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A Meta Learner Strategy for Enhanced Techno stress 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 a meta learner strategy using Support Vector Classifier following the implementation 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 including the use of lemmatization and polarity scoring technique. The study made use of the dataset of X posts (Sentiment140) obtained from the Standford 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 results of the base models were then used as meta features for the meta learner strategy. The performance of the stacked ensemble shows that the meta learner strategy improved substantially the detection of technostress with improved performance across the evaluation metrics such as accuracy, precision, recall, f1-score, and Kappa score values of 97.03%, 96.88%, 93.92%, 91.63%, and 87.60% respectively. The results highlight the importance stack ensembling 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: Random Forest (RF), Extreme Gradient Boosting (XGB), Gradient Boosting (GB), and Light Gradient Boosting Machine (LGBM, Meta-Learner, Stack Ensemble.

I. 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 enhance technostress detection 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 a meta learner strategy to improve the detection of technostress sequel to the training and evaluation of base models (Random Forest (RF), Extreme Gradient Boosting (XGB), Gradient Boosting (GB), and LightGBM (LGBM) whose prediction was used as meta features in stacking ensemble using Support Vector Classifier as a meta learner. This approach combines the base models to enhance the accuracy of technostress detection.

II. ENSEMBLE MACHINE LEARNING AND STAKING

Ensemble Machine Learning technique leveraging on the synergy provided by the combination of two or more individual machine learning models. This integration of two or more models (which might be homogenous or heterogenous) enables overcoming some of the inherent limitations or weaknesses in individual models. Some of these limitations include bias, errors and variance.

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

Types	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

The choice of staking for this paper was informed by its flexibility especially as regards accommodating heterogenous models, robustness against overfitting and its ability to cope with some of the limitations inherent in the individual models. Since the problem at hand is a classification problem the choice of Support Vector Classifier was arrived at as it performed better than when experimented with Random Forest as the meta learner.

The base models carefully selected for this work are RF, GB, XGB and LGBM. Their choice was informed by their performance as seen in literature and in consideration of the limitation of the number of base models that could be used due to the constraints in resources such as memory. They are further explained in some details as follows:

a. Random Forest (RF)

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. Figure.1 depicts the structure of Random Forest.

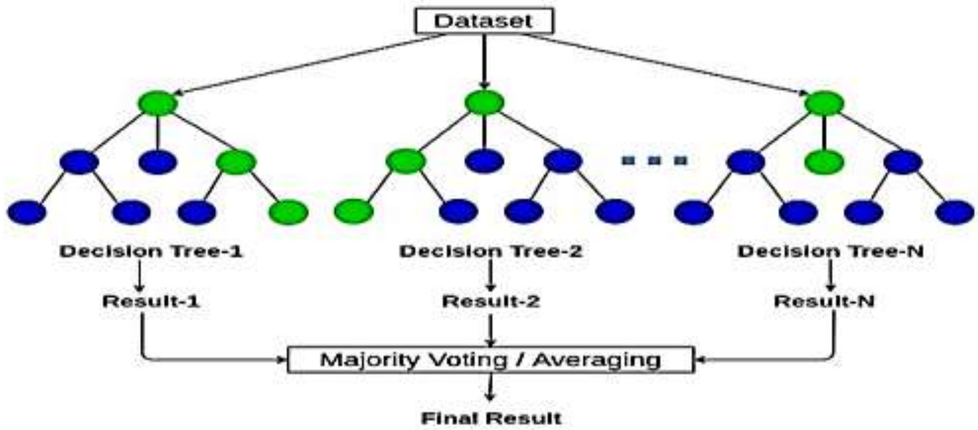

Figure. 1 Architecture of a Random Forest Model [26]

b. 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. Figure.2 depicts Gradient Boosting model.

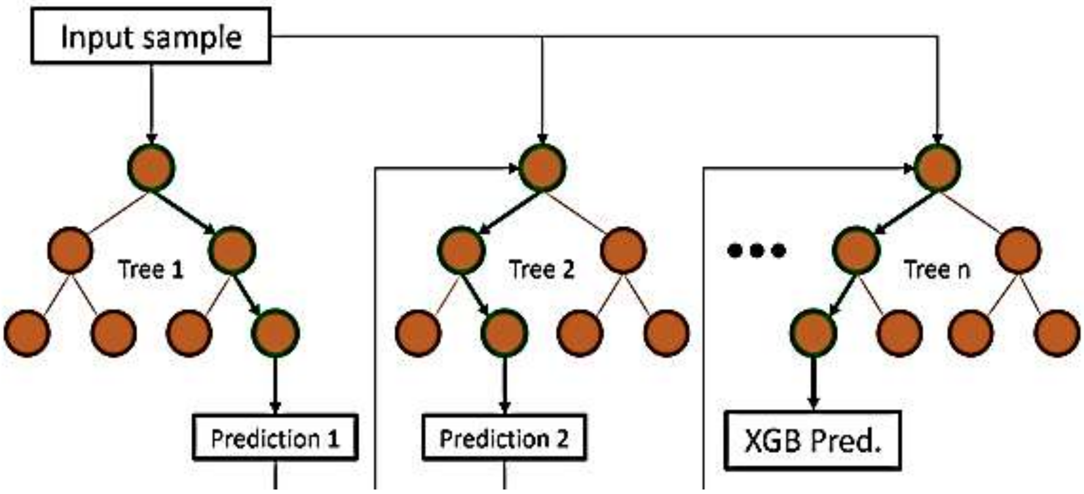

Figure 2. Architecture of Gradient Boosting Model[27]

c. 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. Figure. 3 depicts the workings of Extreme Gradient Boosting.

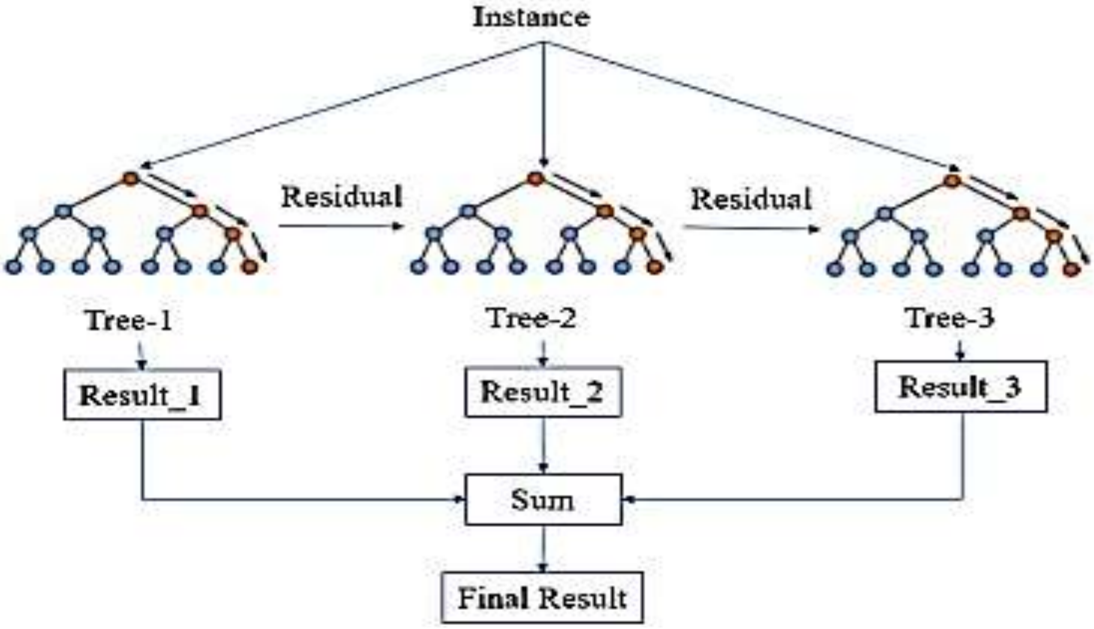

Figure 3. Structure of Extreme Gradient Boosting Model[28]

d. 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. Figure.4 shows the working of Light Gradient Boosting Machine.

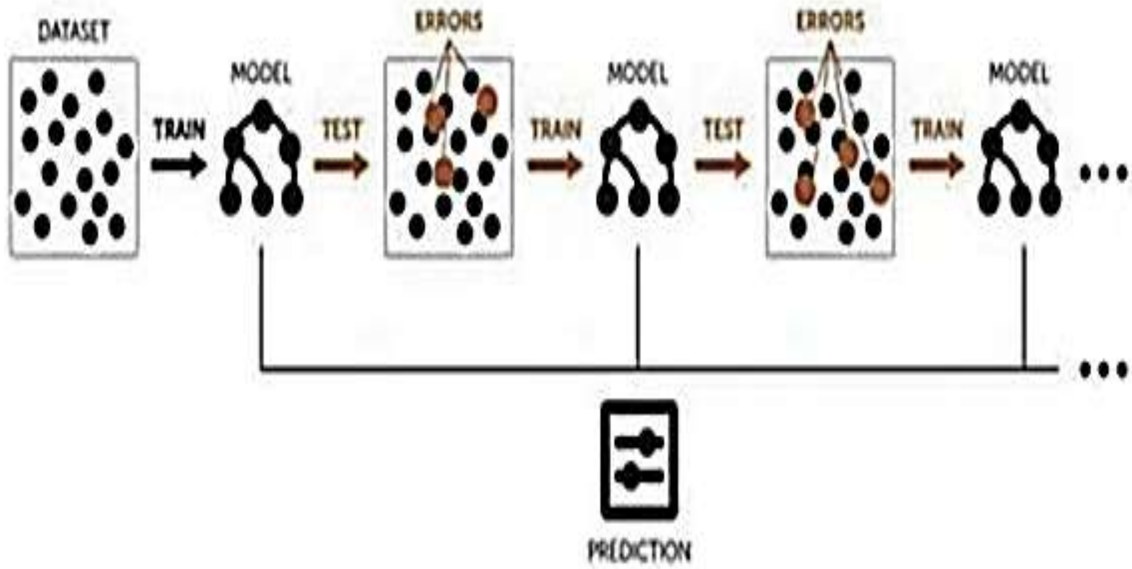

Figure 4. Architecture of Light Gradient Boosting Machine Model[29]

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III. RELATED WORKS

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 net-work 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 data mining provides a basis for technostress detection. They developed two models Decision Tree and Random Forest which achieved 59.1% and 88.7% accuracies 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. Another 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, re-call, 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 over-fit 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 and thereafter implemented the stack ensemble using SVC as the meta learner.

IV. METHODOLOGY

Figure 5 shows the conceptual model of the system starting with obtaining the dataset, preprocessing activities, using Beautifulsoup and regular expression to take care of irregularities in the text such as abbreviations and html tags, employing sentiment analysis and natural language processing techniques such as lemmatization and polarity scoring in order to proper contextualize technostress in the dataset and ensure appropriate labelling of the data. Following these, the research experimented with various data split ratios to arrive at the most effective. However, it was discovered, as shown in table 2, that there is no conspicuous difference in the performances in the split ratios as they relative performed well for all the base models. Hence the work stock with 80:20 split ratios for training and test as they are one of the standard splits often in use. The base models were then trained (usually referred to as level 0 in the scheme of stacking). Their performance in the detection of technostress was then stored in a data frame the result of which became meta features for the stacking (usually referred to as level 1 in the scheme of staking). The meta features were used in the training of the meta learner and the result was

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evaluated and compared with those of the base models.

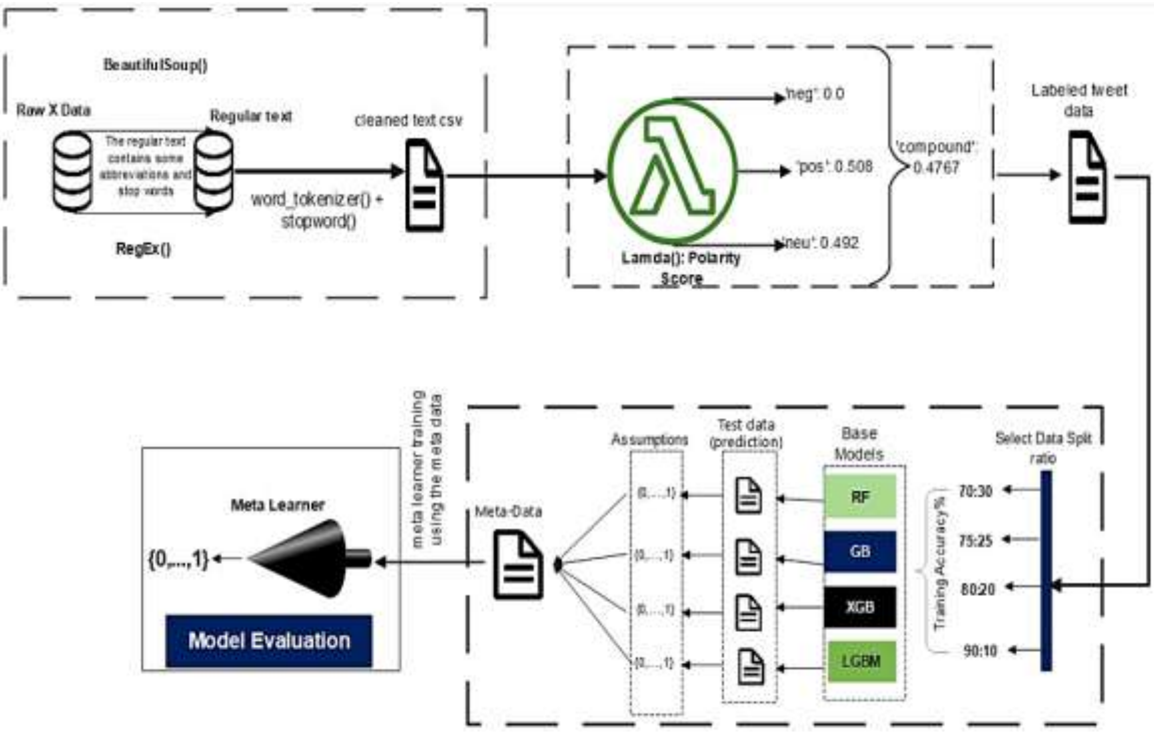

Figure 5: Conceptual Model of the System

Table 2. 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

V. RESULTS

Following the preliminary activities necessary for data preparation and preprocessing such as checking for null values, handling stopwords, special characters, punctuation marks; carryout tokenization, lemmatization and feature extraction, the stacked ensemble model was designed and implemented.

Table 3 shows 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.

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Table 3. 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 Bases Models RF, GB, XGB and LGBM predictions were combined to produce the new features as in Figure 6. The meta features were obtained from the individual predictions of the base models and pooled into a dataframe. These meta features were transformed (each column) using TF-IDF and the result is presented in Figure 7. This is then used as the dataset for the stack ensemble training and prediction. The meta features were split into test-train in the 80:20 ratio.

	RF_preds	GB_preds	XGB_preds	LGBM_preds	Actual/Target Values
0	Neutral	Neutral	Neutral	Neutral	Neutral
1	Neutral	No_Techno_Stress	Neutral	Neutral	Neutral
2	No_Techno_Stress	No_Techno_Stress	No_Techno_Stress	No_Techno_Stress	No_Techno_Stress
3	No_Techno_Stress	No_Techno_Stress	No_Techno_Stress	No_Techno_Stress	No_Techno_Stress
4	Neutral	Neutral	Neutral	Neutral	Neutral

Figure 6. A snap shot of the meta features

	RF_preds	GB_preds	XGB_preds	LGBM_preds	Actual/Target Values
0	0	0	0	0	0
1	0	1	0	0	0
2	1	1	1	1	1
3	1	1	1	1	1
4	0	0	0	0	0

Figure 7: A snap shot of the Transformed meta features

Following the implementation of the meta-model, the model was then evaluated using accuracy, precision, recall, f1-score and kappa statistic as shown in table 4.

Table 4: Performance Evaluation Meta Model

Meta Model Prediction				
Accuracy	Precision	Recall	F1 Score	Kappa Value
97.03	96.88	93.92	91.63	87.60

The result of the meta model was compared with those of the base models in Table 5.

Table 5: Performance Comparison of Base Models and Meta Model

Base Models and our Meta model					
Metrics	**RF**	**GB**	**XGB**	**LGBM**	**Meta Model**
Accuracy	88.03	84.53	84.89	81.85	97.03
Precision	85.98	83.59	83.86	84.53	96.88
Recall	85.68	82.98	81.75	81.14	93.92
F1 Score	85.79	83.89	82.82	80.38	91.63
Kappa Value	79.81	71.40	73.16	67.37	87.60

The stacked ensemble model significantly outperforms all the base models across all metrics. This is further depicted in table 6 in terms of the percentage improvements over the base models.

Table 6: Percentage improvement over the Base Models

Metrics	Performance	Percentage improvement over the base models
Accuracy	97.03%	9-15%
Precision	96.88%	10-14%
Recall	93.92%	8-12%
F1 Score	91.63%	6-11%
Kappa Value	87.60%	14-20%

These results suggest that the meta-model successfully leveraged the strengths of the base models, reduced errors and improved the overall detection of technostress with at least 9%, 10%, 8%, 6% and 14% in terms of accuracy, precision, recall, F1 Score and Kappa value respectively.

VI. CONCLUSION

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 base models performed relatively well and are reliable for the detection of technostress. However, it was obvious that there is room for improvement which culminated in this research looking at stacking ensemble using SVC as a meta learner. This follow up research proved that to combine the predictions of RF, XGB, GB, and LGBM as meta data the stacking achieves enhanced detection of technostress than the individual ensemble models.

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