Detection of Mental State from EEG Signal Data: An Investigation with Machine Learning Classifiers

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***Abstract*— The mental state of a person is a combination of very complex neural activities which determine the current state of mind. It depends on a lot of external factors as well as internal factors of the brain itself. It is possible to determine an individual's mental state by analyzing their EEG patterns. Using a dataset acquired from Kaggle, ten machine learning techniques were investigated and models were built. The *RandomSearchCV* method was used to perform hyperparameter tuning and a comparative study has been portrayed for both tuning and without tuning of hyperparameter. After evaluating the performance parameters, Support Vector Machine (SVM) displayed the best accuracy (95.36%). However, Gradient Boosting (GrB) depicted promising accuracy of 95.24% whereas K-Nearest Neighbors (KNN) and XGBoost (XGB) both depicted 93.10% accuracy. As a result, with effective integration of the ML-based detection method, it is likely to regulate a person's state of mind, which will enable to develop a better understanding of human psychology and forecast their actions.**

Keywords*— *Machine Learning Algorithms, Mental State Detection, Kaggle dataset, Predictive Analysis

I. Introduction

Mental state refers to the state of mind which can be viewed from a variety of perspectives such as consciousness-based, intentionality-based, and functionalism according to various researches and studies [1]. Automated detection of peoples' mental state can be viewed as an effective tool to monitor inappropriate activity (e.g., drowsy drivers), mental health (e.g., anxiety, wandering), or productivity (e.g., weariness) [2-3]. Besides, when it comes to people with disabilities, they face a lot of trouble in movement and daily life conversation depending on the complication. Especially, mentally challenged people or people suffering from autism spectrum disorder (ASD) may have more difficulties with delicate communication and comprehending others' feelings. Meanwhile, the coronavirus (COVID-19) has changed the way of life by forcing people to stay at home and caused negative impact on people's behavior. Country-wide lockdown, losing employment, as well as general grief and suffering, all contribute to stress and mental instability. In a survey, it is found that more than half of the employees were dissatisfied with the preventive measures implemented in the face of the global epidemic [4]. As a result, this epidemic and its aftermath are posing even a greater threat to the mental health of general people; specifically healthcare workers, who may experience loss of concentration, and motivation for work.

There are several multidisciplinary and collaborative research works underway throughout the world to examine different brain states and emotion processes utilizing various modalities of brain research [5]. In particular, superficial brain activity signals have shortened the gap for human-machine interaction and can be useful for detecting mental states. These signals refer to the unique pattern of electrical activity that occurs from the aggregate ring patterns generated from billions of neurons, depending on what a person is thinking, experiencing, or doing [6]. Electroencephalograms (EEG) refers to a non-invasive technique for observing and extracting the patterns in terms of voltage using electrodes placed around an individual's scalp [7]. However, the challenging issue for the healthcare professionals is to classify the EEG signals properly the different mental states can be described and a follow up of appropriate consultation can be suggested. The nonlinear, non-stationary nature of the signals can be discerned by the complicated time-frequency structure which consists of distinct frequency ranges, oscillatory patterns, and noise components (artifacts) [8]. The artifacts, which are physiological signals other than brain activity, need special attention as they make EEG signals unpredictable and reduce clinical usefulness. Besides, the analyses based on scalp EEG can be quite rigorous with the scale of data as it is also an arbitrary dynamic signal derived from numerous cortical bases in the head.

Under such circumstances, artificial intelligence (AI) and machine learning (ML) can be employed on that unpredictable and large number of signals, detecting what state the subject is currently in [9-12]. AI-based solutions rely on the discovery of specific patterns among highly heterogeneous multimodal sets of data and produces results comparable to manual analysis which is limited to the scale of data [13-15]. Moreover, these solutions can then be fed to telemedicine-based healthcare apps as quarantine and remote activities have become the norm during the pandemic [16].

II. Related Works

Several noteworthy researches have left their marks in this domain. Bashivan et al. examined mental responses (logical and emotional) using video playback and they

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demonstrated that wearable EEG devices are quite significant when it comes to making distinctions between cognitive states [17]. In recent times, Agrawal et al. suggested that ANN and DNN tend to outperform classical ML algorithms with more accuracy [18]. From Bird et al, another study was held on three classification tests namely attention state, emotional sentiment, and guessing number, where for attention state, they achieved up to 84.44% accuracy when performing an Adaptive Boosted LSTM [19]. Besides, wearable EEG devices were more explored by Richer et al. where they calculated the sensitivity, specificity, and ROC curve for real-time mental state recognition using naïve score and entropy-based computation score [20]. In another work, Ajith et al. performed a study on DEAP dataset where they proposed a method using a convolutional neural network (CNN) to categorize sentiments into four groups based on the valence and arousal dimensions [21]. Ghosh-Dastidar et al. developed a confounding neural net to categorize seizure exposure using statistical analysis and their model achieved 92.5% accuracy [22]. Bos classified emotional statuses pertaining to EEG data and observed accuracy of 64% using neural networks [23].

Furthermore, Koelstra et al. demonstrated the effectiveness of Common Spatial Patterns for emotion categorization, with a cumulative preeminent solution of 93.5% [24]. Edla et al. developed a BCI model that used ensemble classifiers to envisage concentration and meditation, and when they tested it on their dataset, they obtained up to 75% accuracy [25]. Moreover, Jin et al. made a research work on mind-wandering and after training the support vector machine (SVM) classifier on EEG data, they concluded that the mind-wandering state was different from low vigilance state [26]. Zeng et al. proposed a DNN in order to drive mental states classification and showed that their models tend to perform better than traditional LSTM and SVM-based classifiers [27]. Furthermore, Lee et al. presented a study on this topic in which they reached an accuracy of over 72 percent [28]. Meanwhile, Gulhane and Sajana made a review study lately about human behavior prediction using machine learning during the COVID-19 pandemic where they have concluded that SVM and CNN are the optimum choices for the classification of behavioral patterns [29]. The provider of the dataset that has been used in this paper, Bird et al., have gone through testing different feature selection algorithms and classifier models. In the end, they achieved an overall accuracy of over 87% for the mental state dataset [30].

The main objective of the paper at hand is to carrying out an investigative approach with ten different ML algorithms and detecting three distinct mental states. As seen from the related works, there is room for more investigation about a subject's consciousness/concentration level than to explore other objectives such as emotion classification. Those objectives often demand very delicate approach because of the ambiguity in the nature of analysis and so exhibit mediocre accuracy. Therefore, a three-way classification is achieved in this study where subjects are being categorized into three concentration levels utilizing EEG dataset. A laborious simulation of ML techniques like Logistic Regression (LoR), Gaussian Naive Bias (GNaB), K-Nearest Neighbor (KNN), Decision Tree (DeT), Random Forest (RaF), AdaBoost (AdaB), Support Vector Machine (SVM), Gradient Boosting (GrB), Multi-layer Perceptron (MuLP), and XGBoost (XGB). These algorithms are widely known and expected to be robust in performance for the ML-based studies that are outside the researchers' field of expertise. Further discussion on improving the performance is presented in Section III of the paper which consists of methodology. Section IV presents the performances of the classifiers and a thorough comparative depiction has been demonstrated. Finally, the concluding remarks are shown in Section V.

III. METHODOLOGY

An EEG brainwave dataset was collected from Kaggle repository consisting of 989 columns and 2480 rows [30-32]. Four people (2 males, 2 females) were considered for the experiment and their EEG recordings were extracted for 60 seconds for each of the following states: tranquil, concentrating, and impartial, and numerical feature removal was used to analyze them. The operator employed a commercial Muse EEG headband, which used dry electrodes to record the TP9, AF7, AF8, and TP10 EEG placements. Because statistically defined waves in a sequential style are essential, their statistical extraction method resampled the data. Three states are as below:

- 0 - Tranquil state (the subjects listening to comforting sounds while their body in relaxation).
- 1 - Concentrating state (the subjects were to follow the ball of 'shell game', concealed beneath one of three cups).
- 2 - Impartial state (the brain activity was recorded before the previously mentioned tasks with no specific instructions).

Firstly, in the data pre-processing stage, input and output have been separated using *iloc* function of Python. After that, the inputs are scaled using the minmax scaler, and the features selection is achieved using the k-best algorithm. After this part, feature selection is done where out of 900 features, the best 500 discriminative features are considered. Then, to validate the results, Data was split between train and test sets with a proportion of 75:25, resulting in 4-fold cross validation.

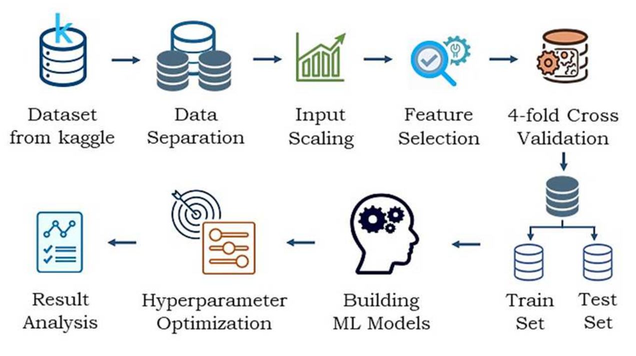

Fig. 1 Entire Illustration of the Method

After that, the confusion matrices were attained from which, various performance measures can be calculated related to the models.

Furthermore, hyperparameters have been tweaked to achieve even higher performance, and the random search cross validation (RandomSearchCV) approach has been employed to do so. This method uses an entirely arbitrary method to acquire the best parameters rather than testing all of them. Fig. 1 depicts the total workflow diagram. Finally, all the ML models were evaluated and a comparative assessment was demonstrated with the aim of determining the applicability of such algorithms in the development of an automated system for detecting mental state from EEG data.

IV. RESULTS & DISCUSSION

The performance metrics have been obtained from the simulations executed in Python and the corresponding confusion matrices are charted in Table I and Table II. These confusion matrices are greatly convenient to estimate the recital of a classifier. From these matrices, the number of instances the model has predicted and the actual values can be visualized easily.

The formulae are stated below:

$$Accuracy = \frac{T_P + T_N}{T_P + F_P + F_N + T_N} \quad (1)$$

$$Precision = \frac{T_P}{T_P + F_P} \quad (2)$$

$$Recall = \frac{T_P}{T_P + F_N} \quad (3)$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

Accuracy shows how many predictions the classifier made correctly out of all predictions. However, Precision displays how many predictions are truly positive out of the sum of predictions, and recall refers to the score that measures the ability to predict positive classes correctly. In Table III, the metrics are shown with default hyperparameters (DHP) first and then with efficient hyperparameters (EHP).

SVM, with an accuracy of 95.36%, topped among all the classifiers. However, GrB with 95.24% took the second position in the rank. This two are followed by K-Nearest Neighbor and XGBoost with 93.10%. The performance of AdaB was the poorest of all (79%). On the other hand, SVM portrayed the finest output in precision (0.9537), followed by GrB (0.9524) and KNN (0.9319) respectively. Again, the lowest precision was attained by AdaB with about 0.7934. The identical outline was witnessed in case of recall, where SVM outperformed the other models with 0.9536. The other algorithms which are followed by this score are GrB and KNN with 0.9524 and 0.9310 respectively and the lowermost value was accomplished by AdaBoost (0.7874). In the case of F1 score, SVM again outperformed others with a value of 0.9535. Besides, GrB (0.9522) and KNN (0.9310) also showed respectable results. The lowermost F1 score (0.7892) was attained by AdaB. However, in terms of ROC score, GrB came out as first having a score of 0.995, trailed by SVM and MuLP as 0.994 and 0.988, in turn. On the other hand, DeT had the lowest ROC result of about 0.890.

TABLE I. CONFUSION MATRICES FOR LOR, GNAB, KNN, DET & RAF

	No	Anticipated	LoR			GNaB			KNN			DeT			RaF		
Actual		Classes	0	1	2	0	1	2	0	1	2	0	1	2	0	1	2
	1	0	181	25	1	211	8	3	179	17	1	162	33	2	182	23	2
		1	22	190	7	72	82	26	26	179	2	33	157	17	14	195	10
		2	0	2	192	0	8	205	0	1	215	2	6	208	0	0	194
	2	0	172	23	0	194	5	4	171	11	0	149	32	1	172	23	0
		1	32	169	9	65	113	16	27	212	0	49	176	14	16	187	7
		2	0	5	210	0	4	219	0	1	198	4	15	180	0	0	215
	3	0	188	23	0	176	6	7	198	13	1	171	37	4	181	29	1
		1	16	187	3	95	96	28	28	168	0	34	152	10	16	182	8
		2	0	1	202	0	2	210	0	1	211	2	12	198	0	1	202
	4	0	181	24	1	198	7	0	212	16	0	182	46	0	186	19	1
		1	14	175	6	76	127	29	22	164	2	30	148	10	6	180	9
		2	0	2	216	0	1	181	1	1	201	0	6	197	0	0	218

TABLE II. CONFUSION MATRICES FOR ADAB, SVM, GB, MLP & XGB

	No	Anticipated	AdaB			SVM			GrB			MuLP			XGB		
Actual		Classes	0	1	2	0	1	2	0	1	2	0	1	2	0	1	2
	1	0	154	51	0	190	13	0	195	9	1	182	22	1	185	19	1
		1	57	139	8	12	198	4	7	189	8	23	179	2	16	178	10
		2	0	13	198	0	1	202	0	0	211	0	3	208	0	0	211
	2	0	162	40	0	192	12	0	193	9	0	189	13	0	185	17	0
		1	63	140	9	11	192	3	15	192	5	28	182	2	16	192	4
		2	0	11	195	0	2	208	0	1	205	0	2	204	0	1	205
	3	0	159	55	0	196	10	1	199	15	0	196	18	0	190	23	1
		1	40	144	9	23	176	2	8	177	8	13	178	2	21	164	8
		2	0	30	183	0	0	212	0	1	212	0	5	208	0	2	211
	4	0	147	51	0	194	11	0	188	10	0	187	10	1	186	10	2
		1	60	153	8	10	199	0	16	200	5	36	183	2	14	201	6
		2	0	22	178	0	0	205	0	0	200	0	1	199	0	0	200

TABLE III. COMPARISON OF PERFORMANCE FACTORS

Algorithms	Accuracy (%)		Precision		Recall		F1 Score		ROC-AUC	
	DHP	EHP	DHP	EHP	DHP	EHP	DHP	EHP	DHP	EHP
LoR	91.17	91.29	0.9114	0.9127	0.9117	0.9129	0.9113	0.9125	0.983	0.984
GNaB	81.04	81.16	0.8341	0.8350	0.8104	0.8116	0.7953	0.7966	0.933	0.934
KNN	90.68	93.10	0.9090	0.9319	0.9068	0.9310	0.9064	0.9310	0.977	0.957
DeT	83.99	83.91	0.8405	0.8397	0.8399	0.8391	0.8399	0.8389	0.879	0.890
RaF	92.30	92.54	0.9228	0.9253	0.9230	0.9254	0.9224	0.9249	0.986	0.987
AdaB	73.18	78.74	0.7438	0.7934	0.7318	0.7874	0.7296	0.7892	0.877	0.918
SVM	93.75	95.36	0.9376	0.9537	0.9375	0.9536	0.9369	0.9535	0.991	0.994
GrB	94.51	95.24	0.9449	0.9524	0.9451	0.9524	0.9449	0.9522	0.993	0.995
MuLP	92.34	92.58	0.9244	0.9273	0.9234	0.9258	0.9233	0.9257	0.986	0.988
XGB	94.79	93.10	0.9479	0.9114	0.9480	0.9117	0.9477	0.9113	0.995	0.983

The scoring pattern that can be observed here is because this research is constructed on a multi-class arrangement. Unlike binary sorting, other performance measures are lenient to the accuracy estimation in this type of analysis. As a result, if a classifier has a higher accuracy score, the other metrics, precision, and recall, are also higher for that specific classifier. Table IV shows a comparison with previous research papers relating to the identification of mental states. The reference works mentioned in the first three rows are based on the same dataset that has been used in this paper. Ashford et al. proposed a method with a different approach that represents the statistical features as 2D images and performing CNN as those image classifiers, achieving up to 89.38% accuracy [6]. Bird et al. also used bioinspired computing methods for classification in another study where the best accuracy came from AdaBoosted LSTM (84.44%) [19]. In terms of other performance metrics, Richer et al. worked on the mental state (Neutral, Focus, Relax) recognition using wearable EEG appointing eleven individuals where their achieved recall score was 0.82 [20]. However, in Zeng et al. showed that SVM and LSTM classifier could not outperform the proposed deep learning model which depicted an accuracy of 84.38% [27]. Bird et al. compiled multiple feature sets and models among which, the OneR attribute selector-based Random Forest classifier was found to be the most accurate (87.16%) [31].

TABLE IV. COMPARATIVE ANALYSIS

References	Algorithms	Best Accuracy
[6]	Convolutional Neural Network	89.38%
[19]	AdaBoosted LSTM	84.44%
[25]	Random Forest	75.00%
[31]	Random Forest	87.16%
[33]	k-Nearest Neighbor	78.80%
This Study	Support Vector Machine	95.36%

Finally, using the SVM algorithm, the technique used in this study achieved the best accuracy of 95.36%. In other studies, Vijean et al. investigated KNN and LDA based classifiers accuracy (from 78.8%) on five different classes whose dataset was relatively small [33], similar to the paper at hand. Ranjith et al. also worked on a dataset with only six individuals for detecting stress levels, where they achieved 94.12% accuracy with Improved Elman Neural Network (IENN) [34]. To the best of our knowledge, hyperparameters tuning using the RandomSearchCV method played a major role in achieving comparatively higher performance across all the results [35]. Based on the findings, there might be some overfitting in the dataset since some algorithms showed lower values even after optimizing the hyperparameters.

V. CONCLUSION

Classification of mental states utilizing EEG signals extracted from brain neural activity shows the possibility of detecting the hidden patterns and psychological disorders. Using the mental state dataset from Kaggle, the current study sought to discover the best classifier. In this regard, SVM outperformed all of the other classifiers with an accuracy of 95.36%. With the rapid advancement in bioinformatics and other medical-based sectors, the outcomes can benefit the early adopters to determine an optimized way. Therefore, ML models can enforce an enormous impact not just in economics but also in aiding healthcare professionals by providing necessary insights. Future work will be focused on deep learning techniques which will be investigated to exhibit the performances of those models in different applications.

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