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A crucial Psychological Analysis of Mental Anxieties of Job-seekers and Working Classes in Society

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Abstract

Corona Virus Infectious Disease (COVID-19) appeared on Earth in December, 2019. This life-threatening disease is taking away numerous human lives at an exponential rate throughout the world. The World Health Organization (WHO) declared a presently appeared (epidemiological) situation due to this infectious disease as Pandemic. This disease not only threatens public health but also socio-economic conditions are also negatively affected by the current scenario. The working environment is devastated by the global virus pandemic situation. In this paper, different classes of peoples such as job-seekers, current employees and their current status are to be considered. It presents concentrations to assess different perspectives of mental conditions of a specific class of peoples. During the pandemic situation, job-seekers feel insecure regarding their placement since campus interviews either online or offline have not occurred due to COVID-19. In addition, currently employed workers are also mentally annoyed about their job-loss due to the financial scenario of the industries are not in a stable condition. In these cases, stress, depression and anxiety are quite evident. To carry out the research for both of these aforementioned cases, 500 students and (specify no. of) employees are surveyed for the period from April 2020 to July, 2020. The collected data are focused on peoples of Kolkata, West Bengal, India. This research work uses Machine Learning (ML) algorithm to assess mental well-being of job-seekers as well as currently placed workers. A hybrid model is presented in this paper that detects mental health status of job-seekers and existing employees. The hybrid model has a mixture of Deep Learning (DL) technique with Convolutional Neural Network. It is a predictive model consisting of two major components such as, CNN and Long-Short term memory (LSTM). LSTM is a variant of Recurrent Neural Network (RNN). This model is applied on the collected data for finding the status of mental anxieties of both classes. Experimental results imply that mental well-beings of job-seekers and presently working employees are predicted with an accuracy of 93.22% and 89.69% respectively. It concludes that the working peoples are more affected than those who may be a working class in near future.

Keywords: Mental Anxiety, Deep Learning, CNN, LSTM, Job-Seekers, Employees.

Introduction

The new Infectious diseases remain one of the leading causes of death worldwide in the present situation. Public health outbreaks are becoming even more complex and challenging to tackle the situation. This is likely driven by multiple concurrent changes in ecosystems, globalization and urbanization, and changes in behaviours of peoples in the society. The WHO announced on January 30 in a Public Health Emergency of International Concern (PHEIC) for the 2019-nCoV outbreak [1]. Later, the human-to-human contact was confirmed as transmission mode of this outbreak. It is a

new virus and scientists are yet to find any vaccine for the virus. Since both the SARS coronavirus and the 2019 novel coronavirus share structural similarity and bind to the same receptor, the researchers tested three monoclonal antibodies specific to SARS virus for their ability to bind to the novel coronavirus. But none of the three antibodies prevent or treat the disease. Coronaviruses are a large family of zoonotic viruses that cause illness ranging from the common cold to severe respiratory diseases. Zoonotic means these viruses are able to be transmitted from animals to humans [2]. Common signs of COVID-19 infection are similar to the common cold and include respiratory symptoms such as dry cough, fever, shortness of breath, and breathing difficulties. Infection can also cause pneumonia, severe acute respiratory syndrome, kidney failure, and death. According to current data, time from exposure to onset of symptoms is usually between two and 14 days, with an average of five days. In some cases confusion arises due to the short period of exposure of symptoms. The fatality rate may be much lower as those with mild symptoms are most likely undiagnosed [3]. To avoid this fatality rate, the Government has imposed lockdown stages either in whole or part of the city. This affects on the current social-economic status of peoples and it in turn weakens the mental health of people as well.

The loss of jobs of People between the ages of 20 and 44 were most impacted by the coronavirus (COVID-19) lockdown in India during April 2020. So it is proved that the most challenging for young Indians aspiring to be a part of the job market during these periods. About 27 million young people have lost their jobs in April alone [4].

The age group between 20 and 44 covers job-seekers and currently placed employees. The final year undergraduate students(Engineering or general streams) are major job-seekers to be placed in companies. Recruitment of these job-seekers proceeds either through on-campus or off-campus placement. On-campus the employers come to the colleges and universities for recruiting their students for their companies. On the other hand, students are to go to companies for the possibilities of off-campus recruitments. The students always aspire to be placed in good companies. The selection of the students in a company is always based on their merits. It is also a measure of students in a particular course. Companies always seek the best talent for their organizations where they visit institutes for on-campus placement. However, in both campus placements, students need to prepare themselves to their level best learning so that they can get the dream job. Normally many colleges as well as universities take extra classes particular for the campus interview. Students have to spend some time and their brains work during these periods. Since the selection of getting a job is a possibility so students have been facing depression as well as anxiety whether they will be selected or not. In the present situation the companies are reluctant to visit the campuses due to the declaration by the Government for closure of colleges and universities for COVID-19. The fates of the passing out students presently are at stake. This obviously leads the students towards mental anxiety because there is no recruitment by companies. This anxiety is much during COVID-19 but is also true that anxieties on job seekers are there before COVID-19. This situation is also true for the final year students in colleges and universities. COVID-19 delayed the academic calendar and colleges/universities postponed the examinations. Online classes for other students have been going on and their anxieties depend on other causes which are not to be considered in the paper. Since mental anxiety creates health problems for students so it is required to analyse the level of anxieties on them. In another case, some students have been selected to be appointed before this COVID-19 situation but most of them are still waiting for their exact joining date. They actually are feeling anxious whether their appointment letters will be valid after the situation gets better or not.

Considering all the possible consequences may lead to a mental instability situation for the new comers in the industries.

Due to the imposed lockdown restrictions, IT employees are asked to work at home for the completion of the clients' work. Since there are no other options but employees are bound to do work at home. The main focus is also here to discuss the problems of mental health of employees who have been working at home till date and some remedial measure for them to remove mental anxiety that may cause certain serious diseases in future. It is important to take care of the mental health of employees during the lockdown period due to COVID-19 whether they are working at home or working at workplaces. Presently most employees of IT organizations have been doing their work from home. Employers of IT companies are giving more works of clients on a regular basis assuming these employees do not get free time in their daily routine. At the same time professional dedication of employees is required since there is a fear in mind that they can lose their job if they did not complete the work on time. So it creates mental anxiety among employees and at the same time the mental health of employees may be deteriorated. The anxiety caused by stress in the workplace as well as in home may have poor outcomes by the employee for the organizations. This situation needs attention by the organization to improve the working conditions in home to increase the throughput of work of employees. Normally, human beings take depression lightly than physical illness. If an employee takes leave for mental illness then it may create negative consequences for other co-workers. The organization will not accept it if durations of leave of employees are more. The work in front of computers continuously for a long time by an employee from home is creating stress on their eyes and sometimes it may cause bad posture, arthritis in fingers and many more types of different diseases. Computer stress can be caused by sitting in one position for a prolonged period of time. Mental anxiety of employees may have intense, excessive and persistent worry and fear since everyday problems are also to be solved by them. If it continues for days or months then fear may reach panic attacks in due time. In the present scenario IT professionals are working from home and have been isolated from co-workers for the first time. The daily routines are disrupted and it causes anxiety, stress and strain—physically, mentally, and financially due fear of losing job. Anxiety creates various mental problems such as sleepless nights, back pain, sweating, breathing problems, etc. For example, sleepless nights may be due to the tasks assigned for tomorrow and completion of these tasks the next day. In the long run anxiety may cause insomnia, high blood pressure and cardiovascular disease. It is true that some of the diseases may occur if there is no COVID-19. In the current situation the Company may force you to resign from the current position without any indication since you are working from home. If you are working at a workplace then you can have an indication in the recent past that the Company is not happy with your work. Since you are working from home then a letter from the Company is sufficient to remove you from the job. This stress is continuing in mind in the present situation. All Governments and some private offices have been opened during COVID-19 except the days of lockdown. In these offices, rotations of presence of employees are set as a constraint due to the present scenario. In the office where financial transactions such as salary, pension, etc. are prepared there is need for the presence of employees. All offices follow proper prevention processes due to COVID-19 but still most of the employees have taken bottles of sanitization for their own safety. Further most the employees use public transports for coming to the office. Each employee feels insecure of being infected by a virus from others. The reason is that they do not believe that each transport is sanitized thoroughly every day. It creates anxiety amongst them which reflects on their work due to loss of concentration. Also

there may be possibility of his/her colloquies affected by corona although there is a strict vigilance on every employee to pass the corona test. Employees use masks and gloves and some use other kits for their safety before starting their journey to the office. After returning back from the office, all employees have to sanitize themselves again along with their dresses and belongings with them. So there is a financial burden on them to make available sufficient dresses as well as a number of sanitizing bottles. Thus extra cost of sanitizers, gloves, masks creates financial burden on them for every month. This will lead to one type of anxiety amongst them. Consider another situation when an employee works at home to solve a serious problem using a computer. Suddenly power-cut takes place, the internet gets disconnected and no power backup infrastructure is not available to run the internet. This normally happens now since many companies are now forced to ask their employees to work from home due to this pandemic situation. The above problem creates a tremendous anxiety to the employee since he/she does not know how the assigned work by the organization will be completed on time. These effects will also reflect on his/her mental health. It requires a proper study of mental anxiety in recent scenarios normally observed in the under-development countries. Symptoms of anxiety and depression (16–28%) and self-reported stress (8%) are common psychological reactions to the COVID-19 pandemic and may be supplementary with distressed sleep. Around 300 million people of all ages suffer from depression worldwide and the disease is expected to become the leading cause of worldwide disability by 2030 [5]. Considering the above mentioned scenarios, it motivates this research to be carried out so that proper care and attention can be provided. In this context, an automated computer aided system may help in analysing the mental health status of job-seekers and currently working employees during the lockdown period.

This paper focuses on considering negative consequences among job-seekers as well as recruited employees raised during the lockdown crisis. This situation will also put an adverse effect on the employer since they do not have the opportunities to recruit good students from colleges/Universities. We will not consider this part in the paper. A Deep Learning (DL) [6] based strategy is employed in this study that detects mental distress observed amongst the future of the country as well as current employees. Mental unstable conditions can affect the work being produced by the employees. It may also cause distress for organizations, customers as well as the country from the financial point of view. This necessity motivates to present an automated tool that will analyze reasons for being mental affected under the ongoing crisis period. This automated tool will identify employees having mental unsteady conditions. This research proposes a hybrid DL model for designing the automated system. This model stacks convolutional layers of CNN [7] and LSTM-RNN [8] under a single platform with necessary fine-tuning of hyper-parameters.

Measuring mental health disorders is quite an attention-grabbing field and many researches have been carried out in this field. In this study, use of DL techniques is exemplified while investigating mental health anxiety prediction. To the best of our knowledge, establishing the relationship between the effects on employee mental health status with the current situation due to COVID-19 is not available yet. Hence, this research can be a promising step towards the current scenario and it will help to overcome the result of general deterioration of overall working efficiency.

The outline of this research can be concisely presented as follows-

1. Study the effects of the ongoing lockdown crisis on mental health of job-seekers and employees.

2. The study is based on the collected data from people who are residing in West Bengal, India. The study covers the age group from 20 to 44. Basically, two target populations are assessed in this study. One group covers the new-comers or job-seekers who are potentially future assets of an organization as well as for the country. The presently working employees for an organization are considered to be another target population. These employees may be government or private sector workers.

3. Data are analyzed using DL technique for deriving mental health status among employees and job-seekers. Finally, the learning outcome obtained by this technique is utilized for mental anxiety prediction among the considered target populations.

4. The DL technique is exemplified by building a hybrid model based on the variant of RNN and CNN components. Convolutional layer of CNN and LSTM-RNN is assembled for designing the predictive model. If early prediction of mental health status can be obtained by this model, then necessary steps may be taken to reduce the anxiety.

Related Works

Assessing the severity of mental stress and its causes is often a challenging task to be carried out. Mental stress, anxiety grows rapidly in recent environments both in place of work as well in other places also. Several researches were made to automate the process of assessing mental health status. Smets et al. [9] perceived mental illness as a binary classification problem with classes corresponding to rest and stress periods. Six machine learning techniques were used for achieving the classification. It is also reported that Bayesian networks and SVM provided reasonable accuracy with 84.6 % and 82.7% respectively. Karthikeyan et al. in [10] studied electrocardiography (ECG) and heart rate variability (HRV) signals for stress assessment. An accuracy of 79.2% was achieved for classifying stressful and not stressful events based on HRV features.

Strauss et al. in [11] explored the application of machine learning algorithms like cluster analysis, K-nearest neighbours (KNN), decision trees and support vector machines (SVM) for clinical forms analysis of mental health. Their study concluded that SVM had the best performance with a precision of 64.6%. Kessler et. al. in [12] analysed survey inputs by applying machine learning models. They predicted major depressive disorder (MDD) keeping its persistence with good accuracy.

Human mental stress is measured using multimodal bio-sensors based dataset and results are classified using SVM and fuzzy logic in [12]. Considering related health parameters, decision-tree model and random forest algorithm classifies mental stress level. A predictive model is finally proposed in [12] that decides wellness of users by using Expectation Maximization (EM).

For predicting the likelihood of developing psychological conditions such as anxiety, behavioural disorders, depression and post-traumatic stress disorders, neural network based technique has been exemplified with an average accuracy of 82.35% [14]. A combined approach involving depth first search and backward search strategy was implemented to diagnose depression and dementia due to depression. An expert system was developed in [15] by incorporating factors such as a patient's behavioural, cognitive, emotional symptoms and results of neuropsychological assessments. Screening of mental anxiety and depression among seafarers is

detected using ML algorithms such as CatBoost, Logistic Regression, Naïve Bayes, Random Forest, and Support Vector Machine. Comparative study confirmed an accuracy of 82.6% as shown the best possible result exhibited by CatBoost [16].

The literature review has been conducted on numerous existing research works for assessing different mental health status on different target populations with the help of machine learning based methods. In our study, the effect of COVID-19 lockdown process has been taken into consideration for mental health disorder analysis. The impact of on-going crisis on job-seeker and employee mental health is measured using DL framework. Hence, the target population for this research is job-seekers and current employees for the age groups between 20 and 45. Early diagnosis of this disorder can help in providing an improved quality of lives, especially under the current scenario.

Backgrounds

The following sub-paragraphs describe learning systems which are used for implementing the proposed method.

3.1 Neural Network and Deep Learning

ML is the super field of DL and the sub field of Artificial Intelligence (AI). ML automates and develops the machines and simulates the actual goal of AI. DL provides a multi-layered hierarchical data representation typically in the form of a neural network when the concept of multi-layer has been incorporated in the model. Since it is self-adaptive in nature so it is not required to perform the manual feature engineering task. It is used to solve complex problems. Like neurons in the human brain, a large number of processing elements (nodes) are present in the neural network for acquiring best problem solving techniques [6][17].

3.2. Recurrent Neural Network and LSTM

Multiple neural networks are incorporated in RNN which is used for analysing sequential data. Here the output of the previous step is fed into the input of the current step. The output obtained in step S_i affects the parameters of step S_{i+1} . So RNN accepts two types of input- one is present input and other one is previous output for acquiring the final output. The signals are travelled both forward and backward if loops present in RNN. It suffers from the vanishing gradient problem [18].

LSTM neural network is a kind of RNN that implements context based prediction which is not considered in traditional RNN. In other words, LSTM is capable of eliminating the problem of vanishing gradients by training RNN. LSTM has a good potential to regulate gradient flow as well as better preservation of long-range dependencies. Every cell in LSTM is composed of gates and it determines when the input gate is to be remembered, forget and output the value. Depending on the performance, there are variants in gates such as input gate, output gate and forget gate. The input gate blocks a value from entering into the next layer when a value close to zero is generated by this gate. This input gate simply eliminates the value from the net input. Forget gate remembers value until greater value than zero is generated by forget gate[18-19].

For an input sequence $x_t = (x_1, \dots, x_T)$, the output sequence is $y_t = (y_1, \dots, y_T)$. These can be obtained using the following equation 1 to equation 6. Weight matrices are W and the bias vector is denoted by b . In the following equations, σ states the sigmoid function, and i, f, o, c are the input gate, forget gate, output gate, and cell activation vectors, respectively. In W_{ix} , weight's matrix, from the input gate where W_{ic} , W_{fc} and W_{oc} denote diagonal weight matrices for peephole connections. $\odot$ and $\emptyset$ indicate element-wise multiplication and softmax activation function for the LSTM [19].

$$i_t = \sigma [(W_{ix} \times x_t) + (W_{ir} \times r_{t-1}) + (W_{ic} \times c_{t-1}) + b_i] \quad (1)$$

$$f_t = \sigma [(W_{fx} \times x_t) + (W_{fr} \times r_{t-1}) + (W_{fc} \times c_{t-1}) + b_f] \quad (2)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh [(W_{cx} \times x_t) + (W_{cr} \times r_{t-1}) + b_c] \quad (3)$$

$$o_t = \sigma [(W_{ox} \times x_t) + (W_{or} \times r_{t-1}) + (W_{oc} \times c_t) + b_o] \quad (4)$$

$$r_t = o_t \odot \tanh (c_t) \quad (5)$$

$$y_t = \emptyset(W_{yr} \times r_t + b_y) \quad (6)$$

3.3. Convolutional Layer

Convolutional Neural Networks (CNNs) are also an improvement over traditional neural networks. CNN can extract underlying hierarchical features by discovering the local relationship between nodes. Convolution operation is exhibited by each neighbour node in order to capture inherent relationships in adjacent nodes. Convolutional Layers are one of the components of CNN. The calculation of the scalar product between their weights and the region connected to the input volume will produce the output of neurons that are connected to local regions of the input. The layers parameters focus around the use of learnable kernels [20]. In other words, an input data and a convolution kernel are subjected to particular mathematical operation to generate a transformed feature map. The kernel filters create feature maps for information of a certain kind in Convolution and so it is referred to as a filter. The convolutional layer performs an operation called a "convolution". It is a linear operation that involves the multiplication of a set of weights with the input. An array of input data and a two-dimensional array of weights, called a filter or a kernel, are multiplied for obtaining results. ReLu activation function is popularly used in the Convolutional layer and is proficient in most situations. Application of non-linearity applied after convolution assists in successful simulation [21].

3.4. Hyper-parameters used in neural network training

Some pre-stage fine-tuning of hyper-parameters is necessary to perform before training this neural network. It contains a number of layers, number of nodes, learning rate, epoch size, batch size and drop-out rate. Adjusting hyper-parameters before providing the training the neural network model assists in obtaining the maximized performance. Hyper-parameters that need to be taken into consideration include number of layers, number of nodes for each layer, learning rate, epoch size, batch size and drop-out rate.

These values should be adjusted to help the network to learn successfully. Activation function is one of the necessary tasks which can maximize the training procedure. These functions allow neural networks to learn non-linear relationships among data and to produce meaningful output signals. Sigmoid activation function may be used for activating output nodes for predicting binary class probabilities. This activation function accepts the input data and transforms it in the range of 0 to 1 and it is shown in equation (4) [21]. Tangent hyperbolic (tanh) is also non-linear activation function and it is a smoother and zero-centered function [21]. The function ranges in between -1 to 1 and the output of the Tanh function is given in equation (5).

$$f(x) = 1/(1 + \exp^{-x}) \quad (4)$$

$$f(x) = (e^x - e^{-x}) / (e^x + e^{-x}) \quad (5)$$

Hyper-parameters such as epoch and batch size are also used in neural network training. These hyper-parameters receive integer values which need to be chosen wisely to make best use of the model's performance. The size of the epoch is defined to be the number of passes to complete through training dataset. The dataset is passed forward and backward through the neural network exactly one time within each epoch. During passing the entire dataset into the algorithm, it must be partitioned into fixed size of batches. The size of the batch keeps track of the number of processed instances before the model updates its internal parameters. It needs to be ensured that batch size should not be too small or too large. If the size of the batch is too small then it will present high variance. It means that it does not represent well the entire dataset. On the other hand, large batch size may not fit in memory to compute samples used for training and may lead to overfitting problem [21]. Over fitting is a problem that appears when the model understands the details as well as noise present in the data during the training process to the extent that impacts negatively for new unknown patterns of data. In other words, over-fitting exhibits higher accuracy for the training data and minimised accuracy for testing data. In order to eliminate such problems, use of drop-out technique is demonstrated. This technique ensures the deactivation of nodes along with their incoming and outgoing connections present in the neural network. Incorporation of this technique into neural network based architecture often ensures the acquaintance of benchmark result as in supervised classification task [22].

The use of optimizer is compulsory for integrating multiple neural layers under a single framework. Adam is computationally efficient with optimised memory requirements and also easy to implement. This method can be applied to optimize for first-order gradient-based optimization of stochastic

objective functions, based on adaptive estimates of lower-order moments. It is quite well accepted due to its applicability on non-stationary objectives and problems with very noisy and/or sparse gradients [23].

3.4 Model Evaluation

In order to discriminate the performance of a model from others, it is necessary to employ some evaluating metrics. Use of these metrics will help in justifying the model's performance. For assessing the performance of any deep model, accuracy and loss are required to be calculated. During training, accuracy and loss for each epoch are measured for justifying efficiency of the learning process. A loss function (or cost function) [24] measures mistakes committed by the model for each instance in the training set. In other words, the loss function acquires the probabilities of how much predicted values get differed from original values. For binary classification problems, Cross-entropy function can be used as a loss function. This function measures the performance of a classification model whose output is a probability value between 0 and 1 [25].

Using true positive (TP), true negative (TN), false positive (FP), false negative (FN), accuracy and f1-score metrics can be evaluated as equation (6) and (9) respectively. It is to be noted that, f1-score is a metric that relies on calculation of recall and precision which are formulated as equation (7) and (8) respectively [26].

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+TP} \quad (6)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (7)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (8)$$

$$\text{F1- Measure or F1-Score} = \frac{2 * \text{Recall} * \text{Precision}}{(\text{Recall} + \text{Precision})} \quad (9)$$

Mean Squared Error (MSE) [26] is another evaluating metric that measures absolute differences between the prediction and actual observation of the test samples. MSE produces non-negative floating point values and a value close to 0.0 turns out to be the best one. It is formulated as equation (10).

$$\text{MSE} = \left(\sum_{i=1}^N (X_i - X_i')^2 / N \right); \text{ where } X_i \text{ is the actual value and } X_i' \text{ is the predicted value} \quad (10)$$

Dataset Used

A survey was conducted covering the time period of April to July, 2020 for the area of Kolkata, West Bengal, India. For this data collection purpose, six groups each of having 5 people were appointed. Total 169, 257, 220, 112 job-seeker details are collected during the month of April, May, June, and July respectively. For employees, total 280, 192, 120, 181 respondent details are collected for the span from April to July respectively. Table 1 to Table 4 shows distribution of data collection over the four months from April 2020 to July 2020. The graphical representations are shown in Figure 1 to

figure 4. Both of the above are for job seekers. Similarly Table 5 to Table 8 show for the anxiety scenario of employees and graphical representations are shown from figure 5 to figure 8.

Day	5	10	15	20	
City	12	12	20	5	
Rural	23	15	11	10	
Urban	30	5	10	16	
Day wise Total	65	32	41	31	169

Table1. Day-wise data collection for Job-Seekers during April, 2020

Day	5	10	15	20	
City	25	21	17	22	
Rural	12	11	10	17	
Urban	30	35	16	36	
Day Wise Total	72	67	43	75	257

Table2. Day-wise data collection for Job-Seekers during May, 2020

Day	5	10	15	20	
City	12	13	43	13	
Rural	10	11	19	20	
Urban	13	17	25	24	
Day Wise Total	35	41	87	57	220

Table3. Day-wise data collection for Job-Seekers during June, 2020

Day	5	10	15	20	
City	12	10	5	14	
Rural	11	6	7	10	
Urban	11	6	6	16	
Day Wise Total	34	22	16	40	112

Table4. Day-wise data collection for Job-Seekers during July, 2020

Figure 1 Pie chart for job seeker in April 2020

Figure 2 Pie chart for the month of May 2020

Figure 3 Pie chart for June 2020

Figure 4 Pie Chart for the month of July 2020

Day	5	10	15	20	
City	25	10	19	20	
Rural	10	10	24	15	
Urban	12	87	33	15	
Day Wise Total	47	107	76	50	280

Table5. Day-wise data collection for Employees during April, 2020

Day	5	10	15	20	
City	23	15	13	20	
Rural	12	10	34	12	
Urban	14	14	15	10	
Day Wise Total	49	39	62	42	192

Table6. Day-wise data collection for Employees during May, 2020

Day	5	10	15	20	
City	16	17	7	8	
Rural	11	16	4	3	
Urban	12	17	4	5	
Day Wise Total	39	50	15	16	120

Table7. Day-wise data collection for Employees during June, 2020

Day	5	10	15	20	
City	16	18	34	16	
Rural	11	13	24	28	
Urban	8	10	29	13	
Day Wise Total	35	41	87	57	181

Table8. Day-wise data collection for Employees during July, 2020

Figure 5 Pie chart for Employee in April 2020

Figure 6 Pie chart for the month of May 2020

Figure 7 Pie chart of June 2020 of Employees

Figure 8 Pie chart for July 2020

During the data collection phase, employees and job-seekers are provided with questionnaires. The information asked in this questionnaire is summarized in this section. Table 9 and 10 provides description of collected details of job-seekers and employees respectively. The information asked to the participants is given along with the possible values provided to the attributes.

Attribute	Description	Values Present
Placement	Whether placed in Off-campus or on-campus placement	Yes, No
Age	Age of the respondent	20-24
Gender	Gender of the respondent	Male, female, Others, Prefer not to say
Apt_letter	Received any appointment	Yes, No

	letter?	
Joining Date	Company declared joining date after lockdown?	Yes, No
Recruitment place	Whether placed in home town or not?	Yes, No
Marks scored in UG	Percentage of marks secured in under graduate	40-95%
PG marks score	Percentage of marks secured in post graduate	40-93%
Sleep Habit	Sleep habit of the individual	Moderate, Over-sleep, Under-sleep.
Loneliness	Loneliness of the respondent	Yes, No
Income	Family income	20,000-10,00,000
Obsessive Thinking	Whether the individual carries obsessed thinking or not	Yes, No, NaN
Stress	Whether the individual suffers from stress or not	Yes, No
Mental anxiety	Mental Anxiety faced by job-seeker or not	Yes, No

Table 9: Student Job-seeker Mental Anxiety Dataset Summary

Attribute Name	Attribute description	Values Present
Service Period	Service Period of the respondent (in years)	<1 year, 2-5 years, 5-10 years, 10-15 years, >15 years
Age	Age of the respondent (in years)	24 to 44
Works at	Government or private organization	'Government', 'Private', 'government aided'
Co-workers	Relationship with co-workers	'good', 'bad', 'moderate', 'extended family'
Supervisor	Relationship with supervisor	'good', 'negative', 'moderate', 'extended family'
Over-time	Measure of over-time (in hours)	1-5, 5-10
Pay	Paid for over-time or not	Yes, No, Sometimes
Other source of income	Is there any other resource of income or not	Yes, No
Computer_Time	Time spends on computer	1-5, 5-10,>10
Leave	Leave grant during current situation or not	Yes, No, Sometimes
Family	Any ongoing serious issue for family of the respondent	Yes, No
Work place	Type of working paradigm assigned	Work from home, work from office
Extra personnel cost	Whether extra expenditure has been increased during lockdown or not	Yes, No, nan
Mental anxiety	Mental Anxiety faced by the employee or not	Yes, No

Table 10: Employee Mental Anxiety Dataset Summary

The collected datasets consist of an attribute ‘Mental anxiety’ which is to be predicted in both the cases. Both the datasets go through some pre-processing techniques for obtaining cleaned dataset. Existing string values in these dataset are encoded into numeric codes to be understandable by any ML classifier model. Presence of NaN values are also checked and replaced by mean value of the corresponding attribute. After performing these steps, training dataset and testing dataset is obtained by partitioning the transformed dataset with the ratio of 7:3. The training and testing dataset is distinguished by the presence of target attribute ‘Mental anxiety’. Classifier model proposed in this paper receives training data for understanding the essential relationships among the attributes. The knowledge acquired by the classifier model is evaluated using the testing dataset while obtaining prediction for mental health anxiety.

Methodology

Classification procedures employed in this framework have been applied on the collected dataset in order to obtain mental health status among current as well as future employees in advance. Especially the present crisis condition is taken into consideration for the analysis procedure. The proposed methodology uses a deep neural network as classification strategy. The target of this research is to design a recommender system that will accept attributes present in the dataset and utilise the underlying relationship among those features in order to fulfil the objective of this study. The recommender system is implemented by designing a hybrid neural network model that assembles Convolutional and RNN layers under a single platform. While designing this model it is necessary to fine-tune hyper-parameters so that maximised performance can be attained. This section describes the specification of the model along with its hyper-parameters.

The deep model comprises two 1-dimensional Convolutional layers with filter sizes of 128 and 64 respectively. Each of these layers is adjusted with kernel size of 1. Next, two LSTM layers are stacked into this model with 32 and 16 nodes respectively. All these four layers receive dropout layers having dropout rate of 0.2. Finally, four fully-connected dense layers are amalgamated into the deep model with 8,4,2,1 numbers of nodes respectively. Note that all these layers receive node size divided by 2 than that of its previous layer. Finally these aforementioned layers are compiled using adam solver by means of 30 epochs and with a batch size of 64. Layers in this model are activated by sigmoid, relu or tanh functions. All these aforementioned adjustments of these hyper-parameters are mandatory since it assists in achieving the best predictive result. Components of the model in terms of layers, number of nodes, activation function received in each layer are defined in Table 11. The employed hyper-parameters while designing the proposed deep model are summarised in Table 12. The experiment has been carried out in Windows 10 Home with Intel Core i5-9300H (9th Gen), 8GB memory, and an NVIDIA GeForce GTX 1650 GPU.

Layer Type	Number of Nodes/ filter size/ Rate	Activation function Used
conv1d_1 (Conv1D)	128	ReLu
dropout_1 (Dropout)	Dropout Rate-20%	None
conv1d_2 (Conv1D)	64	ReLu

dropout_2 (Dropout)	Dropout Rate-20%	None
lstm_1 (GRU)	32	ReLu
dropout_3 (Dropout)	Dropout Rate-20%	None
lstm_2 (GRU)	16	ReLu
dropout_4 (Dropout)	Dropout Rate-20%	tanh
dense_1 (Dense)	8	Tanh
dense_2 (Dense)	4	Tanh
dense_3 (Dense)	2	Tanh
dense_4 (Dense)	1	Sigmoid

Table 11: Summary of the Stacked Convolutional-LSTM model

Number of Epochs	100
Batch Size	64
Loss function	Binary Cross-entropy
Optimizer Used	Adam

Table 12: Specification of Hyper-Parameters Used

Experimental Results

During training, while fitting the training data into the stacked Convolutional-LSTM classifier, the training process is evaluated in terms of accuracy as well as loss. For each epoch, data loss and accuracy is calculated. The best performing model will show accuracy to be increased as the number of epochs is increased. Similarly, the best model will show loss to be decreased when the number of epochs is increased. The model is trained for two different problem areas addressed in this paper. Mental anxiety for job-seekers and currently employed workers are considered in this study. Accuracy and loss obtained for each epoch during the training process for the job-seeker mental status problem is shown in Figure 9. Similarly, the same model is trained for the other addressed problem, i.e., present working employees' mental health condition analysis. The training evaluation procedure is shown in figure 10. In both the cases, testing dataset is used for acquiring predictions once the training process takes place. The prediction result exhibited by both these models is evaluated in terms of accuracy, f1-score and cohen-kappa score and MSE. The evaluated results are shown in table 13 and 14. The proposed stacked convolutional-LSTM model can predict mental anxiety of job-seekers and current employees with an accuracy of 93.29% and 88.89% respectively.

Figure 9 Training process evaluation for job-seeker mental health problem

Figure 10 Training process evaluation for employee mental anxiety problem

Stacked Convolutional- LSTM Model	Accuracy	Cohen-kappa Score	F1-Score	MSE
	93.29%	0.88	0.93	0.07

Table 13: Job-seeker Mental Anxiety Prediction Performance

Stacked Convolutional-LSTM Model	Accuracy	Cohen-Kappa Score	F1-Score	MSE
	88.89%	0.81	0.88	0.08

Table 14: Employee Mental Anxiety Prediction Performance

Conclusions

The interaction between mental illness observed in professional life and current lockdown situation is complex to be studied. In this current era of globalization, greater attention needs to be provided to address the imbalanced mental health of employees. This study has contributed to reduce the high risk of impairment happening among job-seekers and current workers. Comfort of these populations is majorly affected by the present lockdown scenario. An extensive data collection has been carried out on people residing in West Bengal, India. The age group from 20 to 44 is majorly concentrated in this context. Collection of these data is further examined using DL framework that

hybrid convolutional layer and LSTM layers under a single entity. A computer aided classification can help to predict the mental health status of a group of employees which in turn can save the persons from any unwanted situation. This will even reduce the chance of work errors, workplace accidents, poor decision making committed by the employees and extend the productivity of an organization with uninterrupted workflow. This predictive model automatically finds the underlying relationships among the collected features and makes an informed decision about whether a person has mental health anxiety or not under the current job environment scenario. Prediction of their mental status at an advanced stage may support psychiatrists from diagnosis and treatment perspective. However, this study can even be prolonged by considering the mental health disorders among retired employees which provides insight of the future direction of this research. The proposed method aims at an innovative idea of predicting mental anxieties for two essential classes of peoples in the society.

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