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Stack Ensemble Model to Detect the Stress in Humans by Considering the Sleeping Habits

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Abstract*— Recently, one of the big challenges encountered by humans is experiencing and managing stress. Beyond the age restriction, people of all ages, from teenagers to seniors, experience issues as a result of stress. Acute and chronic stress are the two main categories of stress. Acute stress is a typical human response that aids in your body's adaptation to a new situation. In actuality, this form of stress has positive effects. However, the second type of stress, chronic stress, is a crucial type of stress, and this study focused on determining the stress level of this type in advance. This research examined eight attributes related to chronic stress to investigate the chosen person's sleeping patterns. The Kaggle website provided the dataset that was used in this study. The user's snoring range, body temperature, limb movement rate, blood oxygen levels, eye movement, number of hours of sleep, heart rate, and stress levels (0-low/normal, 1-medium low, 2-medium, 3-medium high, 4 - high) were all taken into account. The stack ensemble approach was utilized with two levels during this approach. At level 0, the classifiers such as Random Forest, Decision tree, K-nearest neighbour, and XGBoost were considered. At level 1, as a Metamodel, Logistic regression was adopted. Moreover, the predictions obtained from the level 0 models added an additional attribute to the original dataset and fed it to the level 1 model as a new training dataset. Additionally, five folds of fold cross-validation were performed along with the basic assessment to validate further the model for various ratios of training and testing data. Following the cross-validation, the model's mean accuracy obtained for RF, DT, KNN, XGB and stack ensemble models. From the results discovered, it was represented that the combined model (stack ensemble model) produced more precise results rather than the models considered in isolation.

Keywords*— *Stack Ensemble Model, Chronic Stress, Meta Model, Machine Learning

I. INTRODUCTION

Stress is one of the most significant threads and commonly used words nowadays. Researchers have understood the relationship between sleeping habits and stress. There were many studies [1] to focus the changes according to the sleeping behavior and their stress level. There were several other factors which positively affect the stress but sleeping pattern plays major role. Either inadequate change in sleep leads to stress, or the outcome of the stress leads to sleep inconsistency too. Stress is a mental or emotional state that occurs due to unpleasant or complex conditions, often known as stressors [2]. Stress is a usual hormone production to handle specific situations, but chronic stress is known as the extend level of that hormones release. This stress type lead to severe health issues [3] like depression, insomnia and heart issues. Stress is also defined as a physical burden on the body triggered by a variety of stressors. Stress hormones are released when the human body is exposed to a stressful situation. Physiological, psychological, absolute, and relative stressors are the four types.

Psychological stress can be acute and chronic [4]. Acute stress is a temporary stressor that will pass fast. You feel it when you slam on the brakes, fight with your partner, or ski down a steep slope. It assists you in dealing with potentially harmful scenarios. It can also happen if you try something new or intriguing. At some point in their lives, everyone experiences intense stress. Chronic stress lasts for a long time; if you have money troubles, an unhappy marriage, or work problems, you may be suffering from chronic stress. Chronic stress is any stress that lasts for weeks or months. Chronic stress might become so habitual that you are unaware it's an issue. Stress can lead to health problems if you don't learn to control it.

Researchers identified that certain stress levels must be essential to quick up our goals in our life[3]. But if that exceeds, it will lead to severe issues. Mostly nowadays, without any age difference, all the people face stress issues. Specially adults have many platforms which causes stress. The amount of electrical and electronic uses was increased. Even though we had many reasons to release more amount of hormones which lead to stress but significant studies [1] found that sleeping had the closest connection to forming stress and reflecting stress. Sleep is an active phase that aids in the development of optimal health and well-being by restoring processes and strengthening the human body. This study considers characteristics such as the number of hours of sleep, snoring range, respiratory rate range, heart rate range, oxygen in blood range, eye movement rate or duration of time spent in REM, limb movement rate, and change in body temperature to monitor the quality of sleep.

II. Literature Review

There were lot of studies focused on Machine Learning approaches, but we can find lack in the comparison of effective algorithms. When it comes to accuracy of a final model for the same dataset vastly verify each algorithm. But the surprise was even the latest algorithms exist but researchers in recent years too used very old algorithms as well as get inefficient model. When it comes to health domain specially the IT side people affected, and they are the real customers to the health domain. So, we can see most of the studies incorporated with technical and health domain collaborations. The below sections were the analysis of very recent studies which focus on stress and ensemble approaches with the relations of sleeping habits.

Russell Li and Zhandong Liu[3] were published a research work to analyze the stress from the data which collected from attached sensors from human body. They compared the result from traditional machine learning methods and Deep Neural Network models. This study created two deep neural networks: a deep multilayer perceptron neural network and a deep 1D convolutional neural network. The networks conducted the two tasks of binary stress detection and 3-class emotion classification by analyzing physiological signals obtained from wrist- and chest-worn sensors. The two deep neural networks' performance was assessed and contrasted with that of conventional machine learning techniques employed in earlier studies.

A detailed review study [5] was conducted to detect the stress mainly focus on the data sets from wearable and non-wearable sensors. Data collecting methods were highly influence the accuracy and the output of the research. They thoroughly analyzed the datasets and stressors with the recent research papers. Also, in this study they discussed about subjective stress assessment like wide range of questionnaires developed by psychologists to calculate the various stresses and objective stress assessments include physical and physiological measures. Future studies on stress measurement should consider multimodal ways for detecting human stress as well as a review of the shortcomings of the existing research and open research problems. We have given particular attention to solutions that make use of or are appropriate for using artificial intelligence methods for automated stress identification. The information offered here will serve as a foundation for future research on stress detection, especially when using AI and domain expertise. With this, we also better contextualize techniques for acute stress detection in normal life and for more demanding scenarios (chronic).

An Indian researchers automated the mental stress detection and detailed the difference between data collected from wearable device and individual data. Using a same dataset to process the various Artificial Intelligence models like Artificial Neural Network (ANN), Hybrid of Artificial Neural Network and Support Vector Machine (ANN- SVM), Stacking Classifier and Radial Basis Function (RBF) Network. The results were compared in the process of predicting stress level. During the study, Stacking Classifier gave the highest accuracy value of 99.92% while the RBF gave the least accuracy of 84.46% for three class classification of stress [2].

Ensemble Machine learning approach [6] was used for improving the prediction of posttraumatic stress disorder (PTSD) formed in a substantial minority of emergency room patients. Cost- efficient and accurate person-level assessment of PTSD risk after trauma exposure was a critical precursor to wide level deployment of early interventions that increased individual suffering and societal expensive development after emergency room hospitalization. Progress in identifying more useful predictors that can be routinely collected, and eliminating the unwanted stuffs, may increase efficiency while improving the accuracy of algorithms that can guide decision-making among patients and providers considering a targeted preventive care intervention after trauma exposure. This paper used gradient-boosted decision trees that rely on the collective performance of individually weak classifiers. Each model is comprised of decision trees with branches representing logical structures terminating at a leaf representing a probability weight. The number of trees in a model and branches in a tree vary as a function of model parameters.

The type of work people does also affect the stress level. This paper [7] predicted the stress level in IT employees. With the increasing work load especially the IT professionals affected by stress compared to other environments. In this paper researchers analyzed with many machine learning algorithms to predict the stress level. Logistic Regression, K-Nearest Neighbor Classifier (KNN), Decision Tree, Random Forest Classifier, Boosting & Bagging algorithms were used to predict stress level for the same data set. In the final prediction model boosting algorithms predicted the highest classification accuracy and precision followed by random forest. Also in the future work they suggested to include Naives Bayes classifier and Convoluted Neural Network(CNN) to verify the models to get the highest accuracy.

In both eukaryotes and prokaryotes, DNA N6-methyladenine (6 mA) is an epigenetic alteration that is essential for number of cellular activities. In this study a brand-new online tool for predicting DNA 6 mA sites used to further increase the prediction accuracy for two species, they investigated several feature encodings approaches and ML algorithms. This study combined five encoding techniques to create a single set of 1570 feature vectors first. The ONF (210 features) subset is then extracted from the 1570-dimensional set using the Recursive feature elimination with cross-validation (RFECV) technique, independently for both species [9].

Tagel Aboneh and et.al [10] researched on Stacking – Based Ensemble model which shows the majority of conventional machine learning algorithms struggle to provide optimal classification on multi-spectral picture data. To improve the performance of picture categorization, we suggest a stack-based ensemble-based learning strategy in this study. To further boost the suggested ensemble learning method's classification accuracy, we combine it with XGBoost. The Landsat picture data for the experiment was obtained from the Ethiopian town of Bishoftu in the Oromia area. The major goal of the current study was to evaluate how well multi-spectral image data was used to analyze land use and cover. Our experiment's findings show that the suggested ensemble learning method beats any strong base classifiers, with a classification rate of 99.96%. Performance precision.

III. METHODOLOGY

The approach used to develop the final stack ensemble model consists of several processes. It was briefly depicted by the Fig.1 below.

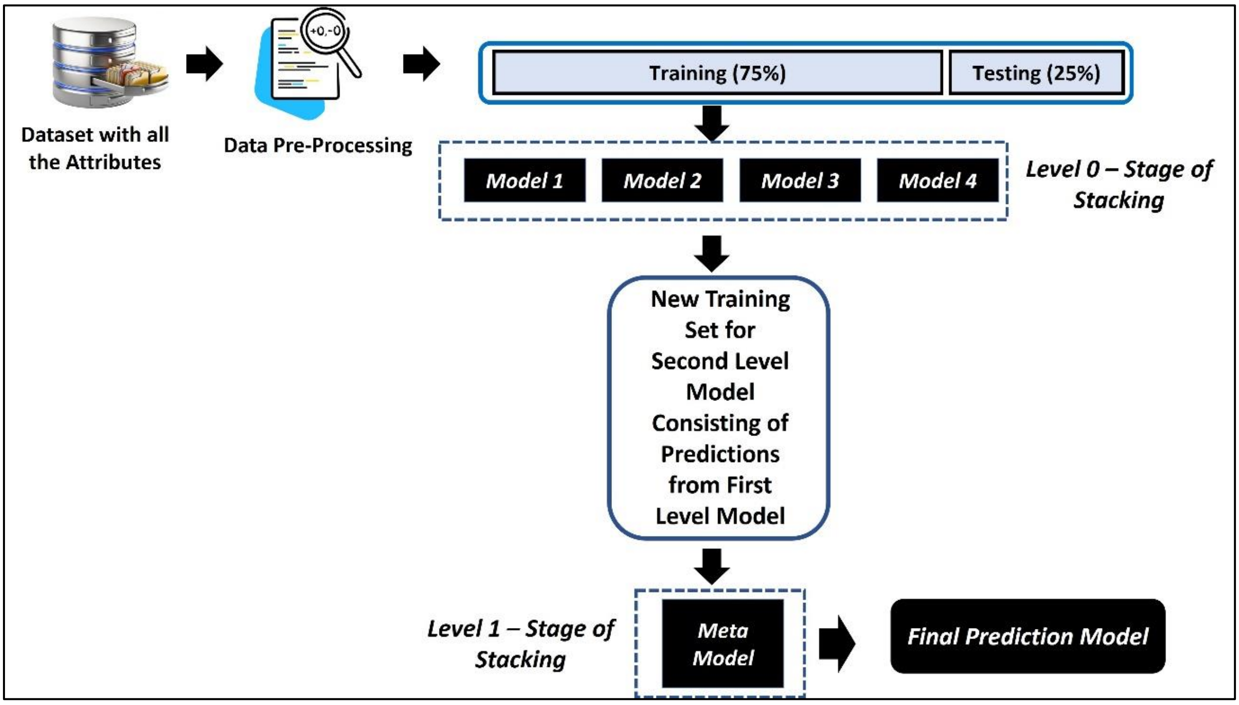

Fig. 1. Approach for stack ensemble model development

a. Data

The dataset utilized during this research was obtained from Kaggle Website [8]. Details belonging to 630 people along with 9 attributes related with stress and sleep were thoroughly analyzed. L. Rachakonda and his team obtained this dataset by developing a software with IoT and Cloud named "Yoga Pillow(SaYoPillow).The considered attributes were snoring range where the user resides, body temperature, limb movement rate, blood oxygen levels, eye movement, amount of hours of sleep, heart rate, and the stress levels (0-low/every day, 1–medium-low, 2-medium, 3-medium high, 4 –high). The stress level was considered as the target attribute, and the following tasks were executed to develop the final prediction model to identify the stress level in advance for unseen data.

Data Pre-Processing

Initially, the data grabbed from Kaggle was stored in a CSV file format to prepare the data for further analysis. Due to the inconsistency discovered in the data as a first preprocessing step, the entire dataset was scaled on a specific range by incorporating the "StandardScaler" in Python. By Standardizing, the statistical distribution of the dataset converted to the format to equalize the mean value to zero and standard deviation to one.

Once the scaling was finished, to prepare the Stack ensemble model, as prior requirement hyper-Parameter tuning was done with individual classifiers to get the optimum value. To perform the hyper parameter tuning the dataset was divided into two sectors, namely training and testing/validation, with the percentage of 75 and 25 respectively.

A. Design of Stack ensemble model

The stack ensemble model is composed of two levels, which are referred to as Level 0 and Level 1. The level 0 stage of stacking consists of a collection of individual classifiers. These classifiers are utilized to make a prediction about the target for the provided training dataset by taking into consideration the original features. The results that were obtained from each of the various classifiers were included as a new feature in the dataset that was used for training. The newly acquired training dataset, which was put to use in the process of training the Meta model required for the Level 1 stage of stacking. After that, the data that has to be checked, also known as the validation partition of the data, is given as an input to the trained Level 1 stage of the Meta model so that it can make the final prediction.

1) Level 0 stage of Stacking

For the Level 0 stage of stacking, as base classifiers KNN and DT, as bagging classifier RF and as boosting classifier XGB were incorporated and implemented. The process belongs to level 0 depicted by the Fig.2. The training dataset along with 8 attributes and the target value was passed into the level 0 of stacking models. Each of these algorithms were trained and analyzed using the training dataset. At the end of the Level 0 stage of stacking, the prediction of these algorithms were gathered and the performance was also measured. The prediction of level 0 stage stacking was added as a new feature in the training dataset.

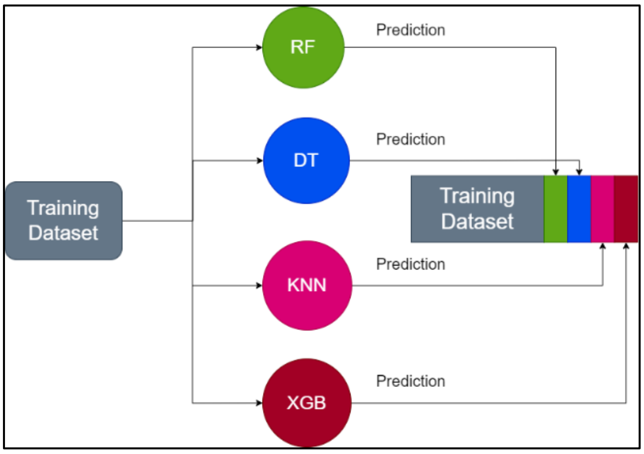

Fig. 2. Level 0 stage of stacking

2) Level 1 stage of Stacking

In the Level 1 stage of stacking, Logistic regression was used for the Meta model. The process belongs to level 1 depicted by the Fig.3. According to the outcome received from Level 0 stage stacking models, the new training dataset was passed to Level 1 stage stacking models. Thereafter, The Meta model was trained with the new training dataset. The testing/ validation dataset was used as an input to the trained Logic regression's Meta model for the evaluation.

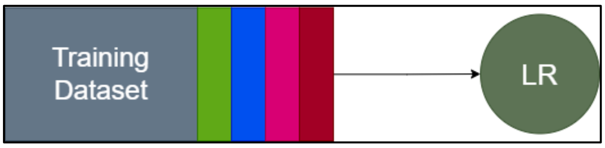

Fig. 3. Level 1 stage of stacking

IV. RESULTS AND DISCUSSION

This section going to explore the results discovered for the individual classifiers during the Level 0 stage of stacking. In addition, this section represents the comparison results obtained between the final ensemble stacking model and the individual predictive models utilized during Level 0.

The performance of the individual classifiers along with hyper-parameters for the original dataset used during the Level 0 stage of stacking was mentioned in Table I below.

TABLE I. PERFORMANCE OF THE INDIVIDUAL CLASSIFIERS DURING LEVEL 0 STAGE OF STACKING

Classifier	Hyper-Parameters	Accuracy	Error rate
Random Forest	criterion='gini', max_depth=None, max_features='auto', max_leaf_nodes=None	91.93%	7.07%
Decision Tree	max_depth=None splitter='best' max_features=None max_leaf_nodes=None	86.57%	13.43%
K-Nearest Neighbor	leaf_size=30 algorithm='auto' n_neighbors=3 p=2	83.12%	16.88%
XGBoost	learning_rate=0.1 n_estimators=100 max_depth = 3 colsample_bytree=1 base_score=0.5	96.29%	3.71%

Based on the results grabbed from the individual predictive models, XGBoost outperformed against all the other techniques with the highest classification accuracy of 96.29% and the lowest error rate of 3.71. Moreover, to validate the individual classifiers' performance K-Fold cross-validation was carried out with 5 folds and the mean accuracy yielded for each individual classifier mentioned in Table II. The mean accuracy obtained from the cross-validation also represented that for different percentages of training and validation data XGBoost produces the best results. In the attempt of trying to increase the accuracy further, the model predictions grabbed from the individual models were incorporated as a new feature into the existing training data set and the new data set was fed into the Meta model which was implemented using Logistic regression at Level 1 stage of stacking for the development of the final ensemble stacking model.

TABLE II. MEAN ACCURACIES OBTAINED FOR INDIVIDUAL CLASSIFIERS DURING K-FOLD CROSS-VALIDATION WITH 5 FOLDS

Classifier	Mean Accuracy
Random Forest	90.21 %
Decision Tree	88.85 %
K-Nearest Neighbor	85.15 %
XGBoost	92.31 %

Scikit-learn machine learning library was used as the main 3rd party library for implementation of the individual classifiers as well as sklearn. ensemble(Stacking Classifier) was utilized to develop the stack ensemble model. The final ensemble stacking model developed by considering RF,DT,KNN,XGB from the Level 0 and LR from Meta model(Level 1) resulted in mean accuracy for the five 5 folds of 97.27%. So, finally, it was discovered that the ensemble stacking model outperformed against all the predictive models considered in isolation for the original dataset. Mean accuracy graph obtained for K-Fold cross-validation with 5 folds to compare the individual classifiers and the final stacking ensemble model represented by Fig. 4 below.

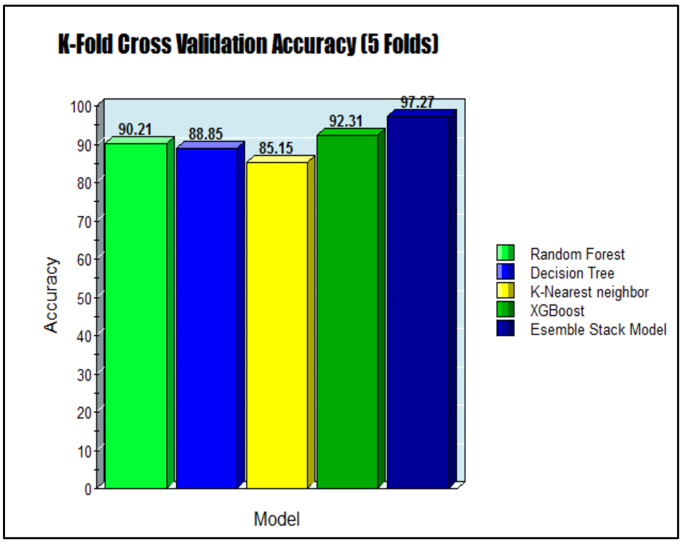

Fig. 4. K-Fold Cross-Validation Accuracy (5 Folds)

V. CONCLUSION

One of the challenges faced by the people nowadays is frequently experiencing the stress. Therefore, determining the stress level beforehand would be a promising way to reduce the causes that may occur from stress. In this work, stack ensemble model approach model was developed to identify the stress level in advance. During this approach, at level 0 RF, DT, KNN, and XGB were implemented and evaluated for better performance in isolation. As we all know, in most cases the combine model given more precise results rather than the results given by the models works in isolation. So, to improve the results obtained from the individual classifiers at level 1, LR was utilized as a Meta model and trained along with the predictions obtained from individual classifiers for the original data. Following the cross validation, the model's mean accuracy obtained for RF, DT, KNN, XGB and stack ensemble model were 90.21%, 88.85%, 85.15%, 92.31%, and 97.27% respectively. From the results discovered, it was clearly represented that combined model produced more precise results rather than the models consider in isolation. This study would be a great beginning for future researchers to concentrate more on the stress level's prediction by taking both internal and environmental elements into account.

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