

Evaluating the Efficacy of Base Models for Technostress Detection

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ABSTRACT

The widespread use of technology has led to an increase in technostress which is a phenomenon where individuals experience stress and anxiety due to their interactions with technology. As social media platforms become increasingly integral to daily life, detecting technostress from online interactions has become a pressing concern and an avenue to enrich the research in the area of detecting technostress. This study evaluates the performance of selected base models on X (Twitter data). Also, the study investigated the effectiveness of a feature extraction technique for the improvement of the model performance through data preprocessing. The study made use of the dataset of X posts (Sentiment140) obtained from the Stanford University. The extracted features were used to train and evaluate four base models: Random Forest (RF), Extreme Gradient Boosting (XGB), Gradient Boosting (GB), and Light Gradient Boosting Machine (LGBM). The performance of each model was evaluated based on accuracy, precision, recall, F1-score and Kappa statistics. The RF model outperformed other base models with accuracy, precision, recall, f1-score, and Kappa score values of 88.03%, 85.98%, 85.68%, 85.79% and 79.81% respectively. The results highlight the importance of preprocessing and feature extraction techniques in improving model performance; contributes to the development of more effective technostress detection systems and provide insights into the application of machine learning algorithms for analysing online interactions.

Keywords: Base models; Ensemble learning; Gradient boosting; Light gradient boosting machine; Natural language processing; Random Forest; Technostress

INTRODUCTION

The contemporary digital age is replete with the ubiquitous integration of technology in human daily lives and activities[1], [2], [3]. Human beings are in an era of connectivity[4], search for convenience[5], and pursuit of efficiency[6]. Connectivity as a goal in a global village is fuelled by the drive for meaningful interactions; the convenience goal is driven by the need for a better service experience and the pursuit of efficiency is for productivity and results. Technostress manifests through symptoms like anxiety, fatigue, and cognitive overload, which can have significant impacts on an individual's well-being. Detecting technostress is important to achieve timely interventions and improve digital health outcomes. Prior research on technostress detection has primarily focused on workplace settings, the use questionnaires and self-reports to detect stress[7], [8], [9], [10], [11], [12], [13], [14]. However, with the increasing availability of social media data, researchers have begun exploring automated methods for detecting stress/technostress through text analysis and machine learning[15], [16]. The proliferation of digital technology has led to the emergence of technostress which is a phenomenon where individuals experience stress due to their interaction with technology. Research has shown that for individuals physical symptoms indicative of technostress include increased heart rates, cardiovascular disorders such as hypertension and coronary heart diseases, gastrointestinal disorders, irritable bowel syndrome, gastritis, muscle tension pains, tingling in the limbs, insomnia, and sleepwalking, headaches, chronic fatigue, sweating, cervical pain, hormonal and menstrual disorders, and stress-related skin disorders. Furthermore, individuals often experience mental symptoms

which impact cognition and behaviour which include irritability, depression, decreased sexual desires, crying spells, and apathy[13], [17], [18].

Attempts to categorize the various ways in which technostress has presented itself have given rise to variants of technostress creators such as techno-overload, techno-invasion, techno-complexity, techno-uncertainty, and techno-insecurity. Techno-overload presents when the use or introduction of technology overtly or covertly increases the workload of an individual or demands that they work at a pace that is too demanding for them. Techno-invasion implies the infiltration of technology into the private space of people and their persistent feeling of the need to be constantly connected as a result of the ubiquitous nature of technology. Techno-complexity speaks to the intimidating or daunting experience that stems from the increasing level of needed learning, skills, and expertise required to keep pace with technological inventions and innovations that are finding their way into everyday life and workspace[19]. Techno-uncertainty on the other hand is triggered by the short life cycle and fast pace of changing versions or upgrades of some technologies which leave people in an unsettling state of not knowing which technology to specialize in[20]. Furthermore, techno-insecurity connotes the negative feeling that comes with people thinking that the introduction of technology will lead to job loss either due to the introduction of technology itself or people who are better at the technology coming to replace them[21]. Essentially, Technostress manifests in a range of negative emotions and other stress-related responses induced by the relentless use of digital tools and applications. While technology undoubtedly enriches our lives, it also introduces new stressors and complexities impacting work and mental health.

There is urgent need to detect and mitigating technostress in order to maintain healthy mental health and productivity. While various machine learning models have been applied to text classification tasks[22], [23], [24], [25], their application to technostress detection remains underexplored. This paper presents the training and evaluation of base models (Random Forest (RF), Extreme Gradient Boosting (XGB), Gradient Boosting (GB), and LightGBM (LGBM) which will then be used in an ensemble learning approach that combines the base models to enhance the accuracy of technostress detection.

ENSEMBLE MACHINE LEARNING

Ensemble Machine Learning is an ML technique that excels by leveraging on the synergy provided by the combination of two or more individual machine learning models. Through this integration of two more models (which might be homogenous or heterogenous) some of the inherent limitations or weaknesses in individual models can be overcome. Some of these limitations include bias, errors and variance.

Types of Ensemble Machine Learning

Ensemble Machine learning algorithm types spans those that can be described as the traditional machine learning algorithms to those that can be put together based on ensemble principles. Table 1 discusses some of the types of the popular ensemble machine learning such as bagging, boosting, stacking, Voting and Blending with their peculiarities while highlighting their strength and weaknesses.

Table 1 :- Types of ensemble machine learning

Type	Description	Strengths	Weaknesses
Bagging	Combines predictions from multiple models trained on different random subsets of the training data, often using bootstrapping (sampling with replacement).	Reduces variance, Effective for high-variance models like decision trees, Robust against overfitting	Less effective for reducing bias, requires many models, increasing computational cost

Boosting	Sequentially trains models, with each model attempting to correct the errors of its predecessor, often with weighted voting.	Reduces bias, Increases accuracy with weak learners, Handles complex datasets well	Prone to overfitting, more computationally intensive, Sensitive to noisy data
Stacking	Combines predictions from multiple base models by using them as input features for a meta-model, which makes the final prediction.	Leverages diverse models, Reduces overfitting, Captures complex relationships, highly flexible	More complex to implement, requires careful model selection, computationally demanding
Voting	Aggregates predictions from multiple models using majority voting (for classification) or averaging (for regression).	Simple to implement, Improves accuracy, Effective with diverse and complementary models	Limited ability to reduce bias, May underperform compared to more sophisticated ensembles
Blending	Similar to stacking but uses a holdout dataset to generate predictions for the meta-model instead of cross-validation.	Simpler than stacking, reduces risk of overfitting, Easier to implement	May not be as robust as stacking, Limited data used for training meta-model

Base Models Descriptions

The base models carefully selected for this work are RF, GB, XGB and LGBM. They are further explained in some details.

Random Forest

Random Forest is an ensemble learning algorithm that combines multiple Decision Trees to improve the accuracy and robustness of the model. It trains each tree on a random subset of features and instances, by aggregating the predictions of all trees the final prediction is made. Fig.1 depicts the structure of Random Forest.

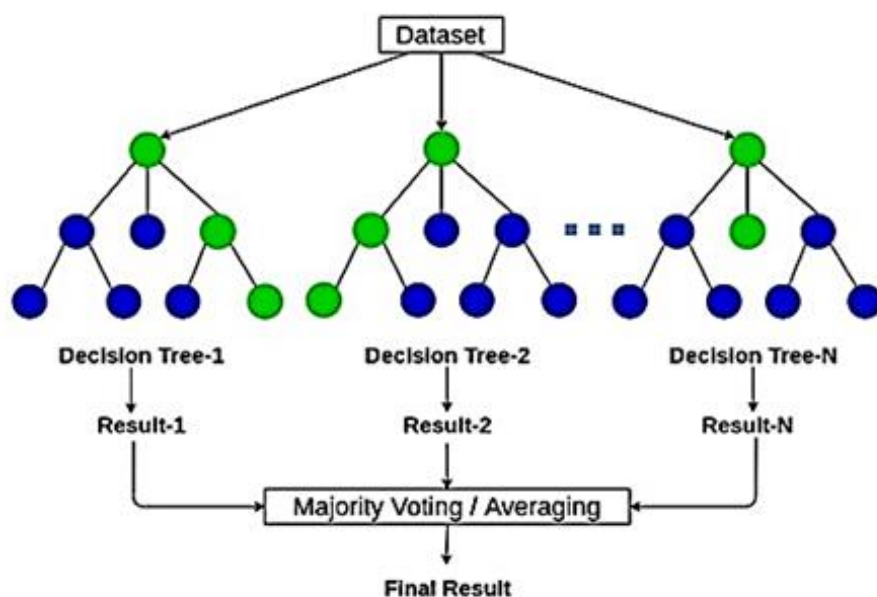


Fig. 1 Architecture of a Random Forest Model [26]

Gradient Boosting (GB)

Gradient Boosting is an ensemble learning algorithm that combines multiple weak models to create a strong predictive model. The algorithm trains each model on the residuals of the previous model, and the final prediction is made by aggregating the predictions of all models. Fig.2 depicts Gradient Boosting model.

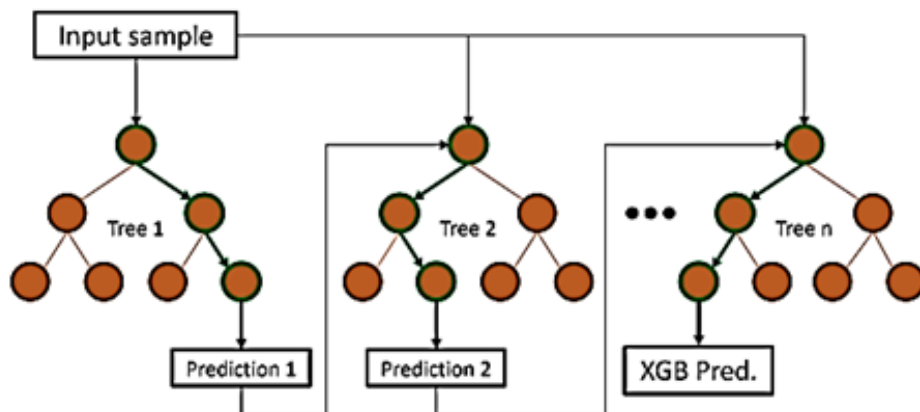


Fig 2. Architecture of Gradient Boosting Model[27]

Extreme Gradient Boosting (XGB)

Extreme Gradient Boosting is an optimized version of Gradient Boosting that uses a more efficient algorithm to handle large datasets. It feeds the residual from tree-1 to tree-2 so as to reduce the residual and this continues depending on the number of trees involved. XGB also provides several hyperparameters that can be tuned to improve the performance of the model. Fig. 3 depicts the workings of Extreme Gradient Boosting.

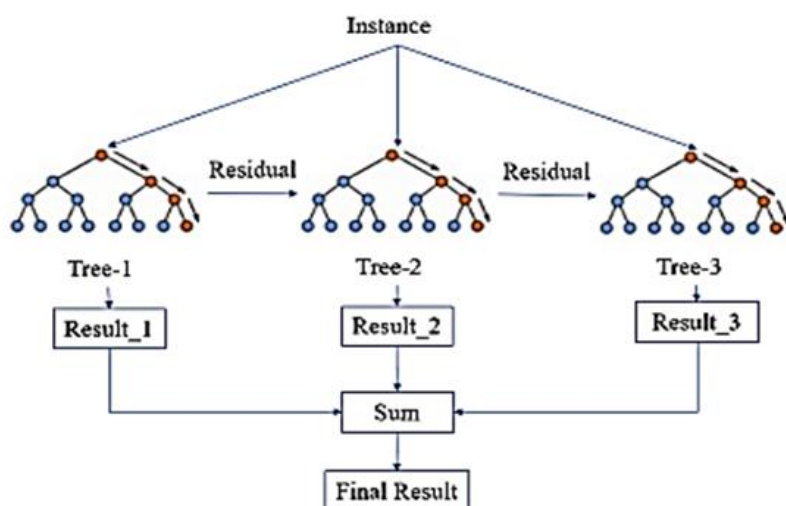


Fig 3. Structure of Extreme Gradient Boosting Model[28]

Light Gradient Boosting Machine (LGBM)

Light Gradient Boosting Machine is a fast and efficient implementation of Gradient Boosting that uses a histogram-based algorithm to handle large datasets. LGBM is a highly scalable algorithm that can handle massive datasets, and it is often used due to its speed and accuracy. It is a decision tree-based model that increases the model efficiency and enhances predictability performance while reducing the memory usage. This is also possible because LGBM provides several hyperparameters that can be tuned to improve the performance of the model. Fig.4 shows the working of Light Gradient Boosting Machine.

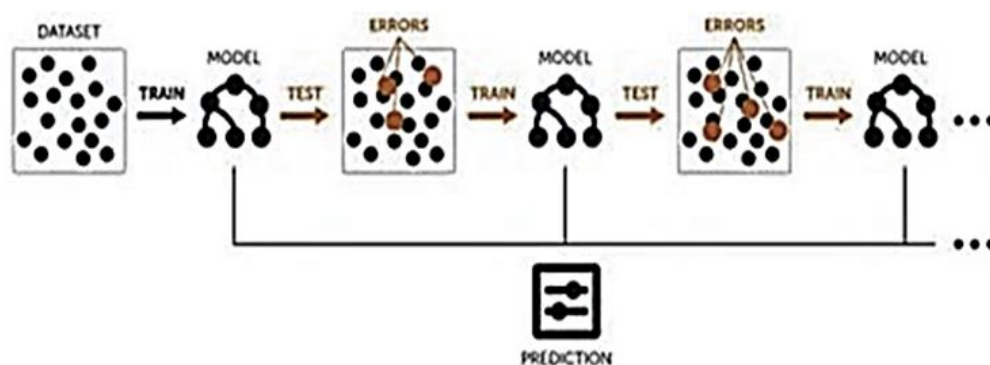


Fig 4. Architecture of Light Gradient Boosting Machine Model[29]

RELATED WORK

Twitter has become a mine for researchers in recent times especially when it revolves around emotion analysis. In their work[30], they looked at the use of SA and machine learning during critical events such as natural disasters and social movement using Bayesian Network Classifiers. They also adopted Bayes Network factor to enable them to yield a more realistic network. Comparing Bayes factor to Support Vector Machine and Random Forest, Bayesian network performed better in the case of dataset 2 while SVM machine performed better in the case of dataset 1. The researchers concluded that Bayesian network is preferable because SVM and RF are Blackbox models making it difficult to interpret while this limitation is partially addressed in the Bayesian Network.

Cristian, Pilar, Joan and Luis[31] analysed the evolution of technostress using a mapping approach. While reviewing scientific literatures from 1982 to 2017, they look at the development of technostress and the trends; they further performed a bibliographic analysis of 246 Scopus indexed record. They were able to find that there is a high level of technostress among rapidly growing economies such as China, Indonesia, India and Malasia. Today, this assertion, can also be made about many parts of the world as technology penetration is on the rise.

Mohamed et.al in their work managing technostress using data mining [32] emphasised that that data mined provides a basis for technostress detection. The developed two models Decision Tree and Random Forest 59.1% and 88.7% respectively. Another study by Klose et. Al[33] attempted to classify technostress using machine learning on X data. They reported that the base models they used performed better than the Deep Neural Network models that they had developed except for the simple neural network which outperformed them with 92% accuracy. The One LSTM and Two LSTM performed poorly with 33% and 39% respectively. A study on technostress prediction used Neural Network-based multi-layer perceptron (MLP) classifier with principal component analysis (PCA) and reported that it outperformed conventional ML algorithms, achieving a 71% classification accuracy as well as over 70% precision, recall, and F1-score [34]. These studies show that there is room for improvement of technostress detection.

Machine learning models, particularly those used as base models in ensemble techniques, are crucial for improving technostress detection[35], [36], [37]. Common base models utilized in ensemble learning include Decision Trees, Support Vector Machines (SVM), and Naive Bayes. Each model has its strengths and limitations in handling social media data. Decision Trees are simple and interpretable but may overfit when dealing with noisy X data. Support Vector Machines (SVM) offer robustness to overfitting and perform well with high-dimensional data, making them suitable for text classification tasks. Naive Bayes works well with large datasets, but its assumption of feature independence may limit its effectiveness in capturing complex patterns in technostress-related tweets. However, Ensemble learning, which combines multiple models has been shown to be particularly effective in similar contexts. The use of Ensemble techniques like Random and Gradient Boosting ride on the strengths of individual base models while mitigating their weaknesses. For

instance, Random Forests which is an ensemble of Decision Trees handle noisy data better and reduces overfitting. The use of other variants of ensemble learners like staking can further improve the accuracy of prediction.

This work builds on these foundations by leveraging stack ensemble learning to improve detection accuracy. However, we first evaluate selected base models for technostress detection.

METHODOLOGY

The methodology details how the research was carried out meticulously with due diligence as explained forthwith.

Data Collection and Preprocessing

This study utilized the sentiment140 dataset from Stanford University, which contains tweets labelled for sentiment analysis. A careful observation of the tweets led to a painstaking and thorough preprocessing steps as the raw data had a lot of irregularities. The dataset contained 1.6 million tweets which was then brought down to 7034 technostress and technology related text using NLTK library SentiWordNet. The study further checked for missing values, dropped irrelevant columns, handled stop words which are common words that do not add value to the sentiment analysis, handled special characters through the use of Beautiful Soup and Regular Expression in a bid to remove noise and ensure consistent text representation. Fig. 1 summarizes the processes earlier described. Furthermore, the study proceeded with Tokenization, Lemmatization, handling out of vocabulary words, N-gram experimentation to determine different word combinations and their impact on the model and adopted n-gram 3 which had a balanced capturing of meaningful constructs without becoming ambiguous as the other n-grams were. These activities culminated in Feature extraction where the study adopted TF-IDF because it outperformed Bag of Words and Word Embedding which are other available vectorizers as depicted in Table 2.

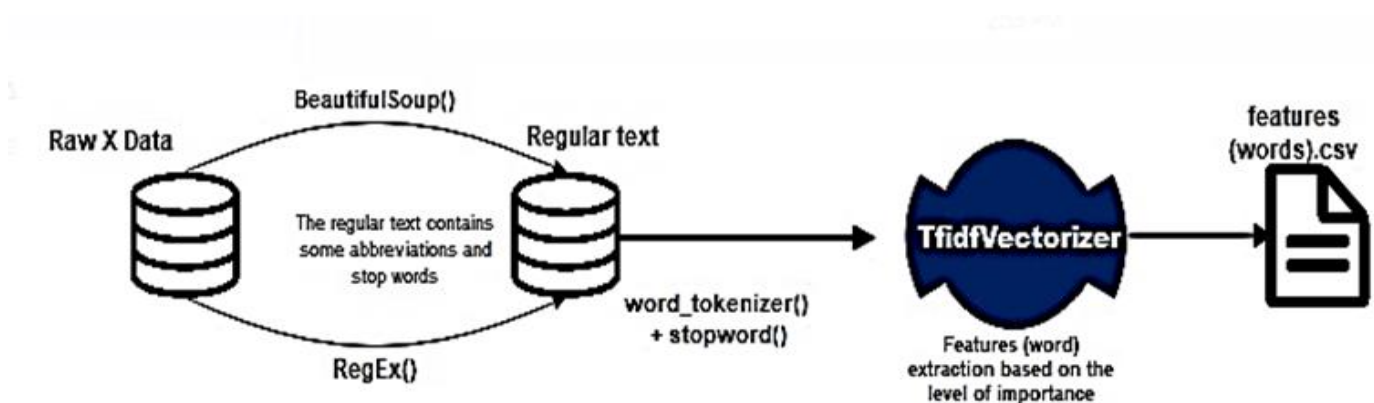


Fig. 5 Data Cleaning Proces

Table 2 :- Feature Extraction Method Accuracy Percentage

Feature Extraction Method	Accuracy (%)
Bag-of- Words	78.81
Frequency- Inverse Document Frequency	92.91
Word Embedding	75.87

Base Model Training and Evaluation

RF, XGB, GB, and LGBM were selected for their proven efficacy in text classification tasks and because they are intended to serve as base learners for further research that will culminate in a stack ensemble

machine learning for technostress detection. Each of these models were trained separately on the preprocessed data following the completion of the rigorous preprocessing and data cleaning activities.

EXPERIMENT AND RESULTS

Experimental Setup

The models were implemented using Python which provides rich machine learning tailored for Natural Language Processing. Libraries such as scikit-learn which provides access to classifiers such as RF, GB, XGBoost, and LightGBM. The 80:20 split ratio was adopted after experimentation with several split ratios (80:20, 75:25, 70:30 and 90:10) where it was observed that, although the performances from the various split ratios were relatively good across board 80:20 and 70:30 performed slightly better than the others. The choice of 80:20 split ratio was premised on its performance and frequent use in standard practice. The outcome of the experiment with split ratios is shown in Table 3. Therefore, the dataset was split into training (80%) and testing (20%) sets.

Table 3 :- Base Model Training Performance Base on Accuracy Across all the Split Ratios

Base Models				
Split Ratio	RF	GB	XGB	LGBM
70:30	100	96.50	91.85	80.89
75:25	99.98	96.53	91.72	80.31
80:20	100	96.66	91.40	80.89
90:10	99.99	96.64	91.02	81.51

Sequel to the model training based on the chosen split ratio, the study proceeded with the prediction of technostress using the test data (20%).

Performance Evaluation Metrics

The research evaluated model performance using accuracy, precision, recall, F1-score and Kappa value which are described in Table 4, the choice of which is informed by their versatile use in researches of similar nature.

Table 4 :- Performance Evaluation Metric Description

Performance Measures	Details
Accuracy	Percentage of accurate predictions in the entire population.
Precision	Percentage of positive predictions correctly predicted
Recall	Measures the proportion of correctly predicted positive instances out of all actual positive instances.
F1 Score	The harmonic mean of precision and recall, providing a single metric that balances both concerns.
Kappa Value	A score that expresses the level of agreement between two annotators on a classification problem.

The formula for the evaluation metrics is as follows:

Accuracy is given by the equation:

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

Precision is given by the equation:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall is given by the equation:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1 Score is given by the equation:

$$\text{F1 Score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

Where TN is True Negative, TP is True Positive, FP is False Positive and FN is False Negative.

Cohen Kappa value is given by the equation:

$$k = \frac{(p_o - p_e)}{(1 - p_e)}$$

where p_o is the empirical probability of agreement on the label assigned to any sample (the observed agreement ratio), and p_e is the expected agreement when both annotators assign labels randomly. p_e is estimated using a per-annotator empirical prior over the class labels.

Results

The results of the prediction evaluation are reported in the table 5.

Table 5 :- Performance Evaluation Across Ensemble Models

Base Models				
Metrics	RF	GB	XGB	LGBM
Accuracy	88.03	84.53	84.89	81.85
Precision	85.98	83.59	83.86	84.53
Recall	85.68	82.98	81.75	81.14
F1 Score	85.79	83.89	82.82	80.38
Kappa Value	79.81	71.40	73.16	67.37

The results are the outcome of the evaluation of the base models. Considering accuracy, Random Forest performed the most with 88.03% followed by Extreme Gradient Boosting, Gradient Boosting and Light Gradient Boosting Machine. On precision, Random Forest performed the most with 85.98% followed by Light Gradient Boosting Machine, Extreme Gradient Boosting and Gradient Boosting. On recall, Random Forest performed the most with 85.68% followed by Gradient Boosting, Extreme Gradient Boosting and Light Gradient Boosting Machine. On F1 Scores, Random Forest performed the most with 85.79% followed by Gradient Boosting, Extreme Gradient Boosting and Light Gradient Boosting Machine. On kappa statistic, RF performance the most as well with 79.81%, followed by XGB, GB and LGBM. It is observed that Random Forest outperformed all the other ensemble models in all the metrics.

SUMMARY AND CONCLUSION

The performance of the Random Forest ensemble model underpins the relevance of using ensemble models in technostress detection. Also, the relatively high performance across the other ensemble learners indicate that ensemble learning can be effective for the detection of technostress in text data.

Technostress remains a very debilitating problem silently ravaging the society and adding to the mental health burden in the world. It is evidenced that at the heart of many other disease conditions or their exacerbation is rising stress levels. The availability of Machine Learning techniques has been seen as a viable tool that can be utilized for the detection of technostress which will reduce the reliance on the use of questionnaires and other methods of data gathering that are unable to capture the presence of technostress early and are plagued with bias. In this study ensemble learning models were employed and their average performance can be put at the following 76.55%, 79.09%, 76.38, 75.81% and 63.84% which reflects the accuracy, precision, recall, F1 Score and Kappa Value respectively. The ensemble learning base models performed relatively well and are reliable for the detection of technostress. However, there is room for improvement which will culminate in this research looking at stacking ensemble learning in the future. The follow up research will endeavour to combine RF, XGB, GB, and LGBM as base models for stack ensemble classifier to see if the stacking will achieve higher accuracy than the individual ensemble models.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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