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A NOVEL META-MODEL BASED ENHANCED LEARNER FOR PREDICTION OF BEHAVIOR TRAITS OF INDIVIDUALS

CHRISTY JACQUELINE[1] , Dr. K RANJITH SINGH[2]

[1]Research Scholar, Dept. of Computer Science, Karpagam Academy of Higher Education, Coimbatore, India, christy.jacqueline@gmail.com

[2]Assistant Professor, Department of Computer Science, Karpagam Academy of Higher Education, Coimbatore, India, ranjithsingh.koppaiyan@kahedu.edu.in

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ABSTRACT

A person's personality can provide information about their behavior, mental health, emotions, choices in life, interpersonal nature, and ways of thinking. Personality traits are pivotal in identifying behavioral disorders. This paper aims to develop a novel meta-model-based classification algorithm to predict the behavioral characteristics of individuals based on the five-factor model. This proposed work is comprised of two stages, initially, the dataset is trained by the candidate learner, Support vector machine with ensemble learning is used as the base classifier. With the acquired knowledge of the base learner, in the second stage, the super learner known as the meta-model is used for understanding the behavioral disorder of an individual by applying an out-of-fold prediction strategy. The performance analysis of the proposed algorithm-enhanced learner is compared with various algorithms including conventional classifiers, boosting models, bagging models, and ensemble learners. The simulation results prove that the proposed enhanced learner achieves the highest accuracy rate of 0.97%, and precision and recall rates are 0.96% and 0.97% respectively.

Keywords: *Behavioral traits, Base Learner, Candidate Learner, Metamodel, Bagging, Boosting, Out-of-fold*

1. INTRODUCTION

The personality of an individual comprises behavior, motivation, emotion, and characteristics of their thought patterns. Since behavioral disorders often result in the loss of years of productive life for those who experience them, they have been identified as an important issue for the public and one of the global causes of disability [1]. According to long-term studies, those who are less happy with their lives are more prone to develop mental health problems [2]. On the other hand, elements that support resilience and good mental health are essential for both preventing mental diseases and improving the prognosis of people who already have them.

Mental disease is the cause of behavioral issues. Severe consequences can be avoided by early detection and treatment. In the worst circumstances, a person's drive and capacity to satisfy specific needs may be beyond balance, which can result in psychological imbalance. Adverse or stressful situations might lead to mental or emotional stress[3]. Later on, this could result in despair, tension, or anxiety. Thus, a thorough understanding of mental disease, its origins, and effects is required, in addition to measures for both prevention and therapy. To evaluate a person's mental health, surveys, wearable sensors, and bio signals are all able to be employed.

Clinical hypotheses can be developed based on novel insights that can be obtained from formerly unexplored data through the application of machine learning techniques. It can also be useful as a clinical practice support tool in mental healthcare [4]. Prediction intelligence should be utilized carefully and prospectively to behavioral health to prevent unforeseen repercussions. By doing this, it will be able to raise the standard and get more help [5]. Researchers looked into the correlation between emotional wellness and significant factors such as relationship excellence, socioeconomic status, level of education, and life happiness. Studies are carried out to evaluate the social and behavioral characteristics of different kinds of people [6].

Studies have increasingly shown that approximately 6% of the world population is affected by personality disorders [5]. Hence this study is significant because it indicates that social functioning issues among people with behavioral disorders are clinically important. Identifying personality traits will help to determine the behavioral disorders at the right time. It also helps to tailor treatment plans to address the behavioral issues, challenges, and vulnerabilities related to their unique traits.

The four different personal characteristics are as follows:

i) Openness: This characteristic includes traits like knowledge, creativity, empathy, alertness, and enthusiasm. Individuals with a high level of openness tend to be imaginative, inquisitive, and receptive to new things.

ii) Conscientiousness: This quality has to do with how much attention, self-control, freedom, and perseverance a person possesses. Individuals with scores that are elevated tend to be focused on objectives and possess strong cognitive and discipline abilities.

iii) Extroversion: This characteristic is associated with an individual's aggressiveness and degree of emotional outpouring. Extroverts are gregarious, at ease mingling with others, and frequently ebullient and agitated.

iv) Agreeableness: This quality is associated with a person's kindness and cooperation. Individuals with high conviviality tend to be courteous, kind, and trustworthy.

v) Neuroticism: It is a personality trait that correlates with a person's emotional stability and propensity to feel depressive and anxious feelings. High neuroticism individuals could be particularly vulnerable to stress along more rapidly prone to shifts in mood.

The main objective behind this research work is to conduct a detailed analysis of the behavioral characteristics and prediction of mental conditions with good performance accuracy with a minimal number of features. The main idea of the proposed work is to come up with a novel classifier algorithm known as enhanced learner which uses parameter fine-tuning for personality trait prediction. Unlike the complex methods, the main focus here is to develop a simpler yet effective method. This paper explores the following noteworthy novel parts listed as follows:

1. Investigate different categories of Machine Learning models used in Machine Learning and propose the best model for personality prediction.
2. Identify the research direction for supervised machine learning in personality prediction.
3. Choosing appropriate features for the models and thereby improving performance accuracy.
4. Explores various ML models for a better understanding and comparison of predicted results.
5. Highlights the performance efficiency of enhanced learners over conventional ML algorithms.
6. A comparison of the proposed enhanced learner with ML models is conducted.
7. Performance analysis of the enhanced learner with conventional machine learning models is conducted.

The rest of the paper is organized in the following manner. In section II, related work of the personality traits prediction using various machine learning algorithms are described. Section III, is a detailed explanation of the proposed methodology for the prediction of personality traits of individuals and its working model. Section IV deals with results and discussions of the proposed model with the existing algorithms. Section V concludes the paper.

2. LITERATURE REVIEW

Many research work had been carried out for predicting personality traits, using various Machine Learning algorithms. Not many works have used enhanced learner in their work. A few studies in this area are reviewed here.

Chang Su et al. [7] used static functional network connectivity (sFNC) data from rs-fMRI to measure each participant's mental health quality. Using the sFNC data as input, the deep learning algorithm predicts four categories of psychological quality and displays the neural patterns characteristic of each category. To determine which patterns were the most prejudiced, they employed guided gradient class activated maps [18].

The main focus of this study, conducted by Uyulan et al. [8], is on related to translation indicators of mental illnesses based on DL perspective. While computational methods are more accurate and faster than classical approaches, they are still highly worthy for the diagnosis process due

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to their promising ability for enhancing the comprehension of mental health conditions. In electroencephalographic based assessment model for mood disorder detection is constructed by advanced computational neuroscience technique paired with a sophisticated convolutional neural network method.

To determine the mental health status of a target population, Srividya et al [10] suggest applying a variety of machine learning classifier. First, unsupervised learning techniques were used to the target group's replies to the survey's questions. By calculating the Mean Opinion Score, the labels that were produced as a consequence of grouping were confirmed. Following that, classifiers were constructed using these cluster labels in order to predict an individual's mental health. The target populations included people from a variety of backgrounds, including working professionals, undergraduates, and high school pupil.

Using multilevel kernel density analysis, Jiaying Gong et al. [11] created brain networks in which Bipolar Disorder was linked to hypo-connectivity for each prior network, as well as the association between dysconnectivity and GMV changes.

Alizadeh et al [12] designed a primary statistical technique for data analysis was Receiver Operating Characteristics Curve analysis. The analysis indicated neuroticism was the strongest prediction for all mental health problems with largest the area under the curve. The current study demonstrated that whereas other traits are major protective factors, neuroticism is an important susceptibility factor for having three psychiatric issues. Personality traits are helpful markers for identifying psychological issues and a good method to start preventative efforts in the broader community.

3. PRELIMINARIES

3.1 Motivation

Supervised ML are used by the developers to solve many of the real-time and sophisticated problems [9]. The major advantage of such models is that they produce good performance accuracy. Some of the ML algorithms used are discussed here.

3.1.1 K Nearest Neighbor

K-Nearest Neighbors is regarded as a slow learning algorithm [13]. The primary focus is not on internal models. It does retain substantial amounts of the data for training purposes. The categorization approach is determined via a simple voting mechanism that focuses on the k-nearest neighbors to each coordinate on the system. For noise training, the method is very easy to use and quite stable. It is also beneficial when substantial volumes of data are being used.

3.1.2 Decision Tree

Decision trees are another simple non-parametric supervised algorithm. It falls under both regression and classification. It is capable of using the knowledge acquired during the training or learning phase by using straightforward decision criteria [14]. It forecasts the given data's outcome during the testing phase. Depending on whether the goal variable is continuous or categorical, the decision tree is referred to as either.

3.1.3 Naive Bayes

When used for classification, the Naïve Bayes algorithm treats each input parameter as independent. The model may extract two types of probabilities directly from the training data: the probability of every category and the likelihood of an occurrence for each class [15]. These probabilities will each have a value. Once established, the probability model can be used to generate predictions for new data using the Bayes theorem. When the data is real-time valued, it is common to assume that the pattern of distribution is Gaussian in order to rapidly calculate these probabilities. gullible Bayes is considered naïve because it assumes that input factors are unbiased [10].

3.1.4 Logistic Regression

It is a classifier that uses the logistic function to classify by figuring out the correlation between the independent and dependent variables. a machine learning algorithm that is frequently utilized [16]. This is used for classifying complex datasets. As this strategy is being used, the likelihood has been evaluated. A logistic distribution function is employed to assess and compute the probability of a possible result from a certain experiment. This algorithm has an unambiguous goal and is quite efficient. It facilitates understanding of variables that could impact the outcome of a given scenario. However, forecasts only come true in binary. This suggests that the predictors need to be independent of each other [11].

3.1.5 Support Vector Machines

Finding a hyperplane in N attributes that significantly distinguishes the data instances or records is the ultimate goal of the Support Vector

Machine (SVM) [18] technique. Because support vector machines produce greater accuracy with less computational complexity, they are considered basic machine learning algorithms. Regression and classification tasks frequently make use of the SVM. However, it is mostly employed as a classifier [17].

To divide the two data instance classes, there are other potential hyperplanes from which to select one. The largest margin plane, however, with the greatest distance between data examples of two classes, that SVM seeks to find. Selecting the plane with the largest margin will increase confidence in the classification of incoming data in the foreseeable future. Those instances that are closer to the hyperplane influence the hyperplane's configuration and position.

3.1.6 Bagging method

As Breiman described in [19] bagging is another ensemble strategy wherein the base model trainees are created in parallel to take advantage of their independence from one another. To create data subsets with the identical size as the original set of data and train the base learners, the bootstrap collection is used. In more detail, sampling with replacement will be used to produce a sample of random raining instances from the whole dataset [34]. Then, for each round, a separate classification of the same kind is trained using each subset of training data. The method employs majority voting for rating and median for regression at the very end when it must produce the final classification [27].

3.1.7 Boosting Techniques

Machine learning employs a method called Boosting to drastically reduce errors during prediction analysis of data [20]. To derive information from unlabeled data, researchers use labelled data to train artificial intelligence software, often known as machine learning models. The accuracy with which the initial training dataset was prepared determines whether or not a single machine learning system generates inaccurate predictions. Boosting improves the performance and projected accuracy of predictive machine learning models by merging multiple weak learners into one strong learner [33]. Algorithms for machine learning can be beneficial or detrimental to learners. The training strategy varies depending on the type of boosting method referred to as the boosting algorithm. Three basic boosting algorithms used in this work for behavioral characteristic classification are described as follows:

3.1.8 Adaptive Boosting

Adaptive boosting (AdaBoost) was one of the earliest boosting models developed. The boosting process adapts and tries to self-correct each time it is carried out [21]. Every dataset is initially given an identical weight by AdaBoost. It then automatically adjusts the data point ranking after every decision tree. It provides misclassified items more weight to reclassify them for the next round. The procedure is repeated if the residual error, or the difference between the expected and observed values, is less than the intended cutoff.

3.1.9 Gradient Boosting

AdaBoost is similar to Gradient Boosting (GB), a sequential training technique. GB and AdaBoost differ in that GB fails to give items that were incorrectly classified a higher weight [22]. GB method, on the other hand, produces base learners sequentially such that each one continues to be better than the last, hence optimizing the loss function. This approach, in contrast to AdaBoost, tries to provide accurate results from the start rather than correcting errors as they arise. It suggests that GB software could produce more accurate findings. Gradient boosting is useful for both regression and classification-based challenges [33].

3.1.10 Extreme Gradient Boosting

XGBoost, which stands for Extreme Gradient Boosting improves gradient boosting in an assortment of aspects for sustainability and speed of computation [23]. XGBoost uses all of the CPU's cores during training to facilitate simultaneous learning. Because it can manage massive datasets, it functions as a promoting technique that is attractive for big data applications. Its primary features include parallelization, remote computing, cache optimization, and scratch processing.

4. METHODOLOGY

The working principle of the enhanced learner involves the prediction of personality behavioral traits. Initially, the dataset is collected from individuals with 20 different criteria. Both personality traits and demographics were included in this survey. We have permission from the topic domain expertise to utilize the questionnaire for data collection, and participant agreement was also obtained. The domain expert's guidelines served as the basis for preparing the survey. The collected dataset, underwent data preprocessing, to treat all the attributes to fall under the range of 0 to 1.

The records are split into v blocks and each block is trained using the support vector machine. The outcome of the model is fine-tuned with the out-of-fold results. The meta-model with its fine-tuned parameters involved in an enhanced learning process to predict the behavior of the individuals. The simulation results proved the prominence of the proposed work Enhanced Learner accomplishes the highest accuracy rate compared with other state-of-the-art arts.

A machine learning technique called meta-learning is used to investigate the training process and comprehend its workings, which may then be used to further learning. As tasks are completed by the base learners, meta-learning [24] is a method of learning that continually obtains information, in contrast to base learning, which learns a single task on the relevant information.

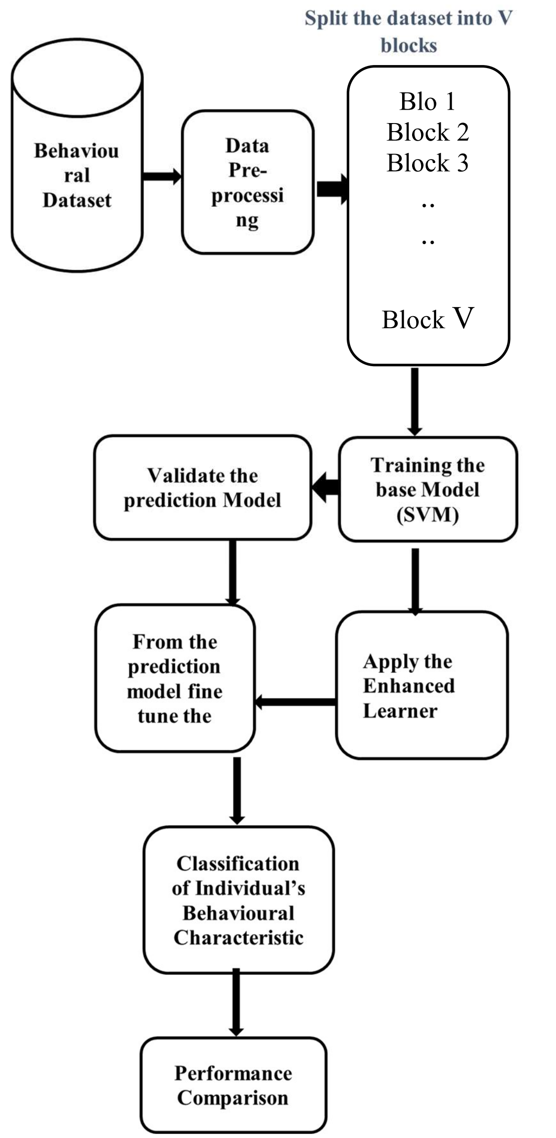

Figure 1. Architecture Diagram for Proposed Enhanced Learner

The figure illustrates the working principles of the enhanced learner for personality prediction The major objective is to create a versatile automatic learning system that can solve various types of learning problems by utilizing meta-data, such as properties of learning algorithms, problem characteristics, or previously discovered relationships between learning problems and the efficacy of various learning algorithms[28]. This will enhance the performance of the learning algorithms.

In this proposed Enhanced learner algorithm, by using previous classifications to this pesonal behavior data, user personality can be predicted.

This suggested paradigm was composed of four distinct parts as follows:

i) The datasets of learning instances are represented by the problem space R.
ii) The features or qualities that are taken out of the databases in R, as a generalization of the examples, are included in the feature space D.
iii) Every potential algorithm taken into consideration in the situation is contained in algorithm space B.
iv) The performance evaluation of an algorithm issue in B on a problem example in R is represented by the performance space Z. Because it can be readily extended to any component and may gradually enhance learning capacity, this framework is widely used for component oriented learning.

The k-fold cross-validation method for each base model involves splitting the training dataset into k distinct groups, utilising each group of instances on a test set and the remaining instances on a training set. This indicates that k distinct models have been trained and assessed. The predictions that the models make for each of the k-folds are used to estimate the model's performance.

Algorithm 1: Behavioral Data Analysis and Prediction

Initialize
- *i)* *Load the behavioral data into the data frame*
- *ii)* *Preprocess the data*
- iii) *Initialize a k-fold splitter with 5 splits*

Compute
- *i)* *Initialize an array to store out-of-fold prediction*

While (k) do
  For (each fold from 1 to k) do
    - *i.* *Train the enhanced learner using out-of-fold*
    - ii. *Fine-tune the parameters*

    Update and analyze
    - *Validate the prediction models*
    - *Calculate Performance Metrics*
    - *Classify behavioral characteristics*
    - *Compare performance results*

  End End
End

5. RESULTS AND DISCUSSION

This section discusses in detail the performance of assessment of the proposed work enchance learner deployed using python software. Our dataset consists of 725 samples with 5 class labels and 20 attributes. The training-to-testing ratio was established at 70:30. Following splitting, the testing set consists of 218 samples, while the training set consists of 507 samples. To explore the efficiency of the proposed Enhancer learner algorithm, it is compared with various conventional classification algorithm, boosting, bagging and ensemble classifer [29].

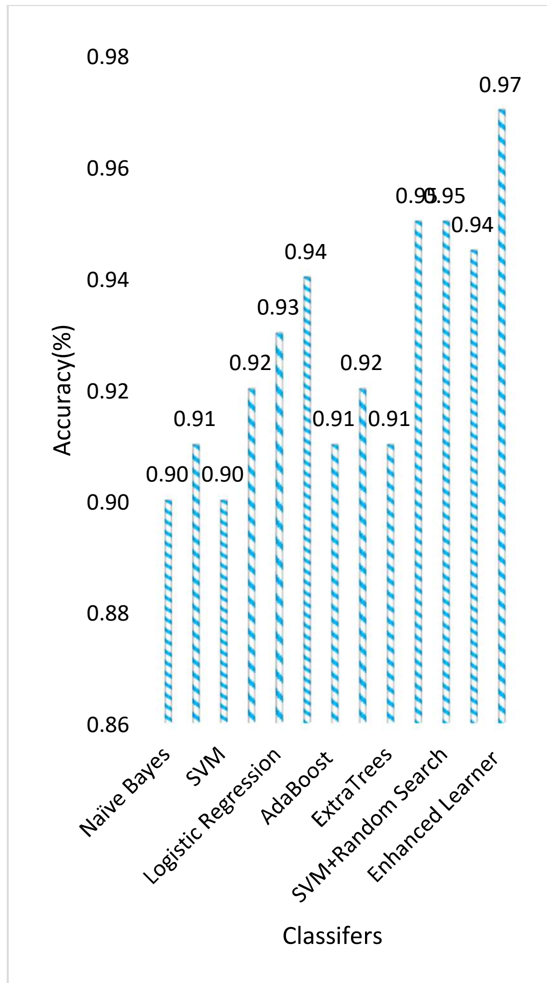

Figure 3. Accuracy comparison graph of ML algorithms employed for training the Model.

The results of various classification models based on the accuracy obtained for the classification of the five different behavioral traits is illustrated in the figure 3. It is observed from the result that the proposed enhanced learner model achieves the highest rate of accuracy in the classification of behavioral characteristics [30].

The meta-learning model strengthens the base algorithm by conducting k–fold cross-validation. The out-of-fold predictions improve the accuracy rate of the enhanced learning model compared with the other existing classifiers.

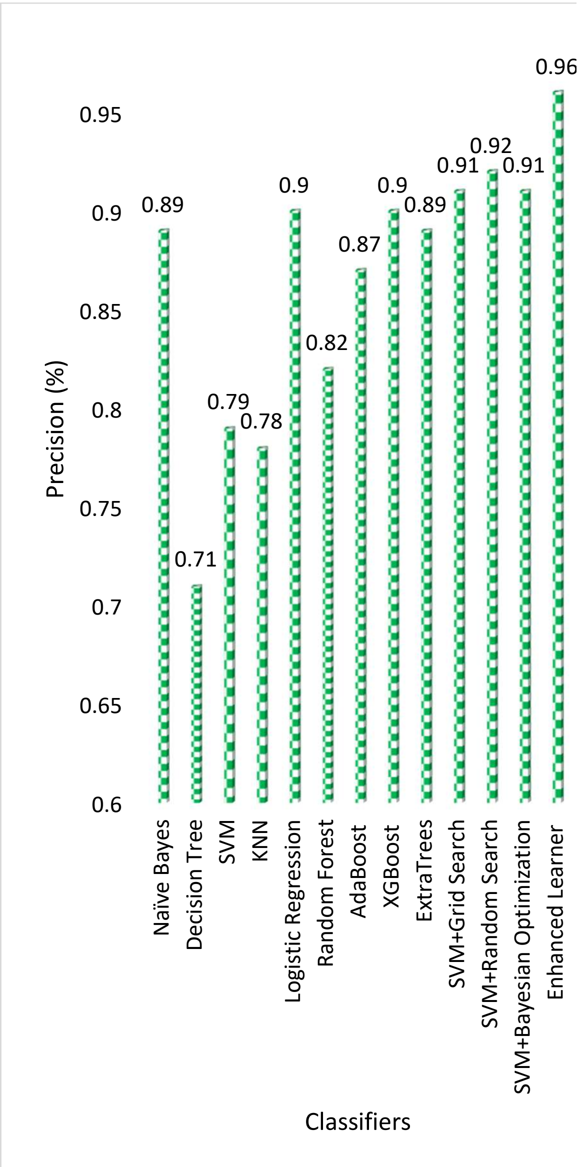

Figure 4. Precision comparison graph of ML Algorithms employed for training the Model

Figure 4. depicts the performance outcome of the different classification models to detect the behavioral characteristics based on the precision rate. The problem of overfitting issue is well handled while using the enhanced learner because the meta-model works on data samples, which are not processed during the training phase by the base classifiers [31].

The enhanced learner utilizes the knowledge of the base learner's prediction strategy and it utilizes for the classification of the dataset during the testing process more precisely. Hence, the enhanced learner algorithm achieves the highest precision rate compared to the other state-of-the-art classification algorithms.

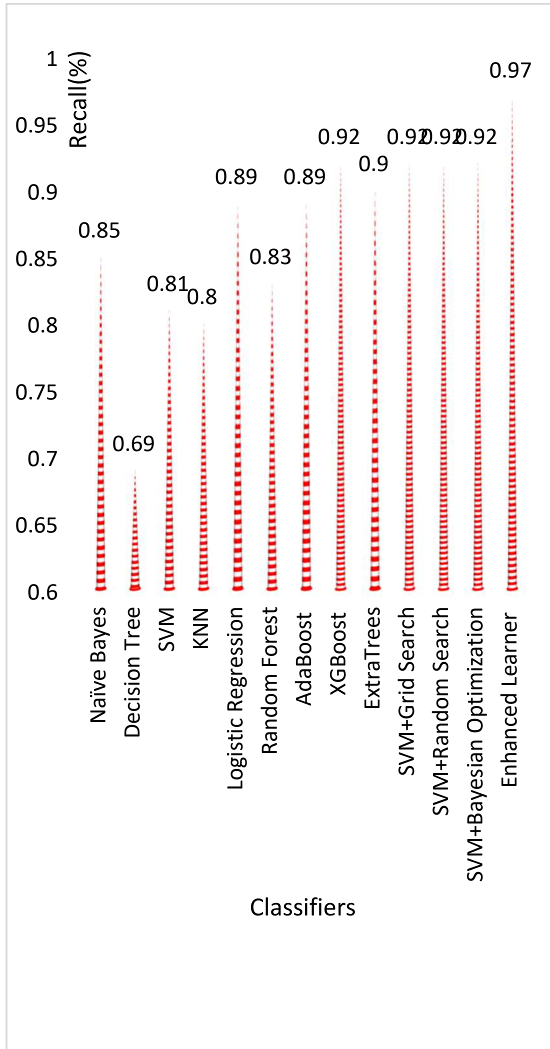

Figure 4. Recall comparison graph of ML models with Enhanced Learner

The proposed enhanced learner, produced the better recall rate compared with other existing classification models in detection of behavioral characteristic of individuals is depicted in Figure 4. The enhanced learner is more effective in terms of recall rate as it indicates the highest capability to capture the true positive instances. The results are depicted in Figure 4. shows that the SVM with

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hyperparameter tuning and XGBoost, an ensemble method has shown a better recall rate.

Due to the class imbalance in the behavioral detection dataset, the problem of overfitting affects the performance of the conventional classification models. But from the result, it is observed that the SVM with its variants after fine-tuning the hyperparameters and utilizing the meta-learning model improves the base model in achieving the highest recall rate compared to other state of arts [25].

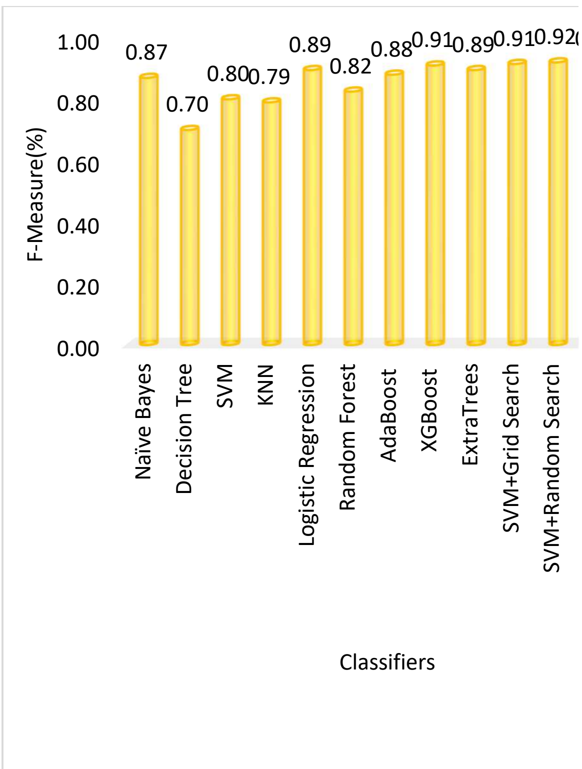

Figure 5. F-Measure comparison graph of ML models with Enhanced Learner

F-Measure results for prediction of the behavioral traits are shown the Figure 5, of various existing algorithms used for comparison. The proposed enhanced learner, with the inferred knowledge of its base model, handles the issue of class imbalance, by analyzing the datasets which are not handled during the training phase of the based model [35]. The testing datasets are classified precisely as the enhanced learner with its k-fold process and the out-of-fold process [32].

5.1 Performance analysis of the proposed Enhanced Learner with existing models

Table 1 depicts the results of the work conducted for identifying and classifying behavioral traits using conventional ML methods. The results demonstrate that the proposed enhanced learner has shown better performance accuracy when compared to the other conventional Machine Learning models.

Table 1. Comparison Analysis of the Enhanced Learner with Conventional ML Models

Reference	Year	Model	Performance Accuracy
Proposed study	2024	Enhanced Learner	.97% accuracy
[6]	2023	Naïve Bayes Logistic Regression ANN	90% (Highest accuracy attained)
[7]	2022	BPT- TF & IGM- TF	78.38%- Facebook 79.67% Twitter 86.84% Instagram
[8]	2022	KNN Naïve Bayes SVM	59.45% Highest accuracy attained for SVM
[9]	2019	KNN Naïve Bayes SVM	71.67% Highest Accuracy attained

The proposed enhanced learner in personality prediction gets better accuracy results is proved in the literature [6-9]. From the study conducted, it is proved that the proposed framework has given very effective results as shown in Table 2.

6. CONCLUSION

Predicting personality traits in an accurate and interpretable manner is a challenging task. This paper investigates and predicts individual behavior traits by deploying a novel enhanced learner that adopts the concept of meta-model which empowers the ability of the base learning to a strong classification model, with the concept of k fold cross validation, out-of-fold data-based training on the full dataset by the base learners. The meta-model improves the understanding of five different traits exhibited by the individuals more prominently than the other existing state of arts. The proposed enhanced learner model outperforms the existing machine learning algorithms by achieving the highest rate of accuracy in behavior trait prediction. This work can be extended in different ways by including various categories of behavioral disorders such as sleep disorder, anxiety issues, depression disorder and so on. The proposed behavioral modeling can be applied to analyze the behavior pattern exhibited within a specific targeted population, facilitating the identification of various behavioral parameters. Incorporating physiological parameters such as respiratory rate, electroencephalographic data, and electrocardiogram proves to be instrumental for the prediction of behavioral disorders. The interpretation of the physiological parameters and choosing the valid features will be a tedious task. The proposed framework can be used for a wide range of mental illnesses. The concept of Deep Learning can be used to improve classification accuracy. This also allows for the involvement of a significantly broader community, thereby increasing the data samples.

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