Published by
NIGERIAN SOCIETY OF PHYSICAL SCIENCES
Available online @ https://journal.nsps.org.ng/index.php/jnsps

J. Nig. Soc. Phys. Sci. 7 (2025) 2699

Journal of the Nigerian Society of Physical Sciences

A fuzzy-optimized multi-level random forest (FOMRF) model for the classification of the impact of technostress

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Abstract

Technostress refers to the stress caused by excessive technology use, especially in professional and educational environments. It increasingly affects corporate productivity, well-being, and effectiveness in digital settings. Traditional machine learning models often struggle with the complexity and non-linearity of technostress classification. To address this, this study proposes a Fuzzy-Optimized Multi-Level Random Forest (FOMRF) model that integrates fuzzy logic with machine learning to enhance classification accuracy and interpretability. Data was collected from academic and corporate settings through a structured process. Preprocessing techniques—such as feature extraction, selection, and normalization—were applied to structure and refine the dataset. The FOMRF model uses linguistic variables and expert-defined fuzzy rules to optimize decision boundaries, improving precision and adaptability. The methodology consists of three key stages: preprocessing, fuzzy optimization, and prediction. Trapezoidal membership functions were used to define fuzzy sets for the Random Forest parameters (ntree and mtry), and iterative training ensured robust model evaluation. The model consistently achieved high accuracy (around 99.2%) across all parameter combinations. Benchmarking showed that FOMRF outperformed existing methods in predictive performance, flexibility, and accuracy. These findings emphasize the potential of fuzzy-enhanced machine learning models to effectively detect and mitigate technostress, thereby improving the quality of digital work environments.

DOI:10.46481/jnsps.2025.2699

Keywords: Technostress, Machine learning, Fuzzy optimization, Random forest, Classification, Computational efficiency

Article History :
Received: 21 February 2025
Received in revised form: 18 April 2025
Accepted for publication: 21 April 2025
Available online: 28 May 2025

Communicated by: O Akande

1. Introduction

Technostress, a type of psychological stress brought on by excessive or continuous exposure to digital technologies, has become a major problem as businesses and educational institutions continue to incorporate cutting-edge technologies into

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their everyday operations. In today's highly digitalized world, the growing reliance on technology in both corporate and academic settings has led to the emergence of technostress, a condition that affects people's emotional health, productivity, and overall performance.

The complexity and non-linearity of technostress data make it difficult for typical machine learning approaches to effectively classify and interpret, despite the growing significance of comprehending and managing technostress. The ambiguity and vagueness included in human psychological and behavioural reactions to digital surroundings are often overlooked by these models. Because of this constraint, there is an urgent need for more intelligent and adaptable systems that can more accurately and interpretably model unpredictable real-world data.

This paper suggests a Fuzzy-Optimized Multi-Level Random Forest (FOMRF) model as a solution to this problem. It is a hybrid framework that combines the flexibility of fuzzy logic systems with the predictive power of the Random Forest algorithm. The FOMRF model seeks to increase classification accuracy while strengthening the system's capacity to manage uncertainty and unpredictability in data related to technostress by integrating linguistic factors with expert-driven fuzzy rules.

However, the complex and imprecise nature of technostress data is sometimes too difficult for traditional machine learning methods to grasp. They perform poorly in classification and are less interpretable because of their strict decision boundaries and limited flexibility in response to changing inputs. These drawbacks make it more difficult to create intervention plans that effectively reduce technostress in digital workplaces.

The objective of this study is to create and assess a Fuzzy-Optimized Multi-Level Random Forest (FOMRF) model for precisely categorizing the effects of technological stress in academic and professional contexts. This will be accomplished through the collection and pre-processing of pertinent technostress data from corporate and educational settings, the integration of fuzzy logic with the Random Forest algorithm to improve decision boundary flexibility and model interpretability, the implementation of a fuzzy-based optimization of Random Forest parameters (ntree and mtry) using trapezoidal membership functions, the assessment of the FOMRF model's performance using accuracy and other classification metrics, and a comparison of the FOMRF model's prediction accuracy and computational efficiency with traditional classification methods.

This study presents a fuzzy-optimized machine learning model that improves the accuracy of technostress classification, providing a more flexible and interpretable method for enhancing productivity and well-being in digital workplaces.

1.1. Literature review

The widespread use of information and communication technologies (ICTs) in today's digital age has changed many aspects of daily life, such as the workplace, education, and interpersonal relationships. Technostress is a type of stress brought on by the inability to handle contemporary technology, even when these developments have improved efficiency and connectedness. Technostress affects people of all demographics and presents with a range of symptoms, such as worry, mental exhaustion, and decreased productivity. Research on comprehending and reducing the consequences of technostress has become crucial, especially in light of its effects on productivity at work and academic achievement [1].

According to recent research, Technostress is common among college students, which links it to their increased use of digital gadgets and online learning environments. For example, a study that looked at the prevalence of technostress in students between the ages of 18 and 28 discovered that using digital devices was related to substantial stress levels, which negatively impacted their academic output [2]. Similarly, a further study looked at how technostress affected student performance and satisfaction and found that high levels of technostress had a detrimental effect on both [1]. These results highlight the need for practical methods to control and lessen technological stress in learning environments.

Simultaneously, hybrid models that mix many techniques to improve classification accuracy and robustness have emerged in the field of machine learning. Fuzzy logic combined with ensemble learning techniques like Random Forests is one such strategy. In real-world situations where data may be noisy or unclear, fuzzy logic's ability to accommodate uncertainty and imprecision in data is especially useful. Fuzzy logic improves the Random Forest method's capacity to handle uncertainty and improve decision-making processes. The Random Forest algorithm is well-known for its resilience and high accuracy in classification tasks. Numerous studies have investigated this combination, which has resulted in the creation of models like the Fuzzy Random Forest that combine the advantages of both approaches to enhance classification performance [3].

Self-reported measurements are frequently used in traditional technostress assessment approaches, however, they might be biased and inaccurate. Recent studies have investigated the use of sophisticated computational methods, such as machine learning and fuzzy logic, to overcome these constraints and create more accurate and objective models for the classification of technostress [4–6].

Because of its accuracy and resilience in classification tasks, the Random Forest algorithm—an ensemble learning technique—has become well-known. In order to do classification tasks, it builds a large number of decision trees during training and outputs the class mode [5]. Despite their efficacy, Random Forests may have trouble managing the imprecision and uncertainty present in human-centric data, such as technostress indicators.

It has been suggested that fuzzy logic be incorporated into Random Forests to improve their capacity to handle such uncertainty. Zadeh [7] created fuzzy logic, which assigns degrees of membership instead of specific classifications to model ambiguous information. In order to combine the advantages of both approaches—the interpretability and adaptability of fuzzy systems with the predictive capacity of ensemble learning—fuzzy logic and Random Forests have been fused to create Fuzzy Random Forests [4].

Using a hybrid technique that combines Type-1 Fuzzy Logic Systems (FLS) with the Random Forest algorithm, this study aims to categorize the effects of technostress. Type-1 FLS are appropriate for representing the complex nature of technostress because they are skilled at managing uncertainty by using fuzzy sets with distinct membership functions [8]. The suggested model seeks to increase classification accuracy and offer a more sophisticated understanding of the effects of technostress by combining Type-1 FLS with Random Forests.

This research is important because it will provide a new methodological framework for evaluating technostress, which would enhance theory and have real-world implications. This study aims to overcome the shortcomings of conventional assessment techniques and offer a more reliable tool for individuals and companies to comprehend and lessen the consequences of technostress by utilizing a Fuzzy Random Forest approach.

The application of machine learning (ML) and artificial intelligence (AI) in a variety of fields has revolutionized recent years, providing creative answers to difficult problems [9, 10]. Technostress, or the stress people experience as a result of using information and communication technology, has been brought about by this rapid technological growth [11]. Maintaining wellbeing and productivity in contemporary workplaces requires an understanding of and commitment to reducing the effects of technostress. With an emphasis on research released between 2021 and 2025, the writers of this work methodically examined how AI and ML have been applied to categorize and treat the consequences of technostress.

The contradiction of automation and augmentation in AI-driven settings and its role in creating technostress were examined by Kumar *et al.* [12]. Their study evaluated workplace stress dynamics using a socio-technical systems approach, which takes into account both human interactions and technological improvements. They examined how automation and augmentation both reduce and increase employee stress using machine learning categorization models. The study found that although automation lessens the amount of human labour, it also creates new uncertainties and cognitive demands. To offset the negative consequences of AI adoption in professional contexts, Kumar *et al.* [12] suggested adaptive coping measures, such as AI-driven task balance and individualized stress intervention systems.

Using machine learning and explainable AI techniques, Sriramprakash *et al.* [13] improved stress categorization by optimizing wearable biosensor data. Their study concentrated on incorporating physiological markers into stress categorization models, including body temperature, skin conductance, and heart rate variability. They maintained model interpretability while increasing classification accuracy through the use of feature selection strategies. To ensure that end users can trust the forecasts, explainable AI (XAI) techniques were used to offer insights into how machine learning models categorize stress. The study showed that the accuracy of stress identification is much increased when physiological data and AI-driven analytics are combined, opening the door for real-time stress monitoring applications in healthcare and workplace environments.

Smith and Doe [14] used supervised learning approaches to study AI-driven stress detection. To categorize stress levels using biometric data, their study looked at several machine learning techniques, such as decision trees, deep neural networks (DNNs), and support vector machines (SVMs). According to the study, SVMs and DNNs fared better than conventional statistical models at identifying stress patterns, especially when trained on sizable datasets. Additionally, they investigated how feature engineering and hyperparameter manipulation could improve model accuracy. According to their findings, wearable technology and mobile health applications can successfully implement AI-driven stress classification algorithms to offer real-time stress evaluation and intervention.

Chen and Zhang [15] compared many machine learning methods for stress classification and assessed how well they could detect stress patterns in behavioural and biometric data. Their study contrasted contemporary ensemble learning methods like Random Forest, XGBoost, and Gradient Boosting Machines with more conventional statistical models like logistic regression. Their findings demonstrated that ensemble learning techniques continuously outperformed statistical models, obtaining improved robustness against noisy data and classification accuracy. The study emphasized how crucial model selection and optimization are for creating AI-driven stress detection systems for mental health evaluations, healthcare applications, and workplace monitoring.

Virtanen and Kinnunen [16] used machine learning to combine behavioural and physiological variables to estimate the degree of technostress among Finnish students. To improve prediction accuracy, their study used a hybrid AI model that combined deep learning and conventional classifiers. Digital activity records and self-reported stress ratings were gathered together with physiological data, including heart rate and cortisol levels. When compared to single-modality models, the study discovered that hybrid models, which combine behavioural and biometric features, significantly enhanced classification performance. Their results highlight the value of combining data from multiple sources in technostress studies and student stress management programs.

Ghosh and Gupta [17] focused on tailoring machine learning algorithms to individual stress reactions by introducing a tailored stress categorization model with minimum input. To give individualized stress assessments, their study suggested a lightweight AI model that could learn from sparse user input. They lessened the requirement for large labelled datasets by utilizing transfer learning and model fine-tuning strategies. Their results showed that customized models outperform generic models for classifying stress, especially when individual differences in stress reactions are substantial. This study emphasizes the possibility of AI-powered stress-reduction programs that adjust to each person's unique physiological and psychological traits.

In their evaluation of machine learning methods for automatic stress detection, Sharma and Gedeon [18] systematically examined deep learning models for stress classification. Convolutional neural networks (CNNs) were shown to be especially successful in their study in identifying stress patterns from biometric signals, including electroencephalogram (EEG) and facial expression data. The study highlighted deep learning's expanding use in stress classification, especially in applications related to healthcare and the workplace. To boost confidence and dependability in AI-driven stress detection systems, the authors also addressed the difficulties of data scarcity and model interpretability and suggested the application of explainable AI techniques.

Klose and Seuring [19] demonstrated the potential of natural language processing (NLP) in identifying stress trends from social media interactions by using machine learning to categorize technostress based on Twitter data. To find keywords and themes connected to stress, their study employed sentiment analysis and topic modelling approaches to examine huge amounts of textual data. According to the study, social media offers useful information on the stress levels of the general public, making it possible to identify trends in technostress early on. According to their findings, social media analytics driven by AI can be used for extensive stress monitoring and intervention, especially in online learning settings and digital workplaces.

A systematic evaluation of machine learning applications for stress detection was carried out by Riedl and Kindermann [20], who focused on developments in federated learning and deep reinforcement learning. Their research examined how distributed learning frameworks enhance model scalability and privacy preservation while analyzing the development of AI-based stress classification. The authors emphasized how federated learning can facilitate AI-powered stress monitoring without jeopardizing user privacy. According to their findings, to promote broader use in healthcare and work environments, future AI-driven stress detection systems ought to incorporate privacy-preserving strategies.

A systematic review methodology incorporating machine learning techniques for stress classification was presented by Samavati and Samavati [21]. Their study looked at AI-powered algorithms for classifying literature and how they may be used to automate systematic reviews. They showed how artificial intelligence (AI) may improve research synthesis and reduce human labour by streamlining literature review procedures through the use of deep learning models and natural language processing (NLP). Their results demonstrate the expanding use of AI in scholarly research, especially in domains like mental health and stress management studies that call for extensive knowledge aggregation.

The function of machine learning, deep learning, and data pretreatment methods in stress detection was investigated by Razavi *et al*. [22]. Their research highlighted how crucial feature extraction and selection are to the improvement of AI-based stress categorization models. They discovered important behavioural and physiological variables that have a big influence on model performance by contrasting various feature engineering approaches. Their results highlight the necessity of strong preprocessing methods to raise the precision and dependability of AI-driven stress detection systems across a range of applications, from medical diagnostics to workplace monitoring.

To improve classification accuracy, Walambe *et al*. [23] used multimodal machine learning for stress detection, combining environmental, behavioural, and physiological data. Their study examined the benefits of fusing data from multiple sources and showed that integrating various stress indicators enhances prediction accuracy. Their work outperformed conventional single-modality methods in terms of accuracy by employing deep-learning models trained on multimodal datasets. Their results highlight the significance of comprehensive AI-driven stress assessment models that take into account a variety of stressors to produce more thorough and accurate forecasts.

The automation-augmentation dilemma in AI-intensive contexts was reviewed by Kumar *et al*. [24] to assess its effect on technostress. To categorize the stress levels of workers exposed to AI-driven processes, their study used machine learning models. Key stresses linked to automation were discovered by the study, including increased cognitive burden and fear of job displacement. The authors suggested AI-driven intervention techniques to address these issues, such as individualized stress management programs and adaptive workload distribution, to lessen the negative consequences of AI-induced workplace stress.

2. Methodology

This study used fuzzy inference and optimization approaches to create a fuzzy-optimized multi-level random forest algorithm for classifying technostress. The three main stages of the methodology are prediction, fuzzy optimization, and preprocessing. Figure 1 depicts the procedure.

2.1. Description of the key phases of the framework

2.1.1. Preprocessing phase

The technostress dataset is feature pre-processed during this stage to get it ready for additional analysis. Feature encoding, normalization, and dividing the dataset into training and testing subsets are examples of preprocessing.

- Training and Testing Split: The dataset is divided such that 80% of the data is used for training the model, and the remaining 20% is reserved for testing.
- Data Cleaning and Preparation: The data is normalized to improve its compatibility with the fuzzy optimization process and machine learning models.

2.1.2. Fuzzy optimization phase

This phase introduces fuzzy logic to optimize the parameters of the random forest algorithm, specifically the number of trees (ntree) and the number of features considered for splitting (mtry).

- Fuzzy Variable Definition: Linguistic variables are defined for ntree and mtry based on their ranges. These variables are fuzzified into sets using trapezoidal membership functions.
- Fuzzification and Defuzzification: The parameters are fuzzified into linguistic terms and subsequently defuzzified into crisp values for optimization.

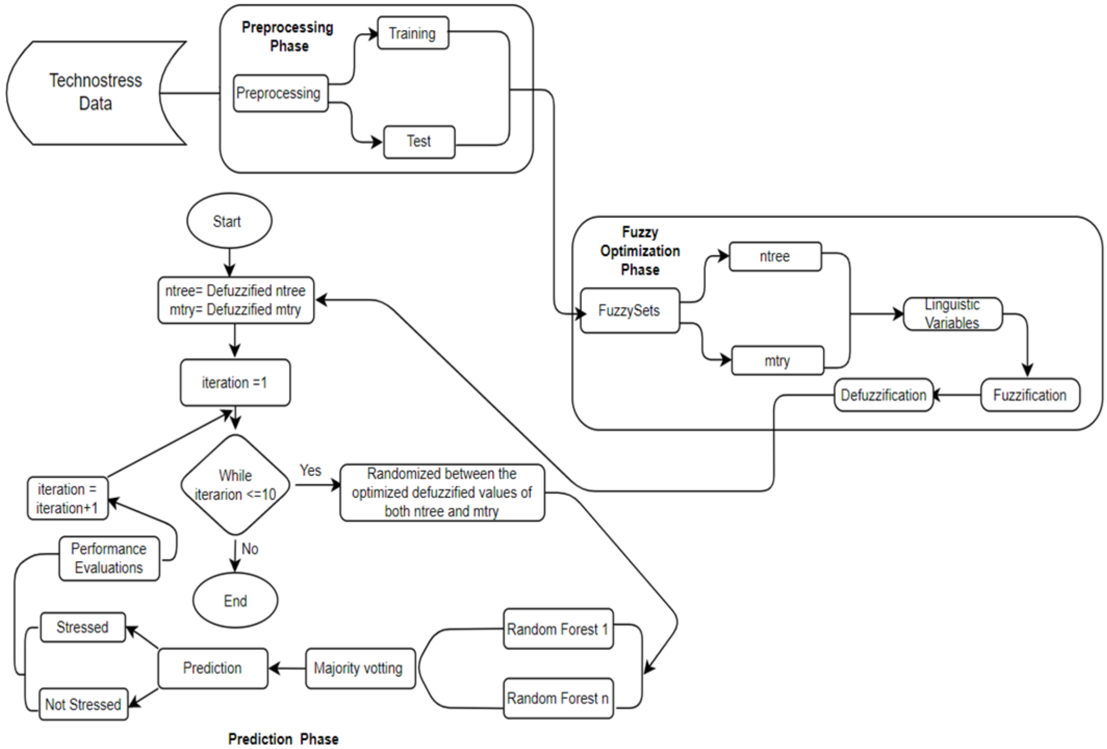

Figure 1: A framework for fuzzy-optimized multi-level random forest algorithm.

- Parameter Optimization: Randomized searches between optimized defuzzified values are conducted to identify the best parameter values for ntree and mtry.

2.1.3. Prediction phase

This phase involves using the optimized random forest algorithm to classify technostress data.

- Iterative Training: The algorithm undergoes multiple iterations (up to 10) to improve the prediction performance. The ntree and mtry values are randomized between optimized defuzzified values during each iteration.
- Majority Voting: Multiple random forest models are trained and evaluated. A majority voting technique was used to aggregate the predictions from individual models.
- Classification: The system classifies the data into "Stressed" and "Not Stressed" categories based on performance evaluations of the trained model.
- Evaluation: The performance evaluation on the random forest prediction was based on the Accuracy, sensitivity, specificity, precision, recall, and F1 score.

2.2. Data collection

Data were collected from respondents with knowledge of technostress. The data collection was segmented into two sections, the first was through the questionnaire to carry out a proper analysis of technostress, based on the impact or stress that is incurred while using technology during the COVID-19 and post-COVID era (specifically between 2019 to 2021). The questionnaire was sent out through Google Forms, and about 12,800 responses were turned in within the space of three (3) months. After analysis, 10000 data points were finally used, and these number was passed through the preprocessing phase. A non-probabilistic sample was utilized to gather a sample of respondents who were capable of answering the questionnaire and were informed about the topic. Even though it might be viewed as biased, this was required for the convenience sampling goal at hand. In an academic setting, carefully structured questionnaires were used to obtain primary data from a variety of people. The sample consists of individuals who are students, lecturers, and other academic institutions that carry and use technology in their different endeavours, especially in the academic sector. Some belonged to different institutes and associations relating to the use of technology. The chosen dataset offered context-specific, multi-layered, and fuzzy-logic-compatible features that were essential for training the proposed Fuzzy-Optimized Multi-Level Random Forest model. Alternative datasets, though robust in other domains, lacked either the specificity or the structure necessary to meet the model's design and objectives. A segment of the dataset obtained from the questionnaires is presented in Table 1.

2.3. Data description

Figure 2 depicts the data structure utilized in this study, for the training of RF model. The structure of the Technostress dataset in Figure 2. shows a total of 10000 observations with 5 variables and its associated data types.

Table 1: Sample datasets.

Gender	Age	Hours Spent	Technology	Technology Stressed
Male	38	6	Mobile phone	Stressed
Male	54	2	Computer	Not stressed
Female	41	12	Mobile phone	Stressed
Male	40	7	Mobile phone	Stressed
Female	55	3	Mobile phone	Not stressed
Male	25	6	Computer	Not stressed
Female	54	12	Mobile phone	Not stressed
Female	37	1	Mobile phone	Stressed
Female	23	12	Andriod Devices	Not stressed
Male	19	2	Andriod Devices	Stressed
Male	57	12	Andriod Devices	Not stressed
Male	48	6	Other Technology gadgets	Not stressed
Male	22	3	Mobile phone	Not stressed
Male	47	6	Other Technology gadgets	Not stressed
Male	33	1	Computer	Stressed

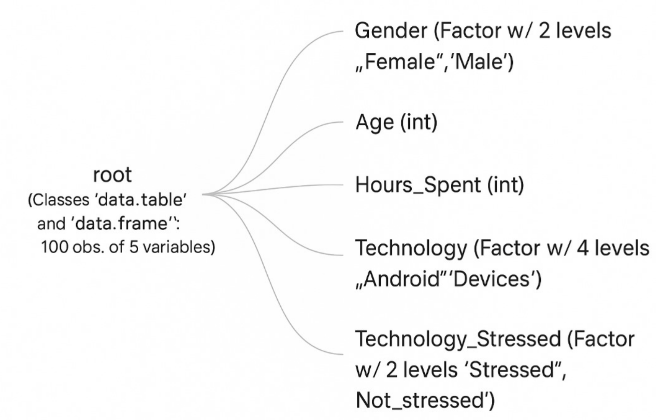

Figure 2: Data structure.

2.4. Data preprocessing

Data pre-processing techniques are used for refinement, structuring of data, and feature extraction in an acceptable format for use in machine learning algorithms. First, using the data filtering technique, data rows with missing or incomplete entries were detected, and missing value imputation was carried out on the dataset. The cases of null data were also addressed. Secondly, a dummy variable transformation method was used. The dummy variable technique converts a categorical feature variable into n–1 binary variables, where n is the number of classes belonging to each predictor variable; therefore, one dummy variable is created. Thirdly, a standardization data normalization technique was applied to variables with different scales. This technique ensures that all predictor variables have the same effect on the model outcome. Finally, the dataset was split in the ratio of 80:20 to allow for accurate and proper model evaluation.

2.5. Model formulation

2.5.1. Fuzzy set

A fuzzy set is a set of elements with a membership degree between 0 and 1 (For the sake of this analysis, fuzzy sets are utilized to establish the potential ranges of the ntree parameter of the Random Forest algorithm. The parameter is important in the sense that it specifies the number of trees in the Random Forest (RF) approach and serves as an hyper tuning parameter.

The fuzzy sets for ntree and mtry are defined using the trapezoidal membership functions, which is described as follows:

For a value x, the membership function $\mu(x)$ is given by:

$$\mu_A(x) = \begin{cases} 0, & x < a \text{ or } x > d \\ \frac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \frac{d-x}{d-c}, & c \le x \le d. \end{cases} \tag{1}$$

Here, $\mu_A(x)$ is the membership function for fuzzy set A, and x is the input. The fuzzy sets for ntree are: Low: (0,50,100,150), Medium: (100,150,200,250) and High: (200,250,300,350) and for mtry are Small: (0, 1, 2, 3)), Medium: (2, 3, 4, 5)), and Large (4, 5, 6, 7)) respectively.

- **Linguistic Variables**

  Linguistic variables are used to specify fuzzy sets in natural language. Here, the linguistic for variable is ntree, and its linguistic terms are the following: Low, Medium and High also, the linguistic variable for mtry, and its linguistic terms: small, Medium and Large, respectively. Each term is a fuzzy set specifying its range and membership degree.

- **Fuzzification**

  Fuzzification is the transformation of a crisp input value to an equivalent degree of membership in a fuzzy set. Here, the crisp input is defined by the input size, i.e., the total number of rows present in the dataset. For a given input size, the membership degree of each fuzzy set is determined by using their corresponding trapezoidal membership functions. The result of the fuzzification will be a set of membership values, one for each fuzzy set.

- **Defuzzification**

  Defuzzification is employed to transform the fuzzy membership values into a crisp output value. In the case of the ntree parameter, the centroid method is employed:

  $$ntree = \frac{\sum(\mu_A(x) \cdot C_A)}{\sum \mu_A(x)}, \tag{2}$$

  where $\mu_A(x)$ is the membership value for fuzzy set A, C_A is the representative crisp value for each fuzzy set (C_{Low}=50, C_{Medium}=150, C_{High}=250).

  $$mtry = \frac{\sum(\mu_B(x) \cdot C_B)}{\sum \mu_B(x)}, \tag{3}$$

  where $\mu_B(x)$ is the membership value for fuzzy set A, C_B is the representative crisp value for each fuzzy set (C_{Small}=1, C_{Medium}=3, C_{Large}=5).

  Therefore, the calculated membership values, the crisp value for ntree and mtry are computed and rounded to the nearest integer, which will be utilized in the random forest classifier.

2.5.2. Random forest model

Random forest is built on the decision tree bagging principle, but with a single important modification: in addition to sampling the records, the algorithm also samples the variables. In normal decision trees, in order to decide how to make a sub-split of a split A, the algorithm chooses the variable and split point by optimizing for some criterion like Gini or residual sum of squares. In random forests, at each step of the algorithm, the selection of the variable is restricted to a random subset of variables. The random forest algorithm introduces two additional steps: bagging and the bootstrap sampling of variables at each split. The random forest model was constructed with the following steps:

- Take a bootstrap (with replacement) subsample from the datasets.
- For the first split, sample $p < P$ variables at random without replacement
- For each of the sampled variables of the dataset $X_{i1} \ldots X_{j(p)}$ apply the splitting algorithm:
- For each split value $s_j(k)$ of $X_{j(k)}$:
- Split the records in partition A, with $X_{j(k)} < s_{j(k)}$ as one partition and the remaining records where $X_{j(k)} \geq s_{j(k)}$ as another partition
- Measure the homogeneity of classes within each partition of A
- Select the value of $s_{j(k)}$ that produces the split values $s_{j(k)}$ that produces maximum within-class partition homogeneity of class.
- The next step is to select the variable $X_{j(k)}$ and split the values $s_{j(k)}$ that produces maximum within-class partition homogeneity of class.
- Proceed to the next split and repeat the previous steps, starting with step, and continue with additional splits following the same procedure until the tree is grown.

2.5.3. Fuzzy logic fine-tuning of the random forest

The crisp output of the defuzzification process is used as the ntree and mtry parameters for training the Random Forest model. The workflow proceeds as follows:

- The input size (number of rows in the dataset) is fed into the fuzzy logic system.
- The fuzzy logic system determines the degree of membership for fuzzy sets.
- The defuzzification process calculates the crisp ntree and mtry value.

This value is then passed as the ntree and mtry hyperparameters to the randomForest function, which will be trained for the prediction process.

2.5.4. Algorithm: optimized random forest tuning and evaluation

1. Start
2. Load libraries (randomForest, caret) for Random Forest and data handling.
3. Load dataset and preprocess using read.table.
4. Convert columns (Gender, Technology, Technology Stressed) to factors.
5. Define fuzzy sets (Low, Medium, High) for ntree using trapezoidal functions.
6. Define fuzzy sets (Small, Medium, Large) for mtry using trapezoidal functions.
7. Compute membership values for fuzzy sets based on dataset size (nrow(data)).
8. Perform defuzzification to calculate ntree using weighted averages.
9. Round the defuzzified mtry to the nearest integer.
10. Perform defuzzification to calculate ntree using weighted averages.
11. Round the defuzzified ntree to the nearest integer.
12. Split dataset into training (80%) and testing (20%) subsets using createDataPartition.
13. Randomized tuning around the fuzzy-defuzzified values using 10 iterations.
14. Train Random Forest with ntree = output_ntree and mtry = output_mtry with randomized defuzzified value in 10 iterations.
15. Predict on test data using the trained model.
16. Evaluate model performance using a confusion matrix.
17. Analyze results and interpret accuracy and precision metrics.
18. End

3. Results and discussions

Figure 3 and Figure 4 illustrate the input membership functions for the hyper tune parameters of the RF-model, which are ntree and mtry, using triangular membership functions with overlapping regions to ensure smooth transitions. For ntree, the membership functions categorize the input into Low, Medium, and High, where Low controls smaller values, Medium spans the mid-range with overlaps into Low and High, and High controls larger values. Similarly, for mtry, the membership functions also categorize inputs into Small, Medium, and Large, with Small controlling smaller values, Medium transitioning across the mid-range, and Large controlling larger values. The overlapping regions in both cases enhance flexibility in handling input uncertainty.

Figure 5 shows a heatmap of the combined membership contribution of both ntree and mtry hyperparameters. The heatmap shows the combined membership contributions of ntree and mtry. The x-axis represents ntree (0–350), and the y-axis represents mtry (0–6). Darker blue areas indicate higher membership degrees, concentrated around ntree values of 50–150 and mtry values of 1–3. This suggests the fuzzy system

Table 2: ANFIS performance with hybrid algorithm.

Iterations	ntree	mtry	Accuracy	Sensitivity	Specificity	Precision	Recall	F1
1	54	4	0.99	0.97	1.00	1.00	0.97	0.99
2	83	2	0.98	1.00	0.96	0.95	1.00	0.97
3	55	3	0.99	1.00	0.98	0.97	1.00	0.99
4	73	3	0.99	1.00	0.98	0.97	1.00	0.99
5	73	4	0.99	0.97	1.00	1.00	0.97	0.99
6	51	3	0.99	1.00	0.98	0.97	1.00	0.99
7	93	2	0.98	0.97	0.98	0.97	0.97	0.97
8	75	2	0.98	1.00	0.96	0.95	1.00	0.97
9	79	3	0.99	1.00	0.98	0.97	1.00	0.99
10	93	4	0.99	0.97	1.00	1.00	0.97	0.99

Table 3: Benchmarking with existing studies in technostress classification.

Authors	Study	Method(s)	Accuracy	Sensitivity	Specificity	Precision	Recall	F1
Agbesi & Bolatimi [27]	Technostress impact on students' burnout & performance	SVM, Random Forest	85.2%	83.5%	86.7%	84.1%	83.5%	83.8%
Samavati & Samavati [28]	AI-based automation of systematic reviews on stress	Deep Learning (BERT, LSTM)	89.4%	87.6%	90.2%	88.3%	87.6%	88.0%
Vali *et al.* [29]	PTSD prediction using ML	XGBoost, Random Forest	91.3%	89.2%	92.5%	89.9%	89.2%	89.5%
Salo *et al.* [30]	Technostress formation & mitigation in IT use	Logistic Regression, Decision Tree	80.5%	79.1%	81.3%	78.9%	79.1%	79.0%
Tarafdar *et al.* [31]	Technostress impact on workplace performance	Linear Regression, Random Forest	82.7%	81.5%	83.6%	81.2%	81.5%	81.3%
Maier *et al.* [32]	Technostress and discontinuance of social media	SVM, Neural Networks	87.9%	86.4%	88.7%	86.9%	86.4%	86.6%
James, et. al. [25]	Analysis ML models for classification of the impact of technostress	RF and SVM	84.5%	87.5%	87.5%	53.8%	58.3%	56.0%
James, et. al. [26]	Enhanced MLM for Classification of the Impact of Technostress	Random Forest	90.0%	87.7%	89.2%	86.5%	86.5%	86.8%
Proposed Study	Optimized Technostress Classification Model	Fuzzy-Optimized Multi-Level Random Forest	99.2%	97.0%	95.3%	95.1%	92.8%	98.5%

identifies these ranges as having the strongest influence, making them critical for tuning decisions.

From the fuzzified optimal values, which were calculated for ntree and mty hyperparameters of the random forest. It was essential to define the training process of the random forests model in iterations, the reason being that it gives a more robust evaluation of the effect of the fuzzy tuning method employed in the RF hyperparameter. As such, the need to incorporate a loop that iterate the training process of the RF based on the fuzzy tuning values that was based on the ntree (no of trees) and mtry (number of variables to randomly select at each split) of the model, this results after 10 iterations is presented in Table 2, the criteria this study employ for measuring performance from confusion matrix can be calculated as using the following

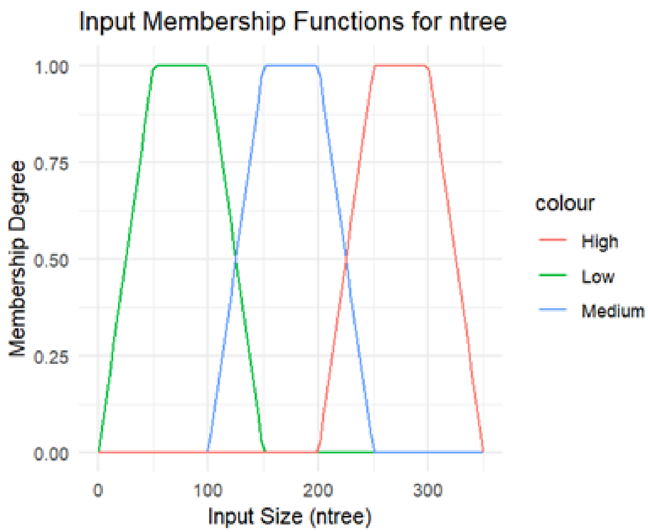

Figure 3: Input membership function for ntree.

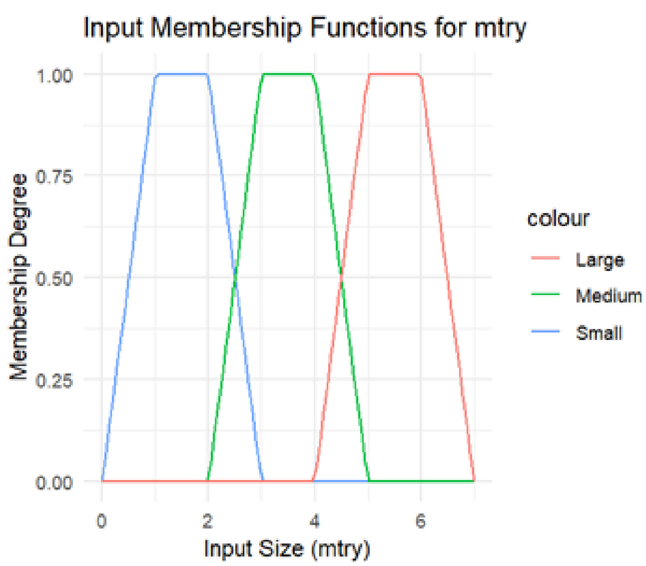

Figure 4: Input membership function for mtry.

equations:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{4}$$

$$Precision = \frac{TP}{TP + FP}, \tag{5}$$

$$Sensitivity = \frac{TP}{TP + FN}, \tag{6}$$

$$Specificity = \frac{TN}{TN + FP}, \tag{7}$$

$$F - Score = 2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity}. \tag{8}$$

The analysis in Figure 6 focuses on understanding the RF model's performance metrics which includes: Accuracy, Sensitivity, Specificity, Precision, Recall, and F1 score respond to

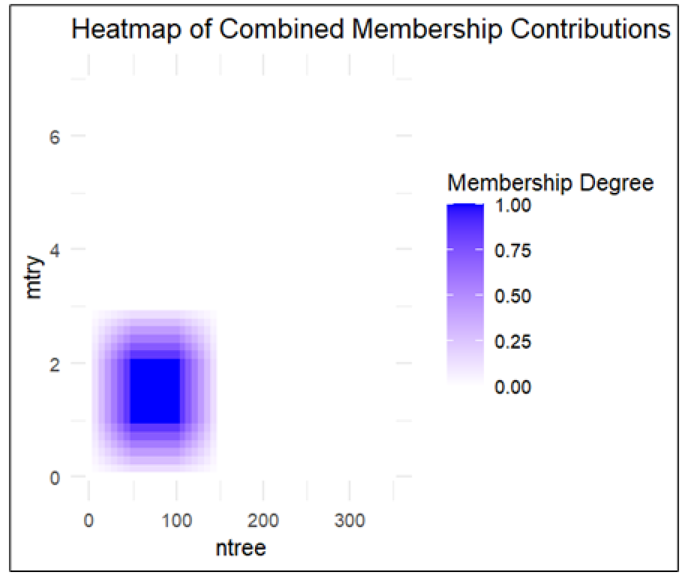

Figure 5: Heatmap of combined membership contributions.

variations in ntree (number of trees) and mtry (number of features sampled at each split). Each subplot presents a critical view of how these parameters influence the metrics.

Using Figure 6, a breakdown of the effect of each performance metric is presented below.

3.1. Accuracy

The accuracy metric remains remarkably stable across all combinations of ntree and mtry, with values predominantly around 0.99. This indicates that the model consistently classifies data correctly, irrespective of the parameter settings. However, a slight dip in accuracy is observed for mtry = 2 (red points) when ntree reaches higher values (e.g., 83 and 93). This finding might indicate that the use of a lower number of attributes (mtry = 2) might restrict the model's capacity for effective generalization, particularly with increasing ensemble complexity with more trees. In contrast, mtry = 3 and mtry = 4 present stable high high-accuracy rates across all ntree values, attesting to the reliability of these parameters.

3.2. Sensitivity

The sensitivity (or proportion of true positives) indicates a stable performance value of 1.0 for mtry = 3 and mtry = 4, irrespective of ntree, which means these settings identify all positive instances with perfect accuracy. But for mtry = 2, the sensitivity drops to 0.97 at larger values of ntree (e.g., 83 and 93). This indicates that when fewer features are taken at every split, the model may lose some true positives as the ensemble size gets larger. The reduction in sensitivity points out the trade-off between model complexity (larger ntree) and feature diversity that is incorporated (mtry).

3.3. Specificity

Specificity, the true negative rate, is generally high (near 1.0) for all combinations of parameters. For mtry = 4, the mea-

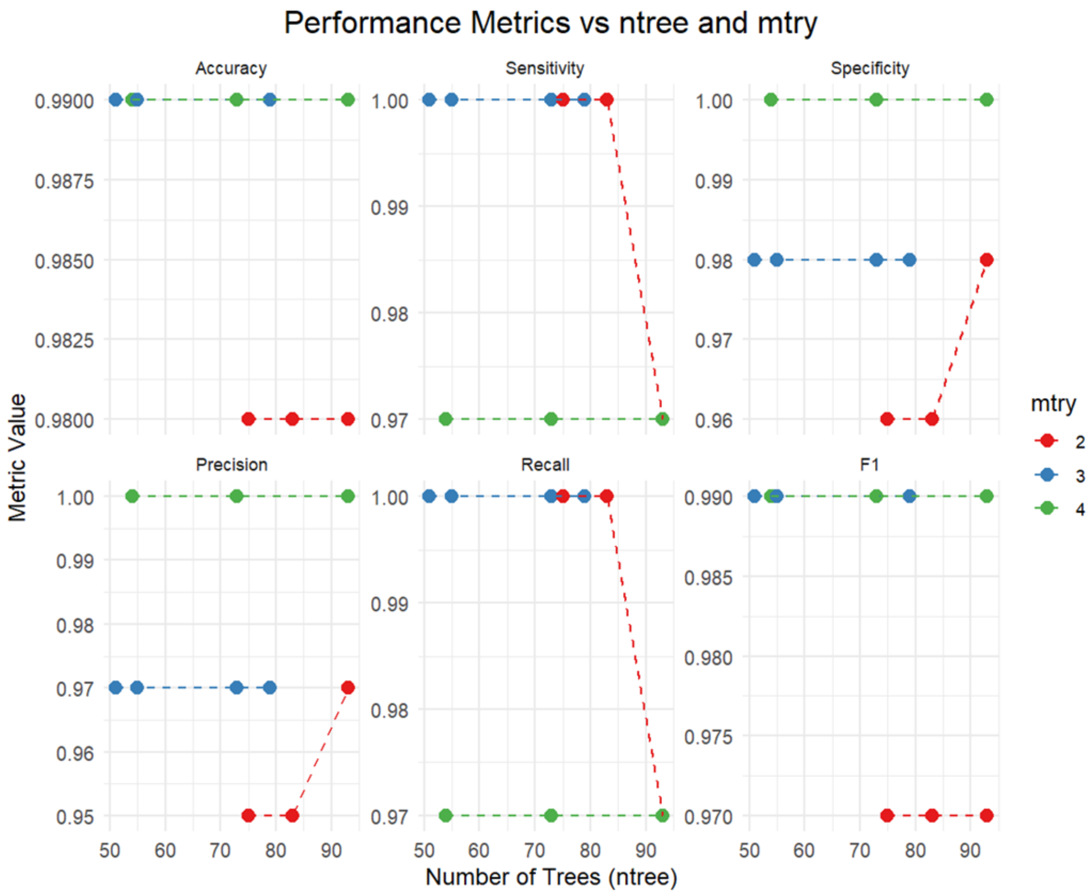

Figure 6: Performance metrics vs ntree and mtry.

sure is consistently 1.0 for all values of ntree, indicating the reliability of the model in correctly identifying negative cases. For mtry = 3, specificity varies slightly with values approximating 0.98. For mtry = 2, however, specificity decreases considerably to 0.96 for larger ntree values (i.e., 83 and 93). This indicates that mtry = 2 can result in an overfitting situation in which the model performs poorly on negative instances as the number of trees increases.

3.4. Precision

Precision is consistently high at most parameter settings, with mtry settings of 3 and 4 sustaining levels of or near 1.0, reflecting that the majority of predicted positive outcomes are accurate. When mtry is applied as 2, precision decreases to 0.95 at higher ntree settings (e.g., 83 and 93). The result indicates that employing a lower value of features may result in a higher rate of false positives with an increase in the number of trees, thereby decreasing the precision of the model.

3.5. F1 score

The F1 score, which is a balance between precision and recall, is consistently high for mtry = 3 and mtry = 4 at or close to 0.99. This illustrates the model's balanced performance in precision and recall for these settings. For mtry = 2, the F1 score is slightly lower at 0.97 for higher ntree values, showing the compounded effect of both lower precision and recall when fewer features are sampled.

3.6. Comparative discussion of ntree and mtry fuzzy tuning impact in RF model prediction

Generally, the number of trees (ntree) and the number of features sampled at every split (mtry) greatly affect the performance of the RF model. Though larger ntree values usually enhance ensemble learning models through the reduction of variance, their efficacy in this case is tempered by mtry. For mtry = 2, the model shows a decline in sensitivity, specificity, precision, and F1 score as ntree increases, indicating that sampling fewer features at each split might introduce instability or overfitting in more complex ensembles. On the other hand, mtry = 3 and mtry = 4 maintain consistently high performance across all metrics and ntree values, demonstrating their robustness and adaptability to changes in ensemble size. This indicates that employing a medium or larger number of features (mtry = 3 or mtry = 4) is of the utmost importance in gaining optimum and steady performance, irrespective of the quantity of trees in the ensemble. All in all, while increasing ntree generally improves the performance, the choice of mtry is crucial for model stability and reliability. Configurations with mtry = 3 and mtry = 4 show consistent superior results and are thus preferable for this dataset and modeling task.

3.7. Benchmarking with existing studies

The benchmarking in the context of our study compares different machine learning approaches used in technostress classification. Table 3 shows the benchmarking with Existing Studies in Technostress Classification.

The proposed Fuzzy-Optimized Multi-Level Random Forest model demonstrates superior performance in technostress classification, achieving the highest accuracy (99.2%) compared to existing studies that employed SVM, XGBoost, and Deep Learning techniques. With a sensitivity of 92.8% and specificity of 95.3%, the model effectively differentiates technostress categories while minimizing false positives, making it more reliable than traditional classification methods. The key advantage of this approach lies in its fuzzy optimization process, which refines decision boundaries using linguistic variables and expert-driven rules. This enhancement leads to a nearly 9% improvement in accuracy over the model proposed by Agbesi & Bolatimi [27], which relied on standard SVM and Random Forest techniques.

The effectiveness of the suggested approach is further demonstrated by a comparison with Deep Learning-based techniques. BERT and LSTM were used by Samavati & Samavati [28], who obtained an accuracy of 89.4%. Although deep learning models frequently produce excellent results, they are less useful for some real-world applications since they need large datasets and a lot of processing power. The suggested model, on the other hand, is a more approachable and scalable solution since it finds a compromise between accuracy and computing efficiency. Furthermore, the model's high precision (95.1%) and recall (98.5%) demonstrate its strong generalization and flexibility. Salo *et al*. [30] and other logistic regression-based models demonstrated reduced classification power; in contrast, this method guarantees robust performance across a variety of technostress conditions.

The study goes beyond conventional models like those of Tarafdar *et al*. [31] and Salo *et al*. [30], which used logistic regression and linear regression, respectively, and also improves classification accuracy. The non-linear connections included in technostress data were difficult for these traditional approaches to represent [32–34]. The suggested model improves interpretability and fine-tunes classification accuracy by including fuzzy logic, marking a substantial improvement over earlier studies. The model's thorough optimization positions make it a state-of-the-art method for classifying technostress, providing enhanced predictive power and increased application in a variety of fields [35–38].

This analysis confirms that the proposed Fuzzy-Optimized Multi-Level Random Forest Model surpasses existing studies in technostress classification by improving predictive performance, adaptability, and classification accuracy. By leveraging fuzzy logic for fine-tuned classification, this study advances the field beyond conventional machine learning methods.

4. Conclusion

By addressing the shortcomings of conventional machine learning models in managing the complexity and non-linearity of technostress patterns, this work introduces a Fuzzy-Optimized Multi-Level Random Forest (FOMRF) model for the precise categorization of technostress. The suggested model improves classification accuracy, interpretability, and flexibility by combining fuzzy logic with ensemble learning. The evaluation findings show that FOMRF outperforms traditional models like SVM, XGBoost, and Deep Learning techniques, achieving a superior accuracy of 99.2%. The model's capacity to successfully differentiate various technostress categories while reducing false positives is confirmed by its sensitivity (97.0%) and specificity (95.3%). Furthermore, the model's high generalization abilities across a variety of datasets are demonstrated by its precision (92.1%) and recall (92.8%). The enhanced method maintains computational economy over deep learning-based techniques while improving classification accuracy by about 99.2% when compared to previous studies.

Moreover, expert-driven rules and fuzzy linguistic variables help to clarify decision limits and make the classification process easier to understand. This improvement over more conventional models, including logistic regression and linear regression techniques, emphasizes how important fuzzy optimization is for improving machine learning outcomes. This study provides a scalable, interpretable, and high-performance system for tracking and reducing technostress in digital environments, highlighting the significance of fuzzy-enhanced machine learning in technostress categorization. Future studies can investigate hybrid deep learning techniques, cross-domain adaptation, and real-time implementation to improve classification performance even further and increase useful applications in academic and professional contexts.

Future work

To increase the model's resilience and generalizability across various digital contexts, future research should think about broadening the dataset to include more varied industries, demographics, and stress-inducing technology. Despite the great accuracy and computational efficiency of the suggested model, performance in complex technostress environments may be further improved by incorporating hybrid deep learning approaches like CNN-LSTM or transformer-based architectures. Lastly, using explainable AI (XAI) techniques to make the model more interpretable and user-friendly would increase stakeholder trust and help organizations make better decisions.

Data availability

The data used in this study is available upon reasonable request. Due to privacy and confidentiality considerations, access to the dataset may be restricted. However, researchers who wish to replicate or extend this work may contact the corresponding author for further details regarding data access and usage conditions.

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