracy within a dataset, showcasing a unique ability to uncover underlying relationships and patterns between parameters, thus resulting in higher percentage scores. Furthermore, upon scrutinizing parameters such as the Cite/Year and K norm index, it is evident that these indices exhibit remarkable performance across various combinations and statistical models. When paired with other parameters using diverse statistical methods, the Cite/Year and K norm index consistently yield excellent percentage scores for identifying awardees. This exceptional performance suggests that these indices possess significant predictive power or strong correlation with the desired outcome. Their combination with other parameters consistently results in high accuracy scores across different statistical models.

## 5 Conclusion

This study undertook a comprehensive analysis of author assessment parameters, comprising 63 distinct parameters categorized into four groups. The dataset utilized included 590 non-awardee authors and an equal number of awardee authors from esteemed scientific societies within the Civil Engineering domain. Due to the substantial number of parameters, we introduced a modified recursive elimination technique to rank these sixty-three parameters. For classification purposes, we implemented a multilayer perceptron classifier algorithm, which generated importance scores for each parameter, facilitating their ranking. Notably, the ranking results highlighted the normalized h index as the top-performing parameter, indicating its significance above all others. Moreover, we identified the top 10 parameters with the highest rankings and subjected them to statistical analysis using seven distinct methods. These methods were employed to combine the top ten parameters into all possible combinations, followed by sorting the resulting lists based on the values derived from the statistical methods. Subsequently, we conducted analyses on the top 10, 50, and 100 records, focusing on the presence of awardees within each list of the top records. The findings unveiled that the TM surpassed the other six statistical models in performance. Furthermore, parameter analysis revealed that the Cite/Year and K norm index consistently yielded noteworthy results across various combinations and statistical models. When integrated with other parameters through diverse statistical methods, the Cite/Year consistently demonstrated excellent predictive ability, particularly in generating high percentage scores for identifying potential awardees.

## 6 Future work

In our future endeavors, we aim to broaden the scope of our research across multiple dimensions. Firstly, we plan to integrate additional newly published indices into our list of metrics, including the Kaptay K index, the H alpha index, the Psi index, among others. This expansion will enrich the range of parameters considered in our analysis, allowing for a more comprehensive evaluation. Secondly, we intend to incorporate datasets from various domains such as Neuroscience, Computer Science, and others. By incorporating data from diverse fields, we aim to enhance the applicability and generalizability of our findings, enabling insights that transcend specific disciplines.

**Data Availability** The dataset used in this study is publicly available at the following link (https://github.com/ghulammustafacomsat/Mathematics_dataset).

## Appendix A: Section title of first appendix

See the Table 7.

**Table 7** Indices calculation formulas

| Name of Index | Calculation |
|---|---|
| Total Publication | Total No. of Publication of a researchers |
| Total Citation | Total No. of Citation of a researchers |
| Total Years | Number of years since the academic's first publication |
| Cites per Year | Total citations/years since first paper |
| Cites per Paper | Total citations/total papers |
| Author per Paper | Add up the total number of authors involved in the publications for the author in question and divide this by the number of papers |
| Cites per author | Divide citations for each publication by the number of authors and sum the resulting citations; this is the single-authored equivalent number of citations for the author in question |
| Papers per author | Divide each publication by the number of authors and sum the fractional author counts; this is the single-authored equivalent number of papers for the author in question |
| h index | h = max (numbers of articles with >= h citations) |
| G index | A set of papers has a g index g if g is the highest rank such that the top g papers have, together, at least g2 citations |
| Hg index | hg index $= \sqrt{h * g}$ |
| | Where h represents h index and g represents g index |
| A index | A index $= \frac{1}{h}\sum_{p=1}^{h} \mathrm{cit}_p$ |
| | Where A is the A index of the scholar, h represents the h index and $\mathrm{cit}_p$ is the citation count of the $p$th article |
| R index | R index $= \sqrt{\sum_{p=1}^{h} \mathrm{Cit}_p}$ |
| | Where h represents the h index and $\mathrm{cit}_p$ is the citation count of the $p$th article |
| P index | P index $= (\frac{C^2}{p})^{\frac{1}{3}}$ |
| | The p index strikes the best balance between total number of citations (C) and the mean citation rate (C/P) |
| $\mathrm{Q}^2$ index | $Q^2 = \sqrt{h * m}$ |
| | Where h represents h index and m represents m index |
| K index | K index $= \frac{\frac{C}{P}}{\frac{C(h-tail)}{C(h-core)}}$ |
| | Where C represents total citation, p represents of $p$th article, h-tail represents h-tail article citation and h-core represents h-core citation |

**Table 7** continued

| Name of Index | Calculation |
|---|---|
| E index | e index $= \sum_{p=1}^{h} Cit_p - h^2$ <br> Where $\mathrm{Cit}_p$ represents citation of $p$th article and h represents h index |
| f index | f index $= \binom{max}{f} \frac{1}{\frac{1}{f}\sum_{p=1}^{f}\frac{1}{Cit_p}} \geq f$ <br> Where $\mathrm{cit}_p$ is the citation count of $p$th article. The f index never goes beyond the total number of publications |
| T index | T index $= \binom{max}{t} \exp\left[\frac{1}{t}\sum_{k=1}^{t} ln(Cit_k)\right] \geq t$ <br> Where $\mathrm{cit}_k$ is the citation count of $k$th article |
| Tappered h index | $H_{T(j)} = \frac{n_j}{2j-1}, \quad n_j \leq j$ and $h_{T(j)} = \frac{j}{2j-1} + \sum_{i=j+1}^{n_j} \frac{1}{2j-1}, \quad n_j > j$ |
| Wu index | The w index of an author is calculated, as if at least w of their articles have garnered 10w citations, while the remaining publications have received less than 10(w+1) citations each |
| Weighted h index | $R_w(k) = \frac{\sum_{p=1}^{k} Cit_p}{h}$ <br> Where h is the h index and $cit_p$ is the citation count of the $p$th article. Then, the weighted h index is defined as follows <br> $h_w = \sqrt{\sum_{k=1}^{R} Cit_k}$ <br> Where $\mathrm{cit}_k$ is the citation count of the $k$th article and R is the largest rank among all publications such that the $k$th weighted rank < $\mathrm{cit}_k$ |
| h(2) index | The h(2) index is the maximum whole number such that the h(2) most cited articles by a scholar have each received at least $(h(2))^2$ citations |
| Woeginger index | $w = \binom{max}{w}(Cit_p \geq w - p + 1) \quad$ for all $\quad p \leq w$ <br> where $\mathrm{cit}_p$is the citation count of $p$th article and w is the maximum number of publications |
| Rm index | $R_m = \sqrt{\sum_{k=1}^{h} \mathrm{Cit}_k^{\frac{1}{2}}}$ <br> Where $\mathrm{cit}_k$ is the citation count of $k$th article |
| m index | A m index is calculated as the median number of citations received by the h-core articles |
| X index | $x = \sqrt{\binom{max}{k} k\mathrm{Cit}_k}$ <br> Where $\mathrm{cit}_k$ is the citation count of $k$th article |
| h2 upper index | $h^2\text{upper} = \frac{\sum_{k=1}^{h}(Cit_k - h)}{\sum_{k=1}^{m}\mathrm{Cit}_k} * 100 = \frac{e^2}{\sum_{k=1}^{m}\mathrm{Cit}_k} * 100$ <br> Where h is the h index, $\mathrm{cit}_k$ is the citation count of the $k$th article, $e^2$is the excess citation and m is the total number of articles |
| h2 center index | $h^2\text{center} = \frac{h*h}{\sum_{k=1}^{m} Cit_k} * 100$ <br> Where h is the h index and $\mathrm{cit}_k$ is the citation count of the $k$th article |
| h2 lower index | $h^2\text{lower} = \frac{\sum_{k=h+1}^{m}(\mathrm{Cit}_k - h)}{\sum_{k=1}^{m}\mathrm{Cit}_k} * 100$ <br> Where h is the h index and $\mathrm{cit}_k$ is the citation count of the $k$th article |
| h' index (h dash) | $h^{'} = Rh = \frac{eh}{t}$ <br> where R represents the head-tail ratio of e and t index |
| Rational h index | $h_{\text{rat}} = h + 1 - \frac{k}{2h+1}$ <br> Where h is the h index and k is the number of citations required to reach h + 1 h index value |
| I10 index | This is a simple and direct measure of indexing that involves counting the total number of papers published by a journal that have received at least 10 citations |
| Normalized h index | normalized h index $= \frac{h}{\text{pub}_{\text{count}}}$ <br> Where h represents h index and pubcount represents total publication |
| Π index | $\Pi$ index $= 0.01C(P\Pi)$ <br> The $\Pi$ index is equal to the 100th of the number of citations, $C(P\pi)$ to the top square root $(P\pi)$ of the total papers(P) |

**Table 7** continued

| Name of Index | Calculation |
|---|---|
| Gh index | $\mathrm{Gh}^a = \sum_{p=1}^{m} \mathrm{sing}(\mathrm{Cit}(\mathrm{pub}_b^a) - GH) \quad where \;\; sing(x) = 1, x \geq 0 \; and \;\; 0, x \leq 0$ |
| | Where m is the total number of publications of scholar a and GH is the h index of the scholar. This index is also difficult to compute in comparison to the h index |
| W index | w index is defined as w, which represents the number of their top articles that have at least 10w citations each. While w index can be a useful measure for finding impact of scholar, it may penalize young scholars who have recently started working or those who have not yet published enough papers |
| Maxprod | The maximum value of i * $c_i$ can be found by examining the publication rank of an author, where $c_i$ represents the number of citations for the $i$th most frequently cited paper among all the citations |
| H core citation | The h-core citation index takes into account only those publications that have been cited at least h times and ignores those that have not achieved this threshold |
| K dash index | $k' = \frac{\mathrm{Cit_{all}} - \mathrm{Pub_{Count}}}{\mathrm{Cit}_T - \mathrm{Cit}_H}$ |
| | Where $\mathrm{cit_{all}}$ represents total citation, $\mathrm{pub_{count}}$ represents total publication, $\mathrm{cit}_t$ represents total citation of h-tail article and $\mathrm{cit}_h$ represents total citation of h-core article |
| M-Quotient | $\text{M-Quotient} = \frac{\text{h index}}{y}$ |
| | Where y represents no. of the year the first publication |
| Hc index | $\text{hc index} = \alpha \cdot \frac{C(i)}{(Y(\text{now}) - Y(i) + 1)}$ |
| | Where $Y(\text{now})$ represents the current year, $Y(i)$ represents the publication year, and $C(i)$ represents the paper i citation count |
| | $\text{hc index} = \frac{C(i)}{1}, \frac{C(i)}{2}, \frac{C(i)}{3}, \ldots, \frac{C(i)}{n}$ |
| Aw index | $\text{Aw index} = \sqrt{\sum_{j=1}^{h} \frac{\mathrm{Cit}_j}{a_j}}$ |
| | Where $\mathrm{Cit}_j$ represents the citation count of the $j$th article and $a_j$ represents the $j$th article, and $m$ represents the total number of articles |
| Ar index | $\text{Ar index} = \sqrt{\sum_{j=1}^{h} \frac{\mathrm{Cit}_j}{a_j}}$ |
| | Where $\mathrm{Cit}_j$ citation of the article and $a_j$ represents $a$th article, h represents total h-core article |
| AWCR | This parameter adjusts the citation count based on the length of time that has passed since each publication |
| v index | $V = \frac{h}{P(y_{\text{this}} - y_o)}$ |
| | Where h is the h index, $y_{\text{this}}$ is the current year and $y_0$ is the year of first publication |
| Platinum h index | $\text{Platinum-h} = \frac{H}{CL} * \frac{\mathrm{cit_{all}}}{\mathrm{Pub_{count}}}$ |
| | Where H is the h index, CL is the career length, $\mathrm{Cit_{all}}$ is the total citation count and $\mathrm{pub_{count}}$ is the publication count |
| Ha index | The ha index against a dataset is the largest number of papers in the dataset that have obtained at least ha citations per year on average |
| HI Index | $h_i = \frac{h}{Avg_a}$ |
| | where h represents h index and $Avg_a$ represents average no. of authors in article |
| hf index | $\frac{Yh_f}{\phi(Yh_f)} \geq h_f$ |
| | where Y(i) represents citation count and $\phi(i)$ represents average no. of authors in article |
| gf index | $gf = \sum_{i=1}^{gf} \frac{Y_i}{\phi_i} \geq g^2 f$ |
| | where Y(i) represents citation count and $\phi(i)$ represents average no. of authors in article |
| gF index | $gF = (\sum_{i=1}^{k} \frac{1}{\phi(i)})^2 \leq \sum_{i=1}^{k} y_i$ |
| | where Y(i) represents citation count and $\phi(i)$ represents average no. of authors in article |
| Normalized Hi index | $\text{normalized hi index} = \frac{h}{\mathrm{pub_{count}}}$ |
| | Where h represents the h index and $\mathrm{pub_{count}}$ is the total number of articles |

**Table 7** continued

| Name of Index | Calculation |
|---|---|
| Hm index | $r_{\text{eff}}(r) = \sum_{r'=1}^{r} \frac{1}{a(r')}$ then $c(r(h_m)) \geq h_m \geq c(r(h_m)+1)$ |
| k-norm index | k-norm = h-norm + $(1-(h-\frac{\text{norm}^2}{\sum_{j=1}^{\text{h-norm}} \text{citnorm}_i}))$, $\vee$h-norm > 1 and k-norm = 0, if h-norm = 0 |
| w-norm index | w-norm = h-norm + $(1-(h-\frac{\text{norm}^2}{\text{totalcit-norm}}))$, $\vee$h-norm > 0 and w-norm = $\frac{\text{totalcit-norm}}{1+\text{totalcit-norm}}$, if h-norm = 0 |
| gm index | $g_{m \leq} C_{eff}(g_m)$ where $C_{\text{eff}}(r_{\text{eff}})$ and $S_{\text{eff})}(r_{\text{eff}}) = \sum_{\acute{r}=1}^{r(r_{\text{eff}})} \frac{1}{a(\acute{r})} c(\acute{r})$ |
| pure h index | $h_p(A) = \frac{h}{\sqrt{E(\text{author})}}$ |
| | Where h represents h index and E average no. of author |
| fractional h index | $h_f = \max(k \leq \frac{\text{cit}(k)}{\text{author}(k)})$ |
| | Where $\text{Cit}_k$ represents citation of article and author(K) represents no. of author in a specific article |
| fractional g index | $g_f = \max(\sum_{k=1}^{p} \frac{\text{cit}_k}{\text{Author}(k)} \geq p^2)$ |
| hi norm index | The hl-norm is a modified version of the h index that normalizes citations based on the number of authors per paper |
| K index | K index = $\frac{c/p}{c(\text{h-tail})/c(\text{h-core})}$ |
| | Where C represents total citation, P represents total publication, C(h-tail) represents total citation of h-tail article and C(h-core) represents total citation of h-core article |
| Real h index | $h_r = \frac{(h+1)\text{cit}_h - h.\text{cit}_h + 1}{1 - \text{cit}_{h+1} + \text{cit}_h}$ |
| | Where h is the h index and $\text{cit}_h$ is the citation count of the $h$th article |

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