Associating Unemployment with Panic Attack Using Deep Learning during COVID-19

Shawni Dutta[1] and Samir Kumar Bandyopadhyay[2*]

[1]*Department of Computer Science, The Bhawanipur Education Society College, Kolkata, India.*
[2]*The Bhawanipur Education Society College, Kolkata, India.*

Authors' contributions

This work was carried out in collaboration among all authors. Author SD designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Author SKB managed the analyses of the study. All authors read and approved the final manuscript.

Original Research Article

ABSTRACT

Corona Virus Infectious Disease (COVID-19) is newly emerging infectious disease. It is known to the world in late 2019. Due to this, the mental health of employees is disturbed. There is always a fear of unemployment amongst employees due to the present scenario of lockdown. This may even create a panic attack. It has been happening rapidly during COVID-19. It has a great effect on human health. This paper analyses multiple factors that have an impact on causing panic attacks. Deep Learning techniques are explored which detects panic disorders on people. Recurrent Neural Network (RNN) based deep learning framework is utilized in this paper that assembles multiple RNN layers along with other hyper-parameters into a single model. This method is implemented by capturing interfering factors and predicts the panic attack tendency of people during COVID-19. Early prediction of panic attacks may assist in saving life from unwanted circumstances. It is also observed that comparative study between MLP and stacked-RNN classifier indicates significantly better results of proposed model over MLP classifier in terms of evaluating metrics.

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Corresponding author: Email: 1954samir@gmail.com;

1. INTRODUCTION

COVID-19 initially happened initially in the city of Wuhan, China, at the end of 2019. The World Health Organization (WHO) called it a novel coronavirus as "2019-nCoV". On March 11, 2020 this Covid-19 was characterized as Pandemic [1]. During COVID-19 symptoms of anxiety and depression co-occurred and are continuously spread in the general population. Psychiatrists recognized it as a disorder of human health [2]. Human to human contacts are considered as responsible for community spread of this disease in exponential growth. Hence social detachment of people should be followed necessarily to combat COVID-19 from the front line as well as in the backend also. Job loss appears to lead to poor mental status, due to loss of social status as well as economic uncertainty. Panic disorder has a strong relation with a chronic progression, which results in economic burden and a loss of quality of life. Therefore, proper prevention and treatment of panic disorder is important [3]. Fake news in COVID-19 increases anxiety, stress, and even depression. The reason behind this is to stay-at-home, curfews, and closing of essential businesses. Many families are now facing an unemployment scenario. Some are forced to work from home due to the direction of companies. Many companies and businesses are working with loss due to coronavirus. This new life is stressful enough. So anxiety of people is clearly increased due to the new lifestyle.

To associate unemployment rate with panic attack, data mining and knowledge discovery approaches are implemented that mainly focus on identifying related factors that have impact on panic attack. The proposed system spontaneously accepts information such as unemployment, previous mental illness records, daily lifestyle, overall income rate of person etc. and detects whether the patient can be affected by panic attack or not. Input variables are mapped into target classes using classification techniques which are supervised learning algorithms. For classification purposes, Deep Learning (DL) [4] based framework is implemented in this paper. DL technique is popular because of its self-adaptive structure that processes data with minimal processing. A Recurrent Neural Network (RNN) [5] is a type of deep learning model with a feedback loop structure that is often helpful in forecasting purposes. A stacked RNN model is proposed in this paper as a recommender system for obtaining prediction results for identifying panic attacks. The proposed model basically cascades multiple RNN layers under a single platform for assessing the panic attack disorders. The identification of panic attacks relies on the RNN model because it can process long distance contexts. Utilising the long distance contexts can help in identifying more efficient and accurate predictive results.

1.1 Related Works

Several researches have been carried out for predicting employee attrition. A prediction system using k-Nearest Neighbours algorithm is implemented for obtaining prediction related to whether an employee will leave a company or not is evaluated in [6]. Average monthly hours at work, Employee Performance and number of years spent in the company and among others are considered as features for analysis. Well-known classifiers such as Naïve Bayes, Logistic Regression, Multi-layer Perceptron (MLP) and k-Nearest Neighbours (K-NN) were implemented for acquiring the prediction. Comparative study indicates that k-Nearest Neighbours outperforms well over other mentioned classifiers. Another study [7] implemented a couple of well-known classifiers such as Decision tree, Logistic Regression, Support Vector Machines (SVM), KNN, Random Forest, Naive bayes methods on the human resource data that for preventing employee attrition [7]. Feature selection methods implemented on the dataset. Next analysis created results in order to prevent employee attrition. Employee attrition prevention mechanism is proposed using logistic regression methods [8]. Division of demographic data as well as present employees are gathered. A cluster of high risk employees was generated. The attention is given on these employees to reduce mental stress. Another study [9] exploited various data mining techniques such as Random Forest, SVM, Gradient Boosted Classifier and Logistic Regression for predicting attrition. Experimental analysis shown in this paper implied that Extreme Gradient Boosting is superior over classifier related to attrition prediction tasks.

The cause of mental stress has been growing rapidly in recent environment i.e. during COVID-

19 both in the place of work as well as in other places also. Smets et al. Researchers used machine learning techniques for the detection of mental illness [10]. Rest and stress periods in terms of classes by binary classification. Bayesian networks and SVM provided reasonable accuracy with 84.6 % and 82.7 % respectively. Karthikeyan et al. [11] utilised electrocardiography (ECG) and heart rate variability (HRV) signals for stress assessment. Their results concluded successful classification of stressful and not stressful events based on HRV features with classification accuracy of 79.2 %. Strauss et al. in [12] explored machine learning algorithms like cluster analysis, KNN, decision trees and SVM for clinical forms analysis of mental health. Their results concluded that SVM had the best performance with a precision of 64.6%. Kessler et. al. [13] utilised machine learning model by taking inputs from survey. They predicted major depressive disorder (MDD) keeping its persistence with good accuracy.

2. BACKGROUNDS

Deep Learning (DL) is a subfield of Machine Learning (ML) that enforces automatic learning of abstract information from large databases without incorporating manual feature engineering methods. Deep neural networks are capable of computing complex functions by extracting features from input data. These computations are dependent on the number of hidden layers and other parameters [14]. For accompanying the complex computations, activation functions are used. Activation functions are capable of executing diverse computations and produce outputs within a definite range. In other words, activation function is a step that maps input signal into output signal [15]. Sigmoid, Tanh and ReLu are popular activation functions that are described as follows-

- Sigmoid activation function [15] transforms input data in the range of 0 to 1 and it is shown in equation (1).

$$f(x) = 1/(1 + exp^{-x}) \tag{1}$$

- Rectified Linear Unit (ReLu) activation function [15] is one of the most successful and widely used activation functions. It performs a threshold operation to each input element where values less than zero are set to zero whereas the values greater or equal to zeros are kept as intact and it is shown in equation (2).

$$f(x) = (0, X) = \{ \ Xi, \ if \ Xi \geq 0 \ 0, \quad if \ Xi < 1 \tag{2}$$

- The hyperbolic tangent (tanh) [15] is a smoother and zero-centred function. The range of this function range lies between -1 to 1, thus the output of the tanh function is given as equation (3).

$$f(x) = (e^x - e^{-x})/(e^x + e^{-x}) \tag{3}$$

RNNs are superior over ANN since RNN has feedback connections those are capable enough to identify spatial and temporal dependencies between input and output sequences. The word 'recurrent' is used since these NNs repeat the same task for every sequence element and the output of current state is dependent on previous state. However, the presence of feedback connections makes the training of RNNs much more difficult as compared to static neural networks [16]. Dropout layers are often useful in order to reduce over-fitting problem in deep learning method. Deactivation of dropout layers uses a fraction of the units or connections in a network during each of the training iterations [17]. Deep models will compile multiple layers into a single platform through an optimizer. The most popular Adam is one of the popular optimizers and is computationally efficient with lower memory requirement. The process is applicable for first-order gradient- based optimization of stochastic objective functions. It is based on adaptive estimates of lower-order moments. It is well accepted due to its applicability on non-stationary objectives and problems with very noisy and/or sparse gradients [18]. After configuring neural network models, training process is executed. The training process goes through one cycle known as an epoch where the dataset is partitioned into smaller sections. An iterative process is executed through a couple of batch size that considers subsections of training dataset for completing epoch execution [19]. Since this entire framework is inclined towards solving binary classification problem, binary cross entropy function is used as training criterion. Binary cross entropy measures the distance from the true value (which is either 0 or 1) to the prediction for each of the classes and then averages these class-wise errors to obtain the final loss [19].

2.1 Dataset Used

For associating the relationship of unemployment and other related factors with panic disorder, a dataset called Unemployment and mental illness survey was collected from kaggle [20]. The dataset consists of 334 rows and each of these rows are considered to be a collection of 31 attributes. The attributes of the dataset along with their description is provided in Table 1.1 and Table 1.2. All the binary attributes present in the dataset is shown in Table 1.2 whereas Table 1.1 consists of all the attributes which is non-binary. Among several attributes, 'Panic attacks' is considered as the target variable for classification. Once the dataset is collected, pre-processing techniques are applied. A multi-step pre-processing technique was carried out for

obtaining a cleaned dataset. Presence of all 'nan' values in the dataset is replaced by zero. The attribute 'Education' is containing several values which are indicating the same thing. For example, attribute value Completed Undergraduate, and Some Undergraduate basically refer to Undergraduate degree. Hence, they are replaced accordingly. After applying the pre-processing techniques, training dataset and testing dataset are obtained by bifurcating pre-processed dataset with the ratio of 67:33. The attribute 'Panic attacks' is the dependent variable in this classification; hence in the test dataset it is not included. Using training dataset, classifier is learned and later testing process is carried out for testing dataset.

Table 1.1 Summary of categorical and numerical attributes present in collected dataset

Attribute Name	Description	Values Present
How many days were you hospitalized for your mental illness	Number of days of hospitalization	0-100 and contains nan values
Education	Pursued Education	High School or GED, Some Phd, Completed Undergraduate, Some Undergraduate, Some\xa0Masters, Completed Masters, Completed Phd, Some highschool
Total length of any gaps in my resume in months.	Length of gaps present in resume	0-100
Annual income (including any social welfare programs)	Annual Income of individual in USD	0-100
How many times were you hospitalized for your mental illness	Number of times of hospitalization due to mental illness	0-100
Age	Age of respondent	'30-44', '18-29', '45-60', '> 60'
Household Income	House hold income of the person in USD	'$25,000-$49,999', '$50,000-$74,999', '$150,000-$174,999', '$0-$9,999', '$100,000-$124,999', '$125,000-$149,999', 'Prefer not to answer', '$10,000-$24,999', '$75,000-$99,999', '$200,000+', '$175,000-$199,999'
Region	Belongs to which region	'Mountain', 'East South Central', 'Pacific', 'New England', 'East North Central', 'South Atlantic', 'Middle Atlantic', 'West South Central', 'West North Central', nan
Device Type	Use of device by the person	'Android Phone / Tablet', 'MacOS Desktop / Laptop', 'Windows Desktop / Laptop', 'iOS Phone / Tablet', 'Other'

Table 1.2 Summary of binary attributes present in collected dataset

Attribute Name	Description	Values Present
I am currently employed at least part-time	Whether an employee was engaged as part-timer or not	0-No 1-Yes
I identify as having a mental illness	Whether the individual has mental illness or not	0-No 1-Yes
I have my own computer separate from a smart phone	Whether the person occupies computer other than smart phone or not	0-No 1-Yes
I have been hospitalized before for my mental illness	Whether the person has hospitalization record	0-No 1-Yes
I am legally disabled	Whether the person has legal issues or not	0-No 1-Yes
I have my regular access to the internet	Whether the person has access to internet or not	0-No 1-Yes
I live with my parents	Whether the individual lives with his/her parents	0-No 1-Yes
I have a gap in my resume	Breaks present in resume	0-No 1-Yes
Lack of concentration	Whether the person is lacking of concentration or not	0,1,nan
Anxiety	Whether the individual is having anxiety or not	0-No 1-Yes
Depression	Whether the person is having depression or not	0-No 1-Yes
Obsessive thinking	Whether the individual carries obsessed thinking or not	0,1,nan
Mood swings	Whether the individual is prey of mood swings or not	0,1,nan
Panic attacks	Whether the individual has panic disorder tendency or not.	0,1,nan
Gender	Gender of the respondent	'Male', 'Female'
I receive food stamps	Whether the person received food stamps or not	0-No 1-Yes
I am on section 8 housing	Whether the person is included in section 8 housing or not	0-No 1-Yes
I am unemployed	Indicates unemployment of person	0-No 1-Yes
I read outside of work and school	Reading habit	0-No 1-Yes
Tiredness	Suffers from tiredness or not	0,1,nan
Compulsive behavior	Whether the person possess compulsive behavior or not	0,1,nan

3. METHODOLOGY

This study focuses on identifying panic attack disorders among people by considering several impactful factors such as unemployment, previous mental illness records, daily lifestyle, overall income rate of person etc. For addressing this problem domain, a stacked RNN model is proposed. The contribution of this study can be described as follows-

1. Consider the impact of numerous factors such as unemployment, previous mental illness records, daily lifestyle, overall income rate of a person etc. for assessing panic attacks tendency.

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2. Using DL technique, multiple RNN layers are stacked into a single platform in order to design classifier model.

3. This model is compared with conventional neural network based MLP classifier in order to justify the superiority of the proposed predictive model.

A stacked RNN model is implemented in this paper that assembles four RNN layers and four dense layers. Each RNN layer is followed by dropout layers. Use of dropout layer will reduce the problem of over-fitting. The structure of the RNN defines the number of inputs, the number of hidden layers, the number of nodes in each hidden layer and the number of outputs for a specified architecture. Finally, the parameters of an RNN are the weights associated with the connections and the nodes. This section elaborates the number of nodes used, output shape, number of parameters received. Four RNN layers have 128,64,32,16 number of nodes respectively. A dropout regularization of 20% is added after each of the RNN layers. After that, four dense layers are stacked into this model where the layers have 8, 4, 2, 1 numbers of nodes respectively. Finally the layers are compiled using adam optimiser and binary cross-entropy is utilised as a loss function. After compilation, training dataset is fitted into this model with epoch size 100 and batch size of 64. During the training phase, this model receives 33,065 parameters and trains those parameters. Once the training process is finished, test dataset is used for prediction purpose. Table 2 provides a detailed summary of the implemented model in terms of layers used, output shape, number of parameters received. This stacked-RNN model is compared with the Multi-layered Perceptron

(MLP) classifier. Multi-layer perceptron [21] can be used as a supervised classification tool that relies on neural network architecture. For a given problem, the number of hidden layers in a multilayer perceptron and the number of nodes in each layer can differ. The decision of choosing the parameters depends on the training data and the network architecture [21]. In this framework, MLP classifier is implemented by incorporating hidden layers of sizes 128, 32,16,1 respectively. The layers are compiled using 'adam' optimizer and this classifier uses 'relu' as activation function.

4. EXPERIMENTAL RESULTS

During the training phase, the learning process is evaluated in terms of accuracy and loss. For each epoch, loss and accuracy is calculated and is shown in Fig. 1. As the number of epochs increases, loss decreases and accuracy increases. After the training process is executed, the implemented model is used for prediction purpose. The prediction result is evaluated against accuracy, f1-score and MSE and is shown in Table 3. The stacked-RNN model is compared against traditional neural network classifier such as MLP classifier. Table 3 also shows comparative study between MLP and stacked-RNN classifier which indicates significantly better results of proposed model over MLP classifier in terms of evaluating metrics.

5. DISCUSSION

This research aims in establishing the relationship between unemployment and panic attacks using DL techniques. The proposed

Table 2. Architecture of stacked-RNN model

Layer type	Number of Nodes/Dropout Rate	Output Shape	Number of parameters received	Activation Function Used
Simple RNN	128	(None,30,128)	16640	ReLu
Dropout	20%	(None,30,128)	0	None
Simple RNN	64	(None, 30, 64)	12352	ReLu
Dropout	20%	(None,30,64)	0	None
Simple RNN	32	(None, 30, 32)	3104	ReLu
Dropout	20%	(None, 30, 32)	0	None
Simple RNN	16	(None, 16)	784	Tanh
Dropout	20%	(None, 16)	0	None
Dense	8	(None, 8)	136	None
Dense	4	(None, 4)	36	None
Dense	2	(None, 2)	10	None
Dense	1	(None, 1)	3	Sigmoid
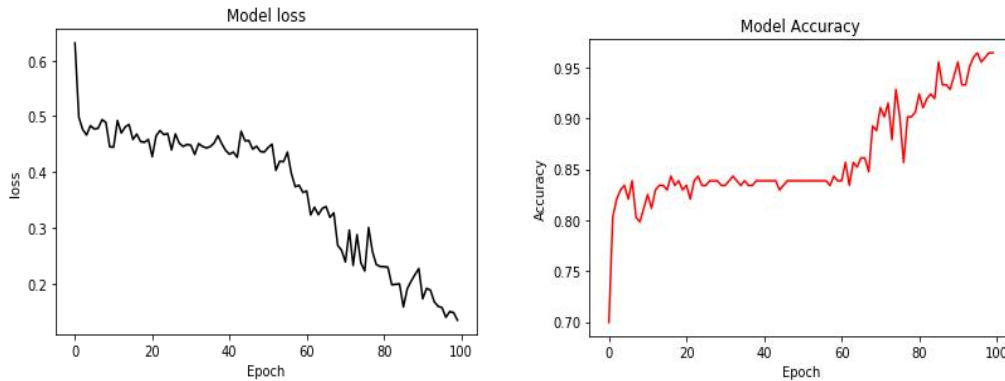
Fig. 1. Accuracy and loss plot obtained for each epoch

Table 3. Performance comparison between stacked-RNN and MLP classifier

Performance Measure Metrics	Accuracy	F1-Score	MSE
Proposed Stacked-RNN Model	91.89%	0.92	0.08
MLP	88.29%	0.88	0.1171

stacked-RNN model follows DL techniques for supporting the objective of this study. This model receives all interfering factors those have impact on panic disorder. Detecting people with panic disorder at an early stage will assist in providing and monitoring them in order to avoid unwanted life loss. The proposed model is evaluated against certain metrics and compared with traditional neural network model. This indicated the superiority of stacked-RNN model in terms of achieving that target of this study.

6. CONCLUSIONS

The objective of this study is to detect the feasibility of utilising related parameters and determine the probability of being affected by mental illness. Early detection of panic disorder may assist in prescribing possible counter measures in order to save life. A stacked RNN model is proposed in this paper that provides mental illness tendency beforehand. Implementation of this model is accompanied by fine-tuning of hyper-parameters for obtaining maximised performance. An accuracy of 91.89%, MSE of 0.08 and F1-Score of 0.92 is offered by this method which is significantly relevant in the domain of psychological disorder detection.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. World Health Organization. WHO Statement regarding cluster of pneumonia cases in Wuhan, China; 2020. Available:https://www.who.int/china/news/detail/09-01-2020-who-statement-regarding-cluster-of-pneumonia-cases-in-wuhan-china

2. Weich S, Lewis G. Poverty, unemployment, and common mental disorders: Population based cohort study. Br. Med. J. 1998;317(7151):115–119. DOI: 10.1136/bmj.317.7151.115

3. Jefferis BJ. et al. Associations between unemployment and major depressive disorder: Evidence from an international, prospective study (the predict cohort)," Soc. Sci. Med. 2011;73(11):1627–1634. DOI: 10.1016/j.socscimed.2011.09.029

4. Liu J, Liu J, Du W, Li D. Performance analysis and characterization of training deep learning models on mobile device. Proc. Int. Conf. Parallel Distrib. Syst. - ICPADS. 2019;506–515. DOI: 10.1109/ICPADS47876.2019.00077

5. Sherstinsky A. Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. Phys. D Nonlinear Phenom. 2020;404:1–43. DOI: 10.1016/j.physd.2019.132306

6. Yedida R, Reddy R, Vahi R, Jana R, GVA, Kulkarni D. Employee attrition prediction.

arXiv:1806.10480 [stat.ML]; 2018.

7. Shankar RS, Rajanikanth J, Sivaramaraju VV, Vssr Murthy K. Prediction of employee attrition using datamining. IEEE Int. Conf. Syst. Comput. Autom. Networking, ICSCA 2018;1–8.
DOI: 10.1109/ICSCAN.2018.8541242

8. Khare R, Kaloya D, Choudhary CK, Gupta G. Employee Attrition risk assessment using logistic regression analysis. Int. Conf. Adv. Data Anal. Bus. Anal. Intell. 2011;1–33.

9. Yadav S, Jain A, Singh D. Early prediction of employee attrition using data mining techniques. Proc. 8th Int. Adv. Comput. Conf. IACC. 2018;8(2882):349–354.
DOI: 10.1109/IADCC.2018.8692137

10. Díaz-García A, et al. Pervasive Computing paradigms for mental health. Pervasive Comput. Paradig. Ment. Heal. 2019;604: 147–156.
DOI: 10.1007/978-3-319-32270-4

11. Karthikeyan P, Murugappan M, Yaacob S. Analysis of stroop colorword test-based human stress detection using electrocardiography and heart rate variability signals. Arab. J. Sci. Eng. 2012; 39(3):1835–1847.
DOI: 10.1007/s13369-013-0786-8

12. Strauss J, Peguero AM, Hirst G. Machine learning methods for clinical forms analysis in mental health. Stud. Health Technol. Inform. 2013;192(1–2):1024.
DOI: 10.3233/978-1-61499-289-9-1024

13. KRC. et al. Testing a machine-learning algorithm to predict the persistence and severity of major depressive disorder from baseline self-reports. Mol. Psychiatry. 2016;21(10):1366–1371.

14. Coşkun, Musab, et al. An Overview of Popular Deep Learning Methods. Eur. J. Tech. 2017;7(2):165–176.
DOI: 10.23884/ejt.2017.7.2.11

15. Nwankpa C, Ijomah W, Gachagan A, Marshall S. Activation functions: Comparison of trends in practice and research for deep learning. 2018;1–20.
DOI: arXiv:1811.03378 [cs.LG]

16. Lipton ZC, Berkowitz J, Elkan C. A critical review of recurrent neural networks for sequence learning. 2015;1–38.
DOI: arXiv:1506.00019 [cs.LG]

17. SHI, Shen Dinggang, Wu Gurrong. Deep learning in medical image analysis. Annu. Rev. Biomed. Eng. 2017;19:221–248.
DOI: 10.1146/annurev-bioeng-071516

18. Kingma DP, Ba JL. Adam: A method for stochastic optimization. 3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc. 2015;1–15.

19. You Y, Hseu J, Ying C, Demmel J, Keutzer K, Hsieh CJ. Large-batch training for LSTM and beyond. Int. Conf. High Perform. Comput. Networking, Storage Anal. SC. 2019;1–15.
DOI: 10.1145/3295500.3356137

20. Michael Corley. Unemployment and mental illness survey, Exploring the causation of high unemployment among the mentally ill. 2019;2.
Available:https://www.kaggle.com/michael acorley/unemployment-and-mental-illness-survey

21. Murtagh F. Multilayer perceptrons for classification and regression. Neurocomputing. 1991;2(5–6):183–197.