Byzantine Neurobiological Phenomenon Analysis and Factors Prediction for Social Network based Adult's Suicides and Cyber Dismay by Hypercritical Machine Learning Techniques

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Abstract

Suicide is a complex neurobiological phenomenon, and there is great changeability in validity of Web Mining based appraisal tools to predict suicidal risk from social medias core. In our research methods provides evidence that we can predict suicide attempts and their depressive mind set accurately. In recent years, the World Health Organization (WHO) Global Mental Health Action Plan, 2013–2020, has been a major step forward in pushing the docket of suicide hindrance globally (WHO, 2013; Saxena, Funk, & Chisholm,2013). This plan was adopted by health ministers in all 194 WHO member states to formally recognize the importance of mental health, which was an extraordinary accomplishment. Generally, Machine learning was primarily used to build faster search engines like Google, for signal detection and for many other engineering achievements. But in our technical scenario, for predicting the suicidal trials using Social Network data that can automatically analyze the sentiments of these social communication. Then we investigate a tool of web data mining to extract beneficial evidence for classification of social communications collected from various social-networks based on Hypercritical machine learning classification algorithms. People are often victims of annoyance or cyberbullying; social networks would thus implement a real-time observation with respect to different risk factors. In this research paper discussed and the terms used by cyber depression and suicidal are well known.

Keywords

Suicide, Web Mining, Machine Learning, Social Network, Hypercritical, Cyber Depression.

I. INTRODUCTION

The goalmouth of this research was to obtain a high-performing web crawling tool for the suicidal factors finding and depression analysis using hypercritical machine learning Technique (HMLT).

HMLT is a Mining plat-form that helps to predict crowdful social data systems in ours approach. Throughout the last years, the Internet has yet seen a broader scope through the development of social media. Based on easy communication techniques and reachable to all, the media promote social interaction through the Internet. Offering free access, social media has greatly promoted the mass and have triggered public dispute on the Internet. Many social networks exist and there are more than 954 social media sites available on the internet scenario *Figure.1*. Millions of people are using social networks like Facebook, twitter, LinkedIn, Etc., and ranked as most visited sites with the average of 73 million cardinal communications per day.

In this regards, social network like Twitter and Facebook are increasingly associated with phenomena such as sexual harassment, cyber bullying and finally met suicide. It is therefore very important to detect potential wounded at the earliest in order to strengthen suicide factor finding and prevention on the web. Undeniably, we can cite as an example the case of two American rappers Freddy E. and Capital Steez are given the death commenting live on their actions their Twitter accounts. In this paper, we discuss the Hypercritical Machine Learning Techniques which have been applied for Social network data analysis and predict the risk with snare cypher social place of internet users [1]. In particular, the paper discusses the application of Support Vector Machines, Linear Regression, Prediction using Decision Stumps, Expert Weighting and Online

Learning in detail along with the benefits and pitfalls of each method. The paper introduces the parameters and variables that can be used in order to recognize the patterns in social user mind set, which can be helpful in the future prediction of suicide kind of activities and how preventive actions can be combined with other learning algorithms to improve the accuracy of such anomaly activity prediction systems.

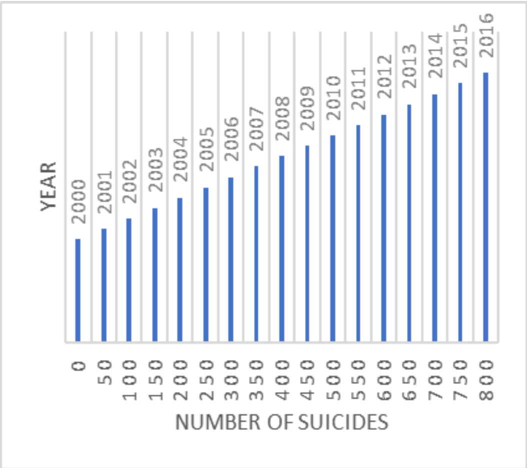

Figure 1. Suicide rate comparison

II.SOCIALDATA PROCESSING METHOD

The proposed method can substantially improve successful classification when applying hypercritical machine learning techniques to web data mining problems [2]. It transforms the social input data into a new form of data, which is more suitable and effective for the learning scheme chosen. Below follows the detailed description of the method.

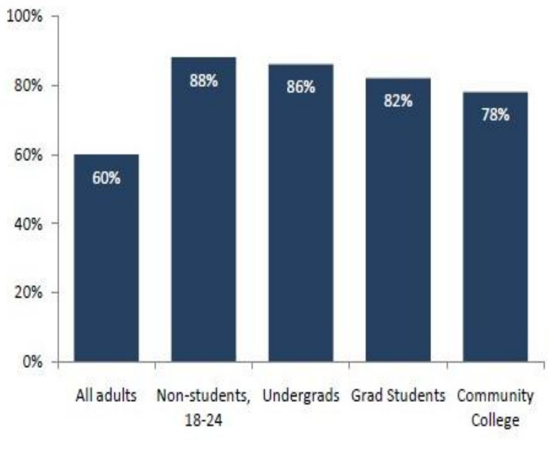

Figure 2. Percentage of social sites users

Hypercritical machine learning's future frontier for artificial intelligence can predict with 83-94 percent accuracy whether someone will attempt suicide as far off as two years into the future *Figure 2*. The algorithms become even more accurate as a person's suicide attempt gets closer. For example, the accuracy climbs to 93 percent one month before a suicide attempt when artificial intelligence focuses on one college hostel student [3].

A. *The Technical Analysis*

This method deals with the determination of the suicide rate based on the past patterns of the social site harming's. When applying Hypercritical Machine Learning to Social Web Data, we are more interested in doing a Technical Analysis to see if our algorithm can accurately learn the underlying patterns in the social sites data abnormalities time series. Hypercritical Machine Learning can also play a major role in evaluating and forecasting the suicide factor finding of the network and other similar parameters helpful in Fundamental Analysis. The most successful automated suicide prediction and factor finding systems use some sort of a hybrid analysis model involving both Fundamental and Technical Analysis [4].

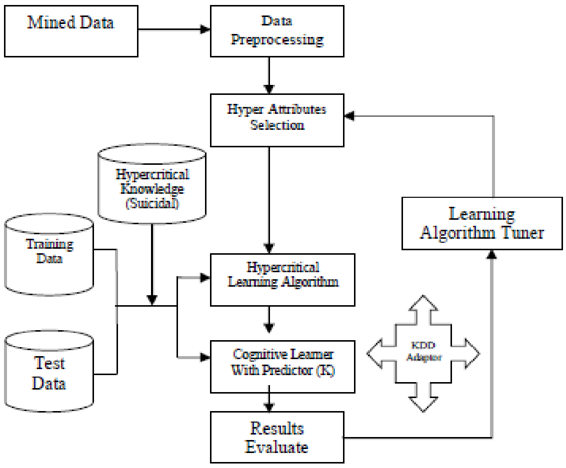

Figure 3. HMLT based Social Data Processing

The next step would be to use Artificial Intelligence to investigate video, audio, and text comments instantaneously. But that is a much thornier engineering feat. We have an attractive good handle on the kind of words people use when they are talking about their own discomfort and emotional states. But in a live stream, the only text comes from commenters [5]. In terms of the video itself, software engineers have already figured out ways to robotically tell when someone is bare on-screen, so they are using similar techniques to detect the presence of a pistol or breadknife. Drugs would be way harder [6].

B. *Input variables and Preprocessing*

To provide our model with information that would be available from the historical social sites data for each social communication and let it extract useful features without the need for extensive feature crawling *Figure 3*.

Two aspects of hypercritical Machine learning with social data are,

Figure 2. Source: Pew Research Center's Internet & American Life Project 2010 tracking surveys. N for all adults - 9,769: n for 18-24 years old non-students=717: n for four-year undergraduates=246, n for graduate students = 112, n for community college students-164.

1) Aspect - Phase I:

Hyper Learning methods focused on working on *live* streamed web datasets. It means, observing only a sample of web data and want to inferred. To deal with *in sample* and *out of sample* issues, *overfitting;* From this viewpoint, web data-mining is more focused on *dead datasets* than statistical learning *Figure 4*. Because statistical based hyper learning is about working on live dataset, the applied math's that deal with them had to focus on a *two scales problem*:

left{begin{array}{lcl} X_{n+1} &=& F_theta (X_n, xi_{n+1}) {hat theta} _{n+1} &=& L(pi(X_n), {hat theta} _n) end{array}right.

where X is the (multidimensional) state space to study (you have in it your explanatory variables and the ones to predict), F contains the dynamics of X which need some parameters theta. The randomness of X comes from the innovation xi. The goal of statistical learning is to build a methodology L i^{th} as inputs a partial observation pi of X and progressively adjust an estimate hat theta of theta, so that we will know all that is needed on X.

Apart from the above, the Total_Mean and Total_Median values are calculated as shown in equation (1) and equation (2) respectively (m is the name of the class and d is the sum of Basic Set rows). Finally, m total_Mean and m total_MEDIAN values result, one for every class of the Basic set.

$$\text{Total\_Mean}_m = \frac{(\text{Mean\_class}_m\text{\_row}_1 + \text{Mean\_class}_m\text{\_row}_2 + \ldots + \text{Mean\_class}_m\text{\_row}_d)}{d} \quad (1)$$

$$\text{Total\_Median}_m = \frac{(\text{Median\_class}_m\text{\_row}_1 + \text{Median\_class}_m\text{\_row}_2 + \ldots + \text{Median\_class}_m\text{\_row}_d)}{d} \quad (2)$$

2) Aspect – Phase II:

The results used to prove the efficiency of statistical based hyper learning methods can be used to prove the efficiency of Learning algorithms. Learning:

left{begin{array}{lcl} M_{n+1} &=& F_rho (M_n, xi_{n+1}) {hat rho} _{n+1} &=& L(pi(M_n), {hat rho} _n) end{array}right.

III. IMPACT AND MEANING OF SOCIAL MEDIA

To determining the broad impact and meaning of social media, our web crawler has tracked the specific social sites and platforms that users turn to in the course of living their social lives online. In that background, a national survey of 2,526 adults conducted February 23-April 24, 2016, finds that Facebook continues to be adults most popular social networking platform by a considerable margin: Nearly eight-in-ten *online* adults (82%) now use Facebook, more than double the share that uses Twitter (32%), Pinterest (34%), Instagram (41%) or LinkedIn (31%). On a total population basis (secretarial for adults who do not use the internet at all), that means that 72% of all adults are Facebook users, while 28% use Instagram, 29% use Pinterest, 27% use LinkedIn and 24% use Twitter [7].

IV. NEUROBIOLOGICAL VULNERABILITIES

Social website and Internet based activity addictions activate a combination of sites in the brain associated with pleasure, known together as the "reward center" or "pleasure pathway" of the brain. When activated, dopamine release is increased, along with opiates and other neurochemicals [8]. Over time, the associated receptors may be affected, producing tolerance or the need for increasing stimulation of the reward center to produce a "high" and the subsequent characteristic behavior patterns needed to avoid withdrawal. Cypher touch use may also lead specifically, to dopamine release in the nucleus accumbens, one of the reward structures of the brain specifically involved in other addictions [9]. An example of the rewarding nature of digital technology use may be captured in the following statement; *Table. I* by a 21-year-old male in treatment for IAD:

TABLE I. REAL STATEMENTS FROM IAD'S (SAMPLE)

Age group	Sex	Designation Type	Statement
19-24 (21)	Male	Student	"I feel technology has brought so much joy into my life. No other activity relaxes me or stimulates me like technology. However, when depression hits, I tend to use technology as a way of retreating and isolating."
25-31 (31)	Male	Professor	"when I feel depressed, I use technology (WhatsApp, Facebook Lite) as a way of receding and detaching."

Numeral of investigators and clinicians have noted that a variety of psychological disorders co-occur with IAD [10]. There is discussion about which came first, the addiction or the co-occurring disorder. The study by Dong et al. had at least the potential to clarify this question, reporting that higher scores for depression, anxiety, hostility, interpersonal sensitivity, and psychoticism were consequences of IAD [11].

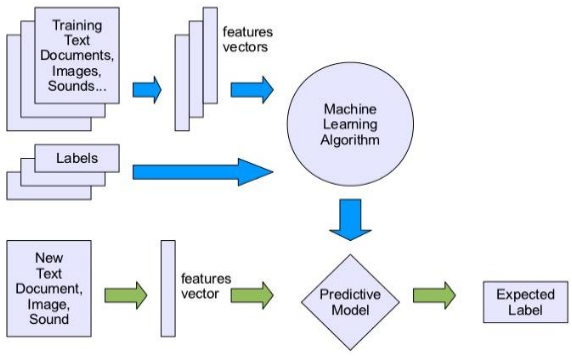

Figure 4. Machine learning for text classification

V. CYPHER SUICIDE REALIZATION

The newest advance in cypher suicide prediction may further establish the highly-controversial precrime concept [12]. Explicitly represented in the Tom Cruise Film Minority Report, the precrime concept entails the police's alleged ability to determine preconceived crime and take advanced actions prior to the crime being committed *Figure 5*. In the film, precrime was identified by near-comatose mutants with powerful psychic abilities.

In the real world, however, big data and sophisticated security systems have already been used by the police to reinforce crime detection [13].

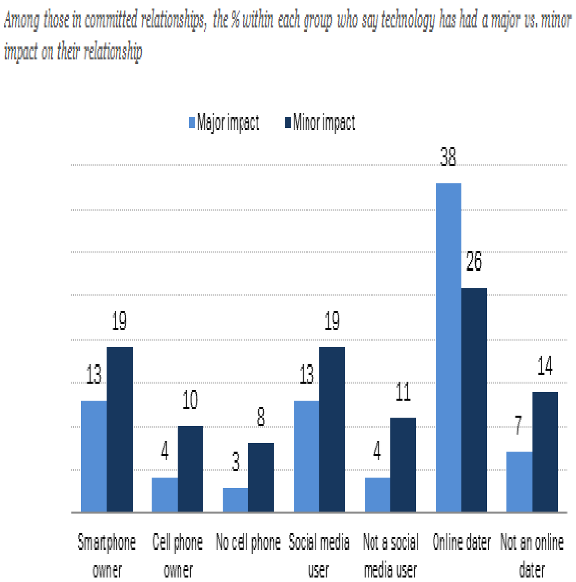

Figure 5. Impact of technology on relationships by cell phone social media and online dating status

Japanese multinational conglomerate Hitachi launched and tested its crime-prediction software in several unnamed American cities back in 2015 [14]. The software, called Hitachi Visualization Predictive Crime Analytics, sifts through various data such as criminal records, social media and weather reports as well as map and transit information to identify important crime-related patterns that may otherwise go unnoticed. The crime prediction software was also created with improved access to video data.

"Digital technologies, like those from Hitachi Data Systems, that provide real-time, aggregate and contextual data, support public safety initiatives that can transform how law enforcement and other first responder agencies locate, alleviate and prevent crimes, and ultimately make our cities safer places," said International Data Corporation officer Ruthbea Yesner Clark [15].

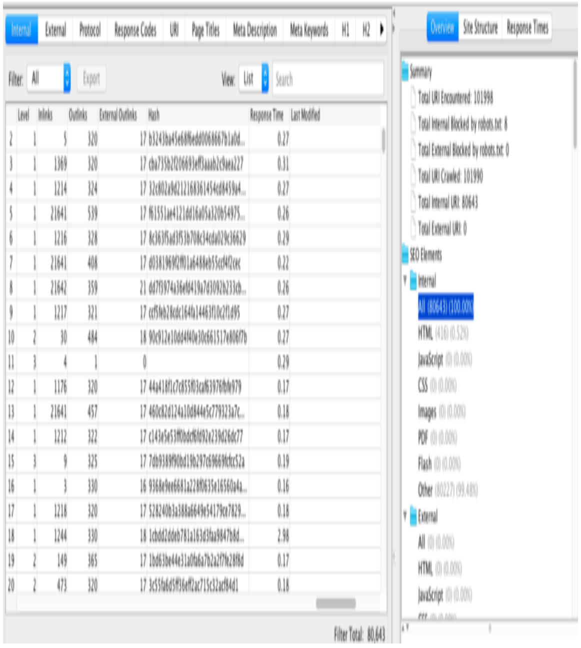

Figure 6. Interface design for Web Information Crawling.

Big data has also become a prominent fixture in precrime detection *Figure 6*. Intrado, LexisNexis and Motorola Solutions have also developed a service that readily scans legal, business and social media data to generate information on certain people and circumstances that police officers might encounter when responding to a 911 call. In addition, New York City police have turned to Facebook "friend" lists to resolve gang killings and burglary rings [16].

A. Psychological Approaches

A few specialists mentioned that physical exercise could compensate the decrease of the dopamine level due to social site usages in ineffective way [17]. In addition, sports exercise prescriptions used in the course of cognitive behavioral group therapy may enhance the effect of the intervention for IAD *Table.II*.

TABLE II. MULTIDIMENSIONAL TREATMENTS

S. No.	Name of Treatment	Description
1.	Motivational interviewing (MI)	Client-centered yet directive method for enhancing intrinsic motivation to change by exploring and resolving client ambivalence.
2.	Peukert – CRFT (Community Reinforcement and Family Training)	Interventions with family members or other relatives.
3.	Reality therapy (RT)	To encourage individuals to choose to improve their lives by committing to change their behavior.
4.	Acceptance & Commitment Therapy (ACT)	It including several exercises adjusted to better fit.
5.	CBT (cognitive behavioral therapy)	A predominantly behavioral group treatment including identification of sustaining conditions, establishing of intrinsic motivation.

In order to achieve our goal, we examined all social occurrences concerning cypher site entries based emotional symptomatology and more precisely, concerning about the digital symptoms that are associated with mood changes [18] [19].

VI. CLASSSIFICATION

Pretentious that Rest-Set from step 3 has r instances (rows) and m classes, a similar to step 3 approach follows. Specifically, matrix right division of every single Rest-Set row with every single row of the Basic Set is performed *Figure 7*. Then, the mean and median values of the division result of every row for each class are calculated (RS_Mean_class$_m$ _row$_j$ and RS_Median_class$_m$_row$_j$ respectively), producing new m+m=2m variables for every row of the Rest Set.

As a result, we have r values for RS_Mean_class$_m$_row$_j$, and r values for RS_Median_class$_m$_row$_j$. Similarly to step 3, we compute mean and medial values (RS_Mean_class$_m$ _row$_x$ and RS_Median_class$_m$ respectively) for every class. Apart from the above, the Final_Mean$_m$_row$_j$ and Final_Median$_m$_row$_j$ values are also calculated as shown in equation (3) and equation (4) respectively (m is the name of the class and j (from 1 to r) is the row of the Rest set.

$$\text{Final\_Mean}_m\text{\_row}_j = \text{total\_Mean}_{m\,(step\ 3)} - \text{RS\_Mean\_class}_m\text{\_row}_j \quad (3)$$

$$\text{Final\_Median}_m\text{\_row}_j = \text{total\_Median}_{m\,(step\ 3)} - \text{RS\_Median\_class}_m\text{\_row}_j \quad (4)$$

Finally, m Final_Mean$_m$_row$_j$ and Final_Median$_m$_row$_j$ values result, one for every class m and every row j of the Rest set.

The rows (variables) RS_Mean_classm_rowj, RS_Median_classm_rowj, Final_Meanm_rowj and Final_Medianm_rowj for every class are selected from previous step and then are placed in a new table. The method ends with the transposition of the Table we described in previous step and the final dataset is now ready to be forwarded in any classification schema. Concluding the description of the proposed method, it is evident that the final dataset consists of 4 variables, namely RS_Mean_class$_m$_row$_j$, RS_Median_class$_m$_row$_j$, Final_Mean$_m$_row$_j$ and Final_Median$_m$_row$_j$ for every class of the initial dataset. Thus, if the original dataset has m classes, the final dataset will have 4*m variables.

In our hyper classification technique, will divide the existing social communication data into training and testing socio-data. By using the training data and our vocabulary, this approach builds analysis model to be able to determine in which social communication part is a high risk that the person have pass the act of suicide or suspect's commune safely is to say, without however the person of the social site goes to the digital performance [20] [21] [22].

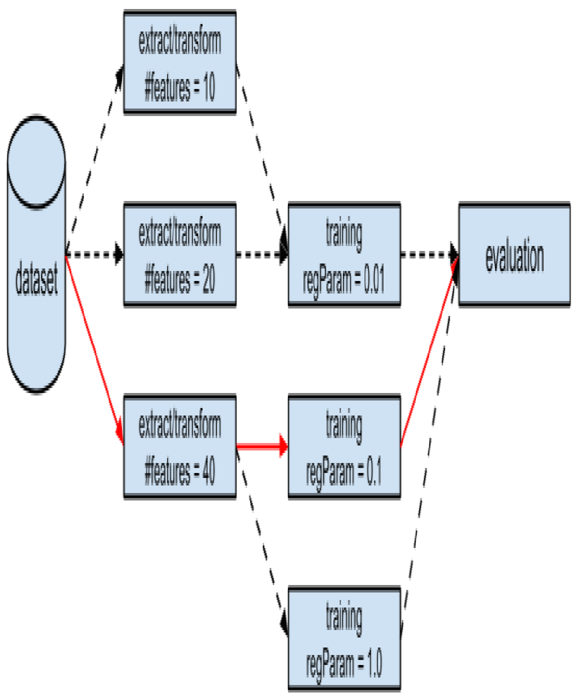

Figure 7. Overall Data Evaluations

A. *Cross-validation Technique*

The following figure shows the testing quality of the emotional analysis of hypercritical machine learning algorithm. Using our web crawling API, Communications related to suicide and depression are collected.

TABLE III. CROSS-VALIDATION OF PERFORMANCE ON DIFFERENT CLASSIFIERS FOR SUSPECTS SOCIAL COMMUNICATION WITH RISK.

A dataset is created using 1044 social website posts of cypher depressive words. Dataset splits in to a training set and a test set. The following tables show the various classification algorithms and the results we have achieved in terms of accuracy *Table.III*.

TABLE IV. CLASSIFICATION RESULTS COMPARISION

Classifiers	Initial Data Set (%)	Evolutionary Search (%)	PCA (%)	HMLT Method (%)
MultilayerPerceptronCS	63.82	74.83	64.79	91.18
MLP (Multilayer Perceptron)	65.83	74.93	65.83	92.08
FURIA (Fuzzy Logic algorithm)	74.71	75.32	79.12	85.83
RBF Network	71.42	76.71	75.81	83.45
Radial Basis Function Classifier	72.64	74.75	75.71	83.91
Random Forest	63.74	75.28	76.63	77.76
HMM (Hidden Markov Models)	77.91	76.75	77.55	75.68
J48-Graft	65.72	73.55	65.72	83.78
IB1	74.73	74.56	76.81	84.94
SMO (Support Vector Machines)	55.82	75.91	66.35	96.64

In our approach, we categorize subjects into two classes (suicide propensity, no-suicide propensity), numerous machine learning classification algorithms were tested in this paper, selected based on their popularity and frequency in socio-medical engineering problems *Table. IV*.

In our research met, several difficulties like high-end adoption of technology. Getting enough data for a project also hard [23]. Combining allegedly confidential data sets could intensify the risk of accidentally identifying individuals. Some of our crawling applications might have very crucial actions.

VII. EXPERIMENTAL RESULTS

For our experiments, classification results the repeated 10-fold cross validation method was used so as to assess generalization of our hypercritical machine learning data preprocessing method. The classifiers developed in WEKA 3.6 data mining software by WEKA parameters. To measure the performance of the classifier Precision, Recall, F-Measure have been used. Table. 3 present the Precision, Recall, F-Measure with risk.

Algorithm	CART	IB1	Naive Bayes	SMO	J48 - Graft	Random Forest
Precision	67.2%	64.0%	62.1%	71.0%	76.1%	73.62%
Recall	59.1%	50.9%	73.3%	52.3%	73.1%	74.72%
Fmeasure	63.1%	56.7%	68.2%	60.2%	64.2%	76.84%

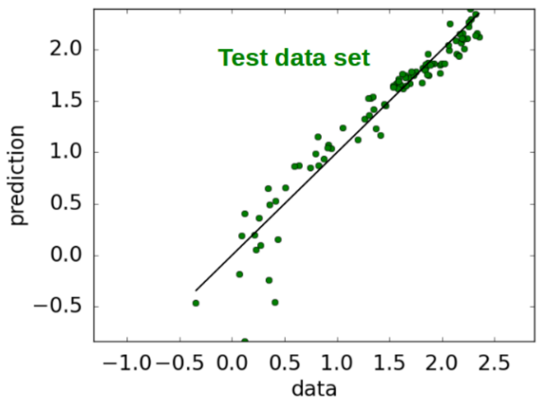

Figure 8. Socio-Data classification result graph

This research paper represents one of the first, as far as we are aware, applications of deep learning to suicide information and makes main contributions to the hyper machine learning literature.

VIII. CONCLUSIONS AND FUTURE WORK

The hypercritical machine-learning method combines hundreds of factors from adult person's health history to improve the accuracy of adult's suicide prediction. This method can easily be implemented across large health care hospital networks with crores of patients. In our future work, it would be preferable to make the same experiments in more datasets using different classifiers. In addition, our proposed data preprocessing method could be modified or extended in order to become a hybrid classification algorithm.

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