

## Machine Learning Vs Human Learning Can Machines get depressed?

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**Abstract:** Building on the unique study on Virtual Patients in Psychiatry by the author, a computer generated model of depression is sought to be generated. To this end a machine learning model for the depressed facies, body language and features of depression needs to be developed for which its opposite Mania as a 3D computer graphic generated model is studied as compared to a Schizophrenia model. These are evaluated by 90 medical students on 5 dimensions each. When statistics were applied to their observations it was found that in the case of Mania only Elated mood was the significant predictor of Mania where as in Schizophrenia Delusions, Passivity phenomena and living in one's own world were the predictors on regression analysis while Auditory Hallucinations also had significance in the correlation analysis. The inference has profound implications for machine learning as a paradigm versus human learning in depression which is discussed at length.

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### I. Introduction

Virtual Patients in Psychiatry was a concept first explored by the author in India and a study of Mania and Schizophrenia was done using computerized 3 D animation Graphics which is a unique study across the world<sup>1</sup>. A similar process for depression presents serious difficulties in terms of reliability and validity. Hence the need for this study, a Hypothesis generating rather than a Hypothesis testing one. The implications of this initial foray go far beyond creating computer generated models for undergraduates to study Psychiatry in a short time.

Machine Learning refers to a field of Artificial Intelligence that uses statistical Techniques to give computer systems the ability to Learn i.e. progressively improve performance on a specific task from data without additional explicit programming. Data driven decisions, predictions, analytics, data mining with seeking relationships and trends in the data and probabilistic reasoning are some of the strategies deployed<sup>2</sup>.

Machine learning to predict financial crisis<sup>3</sup>, medical diagnosis<sup>4</sup>, influence of Art<sup>5</sup>, self driving cars<sup>6</sup>, IBM Watson experiments<sup>7</sup>, human vs machine chess<sup>8</sup> have been partially successful.

Algorithmic Bias may lead to Socio-cultural dysfunctional learning where machines pick up all the racist and sexist language (onTwitter)<sup>9</sup>, prejudice against blacks and minorities<sup>10</sup> (Criminal evaluation), income generating rather than improving healthcare outcomes<sup>11</sup> (Healthcare AI) with greed bias !! This leads us to thinking bias and cognitive distortions of depression in machine learning when fed with negative outcome data sets as stated by Cognitive learning theories when applied to human learning. When humans can learn negativity why not machines which use machine learning principles? Isaac Asimov in his science fiction writes of how Robots take over the Planet which was also explored in films<sup>12</sup>. Is it Science or Fiction?

The new field of Computational Psychiatry has research from Zachary Mainen of Lisbon on AI and depression that views depression as "getting stuck in a model of the world that needs to change" which could also happen in Machine learning and maybe need a digital serotonin pill<sup>13</sup>!! Like Deep Mind's ability to spot more than 50 eye diseases<sup>14</sup>, researchers at MIT have created an AI system that can detect depression in writing and conversational speech samples using a dataset of 142 interactions from the Distress Analysis Interview Corpus containing audio, video and text interviews of patients with mental health issues<sup>15</sup>.

### II. Materials & Methods

The main aims of the study were to study the perception of humans (medical students) in assessing Mood disorder and Schizophrenia in Computer models and to generate hypotheses of mood disorders in machine learning models.

90 Medical students from 8<sup>th</sup> semester of Maharajah's Institute of Medical Sciences, Vizianagaram voluntarily participated in the evaluation of Computerised 3 D Animation Graphics characters of Mania and Schizophrenia. This time we avoided using standardized Rating scales like YMRS and PANSS which we used

in our previous study instead a 6 point Likert Scale was used where 0 signified absence upto 5 extremely Severe. It was administered on 5 Dimensions each for Mania and Schizophrenia with the 5<sup>th</sup> Dimension being overall severity. Each of the dimensions of M1 M2 M3 M4 were compared with M5 i.e. Overall severity of Mania. Similarly S1 S2 S3 S4 were compared with overall severity of Schizophrenia i.e. S5. Regression analysis to find out the significant independent Predictors of Mania and Schizophrenia was done. Similarly a Correlation analysis was done.

M1 – Elevated mood M2 – Grandiose delusions M3- Poor judgement M4 – Increased energy M5 – overall severity

S1 – Delusions S2 – Auditory Hallucinations S3 – Passivity phenomenon S4 – Living in one’s own world S5 – overall severity

### III. Results

In Mania model M1 i.e. Elevated Mood is the only significant independent predictor of M5 (Overall severity) in Regression Analysis and in Correlation Analysis M1 is found to be significantly positively correlated with M5 (Tables 1, 2, 3).

In Schizophrenia model S1,S3 and S4 are the significant independent predictors of S5 while all of S1 – delusions, S3 – Passivity Phenomena and S4 – Living in one’s own world are significantly positively correlated with S5 i.e. overall severity (Tables 4,5)

**Table 1**

Components	N	Mean	Std. Deviation
M1	90	4.40	.909
M2	90	.51	1.084
M3	90	4.58	.793
M4	90	4.46	.962
M5	90	4.19	.820
MAVGS	90	3.63	.418
S1	90	4.24	1.009
S2	90	4.37	.800
S3	90	4.19	1.069
S4	90	4.56	.949
S5	90	4.49	.797
SAVG	90	4.369	.5790

**Table 2**

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	
	B	Std. Error	Beta			
(Constant)	2.001	.754		2.653	.010	
1	M1	.209	.097	.232	2.164	<b>0.033</b>
	M2	.126	.091	.167	1.383	.170
	M3	.131	.106	.127	1.230	.222
	M4	.135	.107	.159	1.265	.209

M1 is the significant independent predictor of M5

**Table 3** M1 found to be significantly positively correlated with M5

		M1	M2	M3	M4	M5
M1	Pearson Correlation	1	-.050	.050	.277**	.274**
	Sig. (2-tailed)		.639	.641	.008	<b>0.009</b>
	N	90	90	90	90	90
M2	Pearson Correlation	-.050	1	-.047	-.517**	.067
	Sig. (2-tailed)	.639		.661	.000	.529
	N	90	90	90	90	90
M3	Pearson Correlation	.050	-.047	1	-.040	.124
	Sig. (2-tailed)	.641	.661		.711	.244
	N	90	90	90	90	90
M4	Pearson Correlation	.277**	-.517**	-.040	1	.132
	Sig. (2-tailed)	.008	.000	.711		.215
	N	90	90	90	90	90
M5	Pearson Correlation	.274**	.067	.124	.132	1
	Sig. (2-tailed)	.009	.529	.244	.215	
	N	90	90	90	90	90

**Table 4**

Model	Unstandardized Coefficients		Standardized Coefficients	t	P VALUE	
	B	Std. Error	Beta			
(Constant)	1.020	.524		1.945	0.055	
1	S1	.181	.069	.230	2.623	<b>0.010</b>
	S2	.082	.088	.083	.941	0.350
	S3	.222	.066	.298	3.371	<b>0.001</b>
	S4	.309	.073	.369	4.239	<b>0.000</b>

S1,S3 and S4 ARE THE SIGNIFICANT INDEPENDENT PREDICTORS OF S5

**Table 5**

		S1	S2	S3	S4	S5
S1	Pearson Correlation	1	.236*	.144	.126	.339**
	Sig. (2-tailed)		.025	.175	.235	<b>.001</b>
	N	90	90	90	90	90
S2	Pearson Correlation	.236*	1	.194	.039	.209*
	Sig. (2-tailed)	.025		.067	.712	<b>.048</b>
	N	90	90	90	90	90
S3	Pearson Correlation	.144	.194	1	.227*	.431**
	Sig. (2-tailed)	.175	.067		.031	<b>.000</b>
	N	90	90	90	90	90
S4	Pearson Correlation	.126	.039	.227*	1	.469**
	Sig. (2-tailed)	.235	.712	.031		<b>.000</b>
	N	90	90	90	90	90
S5	Pearson Correlation	.339**	.209*	.431**	.469**	1
	Sig. (2-tailed)	.001	.048	.000	.000	
	N	90	90	90	90	90

S1,S2, S3 and S4 are significantly positively correlated with S5

#### IV. Discussion

What this indicates is that only Elevated Mood is the main predictor component of the Mood disorder Mania where as in Schizophrenia all the 4 dimensions of Delusions, Auditory Hallucinations, Passivity Phenomena and living in one's own world are important in delineating Schizophrenia.

If one were to extrapolate these findings to Depression which is a Mood disorder and on the opposite end of Mania one would have to infer that unless one portrays the affect of Depression accurately one cannot in a reliable and valid manner make a Computerized 3 D graphics model of Depression. As a mood state Sadness and depressed mood are universally experienced and therefore any attempt to make a model of depression which evokes empathy, rapport, relational transactions especially for Psychotherapy would be a tough ask.

If one were to create a Computer graphic model or a Robot that through artificial intelligence and Machine Learning learns how to be depressed would it be successful? Can a Machine learn Depression? These are the hypothesis generating questions raised by this study.

Depression has hormonal, immune, circadian, vegetative, cognitive and behavioural components. A computer by contrast has only a neural signalling system that involve input(sensory afferent) processing (reverberating brain circuits) and output (motor efferent) systems. Autonomic and hormonal outpouring, bio vegetative, physiological excesses may be viewed as the effect of depression in the Cortical areas leading to dysregulation of limbic structures including hypothalamus (loss of cortical inhibition<sup>16</sup>). Thus inefficiency of cortical processing like inappropriate neural networks processing may be the main underlying reason of depression and may be seen in Machine learning without the biological effects. It increases the gap between predicted reality and actual reality a sort of virtual world the patient and machine created for themselves which impacts judgement(output) and thereby behaviour. Therefore a bio psycho social model may be replaced by a bio electro mechanical model!! An alternative view could be that biologically excessive response of autonomic, HPA axis and an underwhelming response of central neuro transmitters may swamp the thinking process and damage the brain circuits as in a short circuit which needs repair and maintenance (electrical pathways) of circuits. Periodic outages may lead to recurrent depression which requires regular maintenance.

An inefficient self learning system may develop abnormal pathways of thinking and processing by giving greater weightage to minor and irrelevant things and lesser weightage to events which later turn out to be catastrophic, a program that got corrupted and giving undesirable outputs, to use a computer analogy!!

These are some more hypotheses generated by this study. Only future studies can confirm or negate the hypothesis that machines can learn how to be depressed the way humans learn as suggested by the black box approach of behavioural learning theories!!

## V. Conclusion

Any computer interactive graphic model would need to tackle the affective elements of depression as it is a mood disorder.

Machines may learn the cognitive and behavioural aspects of Depression when using Artificial Intelligence and Machine Learning paradigms. This is an interesting hypothesis that was generated by this study which however needs evaluation through further studies.

## References

- [1]. Radhakanth C., Virtual Patients in Psychiatry: A Study of Mania And Schizophrenia. IOSR Journal of Dental and Medical Sciences (IOSR-JDMS) e-ISSN: 2279-0853, p-ISSN: 2279-0861. Volume 15, Issue 10 Ver. II (October. 2016), PP 43-49
- [2]. Machine Learning., Wikipedia
- [3]. Scott Patterson (13 July 2010). "Letting the Machines Decide". *The Wall Street Journal*.
- [4]. Vinod Khosla (January 10, 2012). "Do We Need Doctors or Algorithms?". *Tech Crunch*medical
- [5]. When A Machine Learning Algorithm Studied Fine Art Paintings, It Saw Things Art Historians Had Never Noticed, *The Physics at ArXiv* bloginfluence of Art5,
- [6]. "Why Uber's self-driving car killed a pedestrian". *The Economist*.
- [7]. Hernandez, Daniela; Greenwald, Ted (2018-08-11). "IBM Has a Watson Dilemma". *Wall Street Journal*. ISSN 0099-9660
- [8]. Hapgood, Fred (23–30 December 1982). "Computer chess bad-human chess worse". *New Scientist*. pp. 827–830.
- [9]. Caliskan, Aylin; Bryson, Joanna J.; Narayanan, Arvind (2017-04-14). "Semantics derived automatically from language corpora contain human-like biases". *Science*. 356 (6334): 183–186.
- [10]. Garcia, Megan (2016). "Racist in the Machine". *World Policy Journal*. 33 (4): 111–117.
- [11]. income generating rather than improving healthcare outcomes11 (*Healthcare AI*)
- [12]. Isaac Asimov, *Robots and the Empire*, 1985, Double day books.
- [13]. Sarah K Fineberg, Dylan Stahl, Philip Corlett., *Computational Psychiatry in Borderline Personality Disorder*, *Current Behavioral Neuroscience Reports*, March 2017, Vol 4, Issue 1, pp31-40
- [14]. Jeffery de Fauw et al., *Clinically applicable deep learning for diagnosis and referral in retinal disease*, *Nature medicine*, Vol 24, September 2018, 1342–1350,
- [15]. Jonathan Gratch et al., *The Distress Analysis Interview Corpus of human and computer interviews*, *Proceedings LREC 2014*, 508\_paper.pdf
- [16]. Mark S. George M.D. Terence A. Ketter M.D. Dr. Robert M. Post M.D. *Prefrontal cortex dysfunction in clinical depression* *Depression* 2:59–72 (1994). © 1994 Wiley-Liss, Inc.

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