2019 IEEE Pune Section International Conference (PuneCon)
MIT World Peace University, Pune, India. Dec 18-20, 2019

Surveying Machine Learning algorithms on EEG signals data for Mental Health Assessment

Ela Gore
Computer Engg, TCET
University of Mumbai, Mumbai, India
elagore@yahoo.com

Sheetal Rathi
Computer Engg, TCET
University of Mumbai, Mumbai, India
sheetal.rathi@thakureducation.org

***Abstract*---The use of computer science technology in mental healthcare domain to detect the onset of mental health problems to help people to get treatment on time. The paper aims to present commonly used algorithms and describe their properties and performances which could act as a guide to select appropriate models. The possibilities presented by machine learning can help bridge the gap between the critical shortfall of psychiatrists and patients embarrassment to reveal problems to a therapist they have never met before. Identifying and selecting features from EEG signals data and then developing suitable ML algorithm for mental health issues is the prime task. It tries to give a survey of algorithms for classifying emotional states and for detecting mental health illnesses.**

Keywords---EEG signals, Machine learning, SVN, CNN

I. INTRODUCTION

Mental health problems have taken a center stage in today's lifestyle causing unrest in the human population. Though being the primal problem it remains largely neglected by people who are facing mental health problems like depression, who are undergoing the treatment or who are about to get stuck in the vicious circle of constant depression. Making developments and getting ahead in helping people with serious mental illness will depend not just on new drugs but on good information on which effective policies and treatment regimens can be based out. Underdiagnoses of Mental Health illness has been relatively a long time problem. Approximately half of all the cases of major depression went undiagnosed was the outcome of a survey taken in metropolitan area [24]. The World Economic Forum predicts the global cost on mental health conditions would probably rise to $6 trillion by 2030 from $2.5 trillion as of 2010 surpassing the combined costs for respiratory ailments, cancer and diabetes. The possibilities presented by machine learning can help bridge the gap between the critical shortfall of psychiatrists and patients embarrassment to reveal problems to a therapist they have never met before.

The application of data science techniques on mental health data can at least help to lower the percentage of mental health diagnosis being under reported. The paper tells about the use of EEG signals data for assessing mental health conditions. This paper doesn't claim the use of only EEG signals data is best for monitoring mental health issues but provides literature that made use of machine and deep learning algorithms applied on EEG signals data for predicting the onset of mental health problems.

Section I introduces mathematical figures pressing the severity of Mental Healthcare Domain. Section II provides the survey of algorithms in a tabular format classifying emotional states along with the scope for further improvement is mentioned. It also mentions about the jargons used in the papers studied for surveying of machine learning algorithms along with the Mental Health diseases/illness/disorders explained for the readers which are clear and easy to understand. This section presents survey of algorithms applied over EEG signals data detecting onset of mental health illnesses. Section III concludes with the gist of features, commonly used algorithms to assess mental health conditions and mentions various measures used to judge the performance of the models used by multiple authors.

II. COMPARISON OF ML MODELS ON EEG DATA

TABLE I. SURVEY OF STUDIES CLASSIFYING EMOTIONAL STATES

Sr.No	Author/Year	Task	Classifiers	Performance
1.	Krishna Bairavi et al. [15] (2018)	EEG signals of 18 children (Average age: 13 years) Classify the emotions into Happy, Neutral and Sad	Mean PSD value of all the brainwaves are fed as features to the classifiers: SVM, KNN, Random Forest, Bayesian Classifiers	Random forest achieves highest accuracy of 82% **Building a continuous** monitoring system for the patients

2.	Harsh Dabas et al. [16] (2018)	32 participants gave their EEG and physiological signals of Classify states into nervous peaceful, surprised, bored, disgust, sad, relaxed and excited states	SVM, Naive Bayes for classification, Hierarchical clustering & K-Means for emotional states	Valence-Arousal-Dominance space properly classifies emotions **More number of participants are required** to get useful information and meaningful patterns from the EEG data.
3.	Nisha Kimmatkar et al. [18] (2018)	EEG signals of 15 subjects are taken from 7M/8F in the age group of 23 to 27 Classify into positive, neutral, negative	EMG& EOG were removed manually. Linear dynamical system (LDS) smoothes the features for classifying emotions	High accuracy of 98.67% with KNN than with SVM(Linear), SVM(sigma=9) **Multiple categories of emotions** to be assessed
4.	Yalin Li et al. [19] (2018)	EEG signals of 10 (4F/6M) with mild depression & 10 normal subjects (2F/8M) Classify depressed Vs Normal subjects	Hanning filter to get 3 frequency bands θ,α & β BF,GSW, GS ,LFS and RS were compared with differential evolution + KNN	Combination of DE + KNN gives higher accuracy than KNN. **Improve** the crossover and mutation operations to find better features and perform combination of DE with other classification algorithms & make use of Deep learning
5.	Xian LI et al. [21] (2017)	32 participants (16F/16M) aged between 19 and 37.	SVM assembled in the LibSVM library[19] is used to build 8 channel base classifiers: {C-AF3, C-FP1, C-P7, C-FC2, C-C4, C-T8, C-CP6, C-PO4} using 10-fold cross validation	SVM having RBF kernel function performs better than SVM having linear and polynomial kernel, C-AF3, C-FP1 and C-FC2 achieve relatively high accuracies. Several classifiers fusion method is preferable over individual classifiers and the fusion method of features
6.	Aayush Bhardwaj et al. [2015]	EEG of 32 subjects (14F/18M) from 20 to 25 years old. Classify into 7 emotions as Happy, Anger, Sad, Neutral, Surprised, Fear, Disgust	Features extracted are Power Spectral Density and Energy using Segmentation, Bandpass filter and ICA	Accuracy of SVM (74.13%) better than LDA (66.50%). **To improve accuracies for the 5emotions** other than Happy and Sad
9.	Wei-Long Zheng [1] (2015)	62-channel electrodes EEG signals are retrieved from 15 subjects (7M/8F mean age:23.27) Classify into positive, neutral and negative	DBN, KNN, LR and SVM on 4 various profiles of 4, 6, 9, and 12 channels/electrodes are chosen.	12 channels having SVM has the highest accuracy and least standard deviation (86.65%/8.62%) than full 62 channels having SVM. DBN better than KNN, LR, SVMs **Apply to data** sets with multiple categorization of emotions.
8.	Hayfa BLAIECH et al. [22] (2013)	6 subjects whose age between 22 and 61 years on the arousal, valence and dominance plane Classify into surprise, anger, neutral, disgust, sadness, fear, and joy	Fuzzy logic technique of Mamdani	Clustering by fuzzy c-means achieves Joy, Fear and Neutral with maximum recognition rates as 71.42%,78%, 100% respectively
3.	Mina Mikhail et al. [17] (2010)	EEG data taken from 36 participants (10 M /26 F) ranged from 17 to 24 years Analyzes highly contaminated EEG data into joy, fear, anger, sadness	Feature Reduction by Alpha Band & Asymmetries of Scalp EEG. SVM for classification. For each classifier radial, linear, polynomial kernels were used.	20-fold cross validation used, achieving an accuracy in the range of 51% to 61% that is higher or equaling other similar works. **To reduce the number of features** & to improve our **preprocessing stage by ICA**

In above Table I, The papers undertaken for surveying are primarily from the year 2018 followed with 2010,2013,2015,2017 with number of electrodes used for recording EEG signals, number of males/females participants in the study undertaken by each author, the participants' age ranging over young adult up to 27 years while one study spanned over to 61 years of age. In the performance column, best performance and the research gaps in Bold style are mentioned. Power Spectral density (PSD) has been prominently used feature from EEG data with bandpass filters, segmentation and FastICA processing being applied. The classifiers used Naives Bayes, KNN, LDA, Random Forest, SVM with linear, radial, polynomial basis functions with gaps such as applying these algorithmic techniques over to a larger dataset and the need to reduce number of features.

TABLE II. TERMINOLOGIES

Epilepsy[2]	A condition where awareness is lost and the body shakes due to some improper action in the mind.
Electroencephalogram[2]	Electrical activity of the brain caused due to continuous actions of the neurons recorded from the scalp being non-linear, non-stationary, complex
Hurst Exponent[2]	Non-linear component is used to assess the time series to detect long-range dependence and its variation in degree from the usual pattern using the points of correlation
Depression[3]	Depression is a mental disorder causing continuous overthinking about the tasks/thing thereby affecting day to day activities to wake up, to eat, work during the day, to sleep.
Parkinson Disease[4]	The motor activities like getting up, walking, etc starts declining due to weakening of neurons in the brain
Autism[23]	Lots of obstacles in interacting socially, oral & written communication, repetition in actions.
Alzheimer's Disease[6]	Brain disorder occurring middle or late life with degradation of certain neurons, formation of plaques, tangles in neurofibrillary.
Brain Fog[8]	It is a collection of variety of symptoms that include short/long term memory, loss in cognition, incapability to focus and doing multiple activities.
Attention Deficit/Hyperactivity Disorder(ADHD) [10]	ADHD is characterized by gradual rise in lack of attention, motor over activity, irresistible urge

Table II talks about some terminologies & mental health disorders explained lucidly covered in following Table III. There are many other mental disorders too not covered here.

TABLE III. SURVEY OF STUDIES DETECTING MENTAL HEALTH ILLNESSES

Sr.No	Authors/Year	Task	Classifiers	Performance
1.	Ashok Sharmila et al.[2] (2017)	Depression detection. (LL2N) of six elaborate WSBs and one almost WSB bandwidth-duration localized (BDL) 3-channel/electrode orthogonal wavelet filter bank (TCOWFB) are the features used.	Complex tree, LD, LR, bagged tree, KNN, least square SVM	AUC = 1(on 7features); 99.58% of average classification accuracy (ACA)
2.	Manish Sharma et al.[3] (2018)	Parkinson Disease detection. Extraction and selection of features are not needed in CNN.	CNN with 13 layers consisting of 1D convolution & maxpooling	88.25% of Accuracy, 84.71% of sensitivity and 91.77% of specificity
3.	Shu Lih Oh et al.[4] (2018)	Autism detection.6 feature extraction algorithms such as AR Burg, Levinson Durbin Recursion, AR Modified Covariance, AR Yule Walker, Linear Prediction Coefficient and AR Covariance	Pattern recognition NN, Layered recurrent NN models	AR Burg and LRN combination had the highest accuracy rate of 94.62%
4.	Laxmi Raja et al. [5] (2017)	Alzheimer detection. 40 attributes extracted from single EEG channel	genTrees, J48, Naïve Bayes, Simple Cart, NBTree, IBk, SMO, OneR	genTrees better with accuracy 86.05%,sensitivity 88.89% and specificity 71.43%
5.	V. Podgorelec [6](2012)	Sleep detection. EMD and DFA for feature extraction	Back propagation (BP) neural network	Accuracy of 85%

6.	Yan Zhang et al.[7] (2018)	Brain fog / Confusion learning detection. Alpha1, Alpha2, Gamma1 Gamma2, Delta, Theta, Beta1, Beta2, Predefined Label, Meditation , Attention, Raw	SVM(linear, rbf, sigmoid kernel), KNN, CNN DBN,RNN-LSTM, BiLSTM	Bidirectional LSTM achieves best accuracy of 73.3%
7.	Zhaoheng Ni et al. [8] (2017)	Mental workload detection. User-specific and a user-independent calibration study	CSP, FBCSP, Riemannian Geometry, CNN	CNN better than rest with 63.7%-72.7% accuracy
8.	Aurélien Appriou et al. [9] (2018)	ADHD detection. Deep features extracted from CNN models &13 hand-crafted features of the brain network	CNN (1,2,3,4), MLP, SVM	CNN (1) better accuracy of 94.67%
9.	He Chen et al. [10] (2019)	Suicide, Hoax, Positive & Neutral notes classification. Attention, emotion & memory. Alpha and Beta waves	SVM(linear, Gaussiankernel),KNN, SubSpace Discriminant, Tree	SVM linear for SPN classification & KNN for GH classification
10.	Dilip K. Prasad et al. [11] (2018)	Stress detection. Transitivity, Modularity, Characteristic path length, Global efficiency& beta waves. CDET technique	Multi class SVM	With 4 measures accuracy is 83.90% & with B-waves 92.3%
11.	Saeed Lotfan et al. [12] (2018)	Epilepsy detection. Non-linear component-Hurst exponent from Discrete Wavelet Transform	SVM,KNN	99% accuracy for SVM than KNN

Ashok Sharmila et al. [2] made use of Hurst exponent (HE) non-linear component from each sub band signal by decomposing original EEG signals using Discrete Wavelet Transform (DWT) up to fifth level decomposition as D5, D4, D3, D2, and D1 as frequency components above 40Hz may not contain useful information. Wavelet Transform renders specific frequency and time data unlike Fourier Transform giving only frequency data.

Manish Sharma et al. [3] evaluates the wavelet features chosen from bipolar EEG signals by one channel using lately designed BDP optimized TCOWFB in detecting depression. To surmount the confines of both FT having poor time localization and DWT having poor joint time-frequency localization, a new class of 3 channel(instead of two to get high frequency content& better control over time-frequency tiles) orthogonal wavelet filter bank (TCOWFB) is used. A total of 7 LL2N features extracted from recording which are orderly placed using Student's t-test method. Here LS-SVM (Least Squares- SVM) is used for picking the kernel function which is Gaussian radial basis function (RBF).

Shu Lih Oh et al. [4] used EPOC neuroheadset of 14 channels for recording. 6th-order bandpass Butterworth filter having forward reverse filtering technique is used. In CNN 13 layers with Adam optimization having a learning rate of 0.0001 and few activation functions, size of kernel and number of filters vary as per the layers.

Laxmi Raja et al. [5] made use of 10 electrodes for recording EEG signals. To calculate the feature of Power Spectral density 6 feature algorithm techniques are used. LRN performs better than static Pattern Net because of its dynamic properties.

V. Podgorelec [6] used Short-Time Fourier Transform (STFT) for cutting off the waveform of concern into a number of short segments and doing the analysis on each of these segments. 4 for every of 5 frequency bands equaling to 20 from each of time domain and frequency domain of a patient's EEG signal are extracted. A grand total of 640 attributes for 16 channels arithmetically as 16 times 40. A combination of 4th and 16th EEG channel gave best results

Yan Zhang et al. [7] in classification of sleep stages Empirical Mode Decomposition (EMD) denoising method is employed where there is no need to pre-select the wavelet basis unlike wavelet filtering method. Detrended fluctuation analysis (DFA) used to extract scale characteristics of EEG signals. Back propagation (BP) neural network with error back ropagation algorithm uses 3 layers & the transfer function as sigmoid differentiable function.

Zhaoheng Ni et al. [8] extracted 14 features from EEG signals. A variable selection method is used to get the utmost essential feature in our Bidirectional LSTM mode. Running 12 experiments each of them letting out one feature; gamma-1, beta and attention features decreases accuracy the most which can be left out. Bidirectional LSTMs is best out of the baseline models with a 5 fold cross validation as it learns in both the directions and learns from time series features

Aurélien Appriou et al. [9] compared 4 ML algorithms to classify workload (low vs. high). 3 pairs of CSP spatial filters to get 6 band-power features used to train a Linear Discriminant Analysis (LDA) classifier. the 4 utmost pertinent features were selected out of 36 features using mutual information feature selection by FBCSP and then LDA is applied. The Riemannian distance between the test trial covariance matrix, and each of these two class prototypes with Geodesic filtering. CNN Shallow ConvNet uses least preprocessed EEG signals, temporal and a spatial convolution layers, a mean pooling layer, logarithmic activation function.

He Chen et al. [10] achieved 98.17% on validation set & 94.67% on test data with 10 fold cross-validation using ReLU as the activation function.t-test is used to validate the features learnt by CNN model to study between-group differences of deep features & Pearson correlation is found out between them describing global patterns of the network.

Dilip K. Prasad et al. [11] achieves the classification accuracy of 71% for SPN classification & 70% for GH classification. Attention is less important than memory and emotion.

Saeed Lotfan et al. [12] Synchronization likelihood method is used to compute connectivity matrices in all pair combinations of EEG signals. Compensation distance evaluation technique (CDET) is applied to find optimal feature set.

III. CONCLUSION

A distinct survey of papers on classification of emotional states using EEG signals data by machine learning techniques and other survey on the use of machine/deep learning techniques for detecting the onset of mental health illness/disorders using EEG signals data is presented. This paper cites the use of numerous machine and deep learning models as SVM, KNN, Random Tree, CNN, RNN etc. It majorly highlights the use of variety of SVM models with their different kernels and the use of CNN models with number of layers with and without error /feedback network.

Accuracy and ROC have been largely considered as the measure of the performance of the models employed. To have larger algorithm impact, the proper and precise choice of machine learning models on disorder detection is essential.

This paper gives insights into features used from EEG signals data and state-of-the-art algorithmic techniques with their performances mentioned. The choice of few favorably instructive features from EEG signals data is imperative and the employment of relative ML algorithm to deliver stable classification models with regard to accuracy, specificity, sensitivity, AUC, recognition rates etc. Making use of appropriate features from Time-statistical, frequency and non-linear dynamic domain can be useful to draw specific patterns for the models to gain good performance. The further work is how to combine various machine and deep learning techniques with the analysis suitably.

REFERENCES

[1] Wei-Long Zheng and Bao-Liang Lu 2015 Investigating Critical Frequency Bands and Channels for EEG-Based Emotion Recognition with Deep Neural Networks ieee transactions on autonomous mental development, vol. 7, no. 3, september 2015 digital object identifier 10.1109/tamd.2015.2431497

[2] Ashok sharmila, saiby madan, kajri srivastava 2017 Epilepsy detection using dwt based hurst exponent and svm, k-nn classifiers original scientific paper sciendo Accepted/Prihvaćen: 22.08.2017.UDK: 616.831-073 / Ser J Exp Clin Res 2018; 19 (4): 311-319 DOI: 10.1515/SJECR-2017-0043

[3] Manish Sharmaa, Achuth P. Vb, Dipankar Deba, Subha D. Puthankattilc, U. Rajendra Acharya 2018 An Automated Diagnosis of Depression Using Three-Channel Bandwidth-Duration Localized Wavelet Filter Bank with EEG Signals Article in Cognitive Systems Research · July 2018 DOI: 10.1016/j.cogsys.2018.07.010

[4] Shu Lih Oh, Yuki Hagiwara1, U. Raghavendra, Rajamanickam Yuvaraj, N. Arunkumar, M. Murugappan, U. Rajendra Acharya 2018 A deep learning approach for Parkinson's disease diagnosis from EEG signals Received: 4 July 2018/Accepted: 9 August 2018 The Natural Computing Applications Forum 2018 Neural Computing and Applications Springer http://crossmark.crossref.org/dialog/? doi=10.1007/s00521-018-3689-5&domain=pdf

[5] Laxmi Raja and M. Mohana Priya 2017 EEG based diagnosis of autism spectrum disorder using static and dynamic neural networks vol. 12, no. 21, november 2017 ISSN 1819-6608 ARPN Journal of Engineering and Applied Sciences ©2006-2017 Asian Research Publishing Network (ARPN). All rights reserved.

[6] V. Podgorelec 2012 Analyzing EEG Signals with Machine Learning for Diagnosing Alzheimer's Disease ELEKTRONIKA IR ELEKTROTECHNIKA, ISSN 1392-1215, VOL. 18, NO. 8, 2012 http://dx.doi.org/10.5755/j01.eee.18.8.2627

[7] Yan Zhang, Jing Xing, Chuanjun Guo, Chunling Yang, Xin Liu 2018 Sleep Stage Classification Based on EEG Signal by Using EMD and DFA Algorithm RCAE 2018, December 26–28, 2018, Beijing, China © 2018 Association for Computing Machinery. ACM ISBN 978-1-4503-6102-6/18/12…$15.00 https://doi.org/10.1145/3303714.3303723

[8] Zhaoheng Ni, Ahmet Cem Yuksel, Xiuyan Ni, Michael I Mandel, and Lei Xie. 2017. Confused or not Confused?. In Proceedings of ACM-BCB'17, August 20–23, 2017, Boston, MA, USA., 6 pages. DOI: http://dx.doi.org/10.1145/3107411.3107513

[9] Aurélien Appriou, Andrzej Cichocki, Fabien Lotte 2018. Towards Robust Neuroadaptive HCI: Exploring Modern Machine Learning Methods to Estimate Mental Workload From EEG Signals. CHI'18 Extended Abstracts, April 21–26, 2018, Montreal, QC, Canada ACM 978-1-4503-5621-3/18/04. https://doi.org/10.1145/3170427.3188617

[10] He Chen, Yan Song, Xiaoli Li 2019. A deep learning framework for identifying children with ADHD using an EEG-based brain network. Neurocomputing 356 (2019) 83–96 https://doi.org/10.1016/j.neucom.2019.04.058 0925-2312/© 2019 Published by Elsevier B.V.

[11] Dilip K. Prasad, Shijie Liu, Shen-Hsing Annabel Chen, Chai Quek 2018. Sentiment Analysis using EEG activities for suicidology. Expert Systems With Applications 103 (2018)206-217. https://doi.org/10.1016/j.eswa.2018.03.011 0957-4174/© 2018 Elsevier Ltd.

[12] Saeed Lotfan, Shima Shahyad, Reza Khosrowabadi, Alireza Mohammadi, Boshra Hatef 2018. Support vector classification of brain states exposed to social stress test using EEG-based brain network measures. Biocybernetics and Biomedical Engineering 39 (2019) 199-213 https://doi.org/10.1016/j.bbe.2018.10.008 0208-5216/© 2018 Published by Elsevier

[13] Autism Speaks, Learn more about Autism Speaks [Online]. Retrieved on 15th October 2016. Available: https://www.autismspeaks.org/.

[14] Top Mental Health Apps:An Effective Alternative for When You Can't Afford Therapy?Article by-Jessica Truschel

[15] Krishna Bairavi, Sundhara Kumar K.B EEG Based Emotion Recognition System for Special Children 2018 ICCET '18, February 24–26, 2018, Singapore, Singapore © 2018 Association for Computing Machinery. ACM ISBN: 978-1-4503-6454-6/18/02... https://doi.org/10.1145/3194244.3194245

[16] Harsh Dabas, Chaitanya Sethi, Chirag Dua, Mohit Dalawat, Divyashikha Sethia 2018 Emotion Classification Using EEG Signals CSAI '18, December 8–10, 2018, Shenzhen, China © 2018 Copyright is held by the owner/author(s). Publication rights licensed to ACM. ACM ISBN 978-1-4503-6606-9/18/12…$15.00 DOI: https://doi.org/10.1145/3297156.3297177

[17] Mina Mikhail, Khaled El-Ayat ,Rana El Kaliouby, James Coan, John J.B. Allen 2018 Emotion Detection using Noisy EEG Data AH Augmented Human Conference, April 2-3, 2010, Megève, France. Copyright c °2010 ACM 978-1-60558-825-4/10/04 ...

[18] Nisha Vishnupant Kimmatkar, Dr. Vijaya B. Babu 2018 Human Emotion Classification from Brain EEG Signal Using Multimodal Approach of Classifier ICIIT 2018, February 26–28, 2018, Ha Noi, Viet Nam. © 2018 Association for Computing Machinery. ACM ISBN 978-1-4503-6378-5/18/02…$15.00 https://doi.org/10.1145/3193063.3193067

[19] Yalin Li, Bin Hu , Xiangwei Zheng, and Xiaowei Li 2018 EEG-Based Mild Depressive Detection Using Differential Evolution 10.1109/ACCESS.2018.2883480 2169-3536,2018 IEEE Access

[20] Aayush Bhardwaj, Ankit Gupta, Pallav Jain, Asha Rani, Jyoti Yadav 2015. Classification of human emotions from EEG signals using SVM and LDA Classifiers. Division of Instrumentation and Control Engineering Netaji Subhas Institute of Technology University of Delhi, Delhi, India.

[21] Xian LI, Jian-Zhuo YAN and Jian-Hui CHEN 2017 Channel Division Based Multiple Classifiers Fusion for Emotion Recognition Using EEG signals ITM Web of Conferences 11, 07006(2017) IST2017 DOI: 10.1051/itmconf/20171107006

[22] Hayfa BLAIECH, Mohamed NEJI, Ali WALI and Adel M. ALIMI 2013 Emotion recognition by analysis of EEG signals Conference Paper · December 2013 publication at: https://www.researchgate.net/publication/266967599 DOI: 10.1109/HIS.2013.6920451

[23] Autism Speaks, Learn more about Autism Speaks [Online]. Retrieved on 15th October 2016. Available: https://www.autismspeaks.org/.

[24] Gwynn, R. C. et al. Prevalence, diagnosis, and treatment of depression and generalized anxiety disorder in a diverse urban community. Psychiatr Serv 59(6), 641–647 (2008).

[25] Dongren Yao, Xiaojie Guo, Qihua Zhao et al. 2018 Discriminating ADHD from healthy controls using a novel feature selection method based on relative importance and ensemble learning, 978-1-5386-3646-6/18/$31.00 ©2018 IEEE