Research Article

Demographic Factors Based On Predicting Mental Health Of Caronavirus Victims

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ABSTRACT

The epidemic has been causing chaos in society, rendering it in ruins. In March 2020, WHO predicted it takes a significant toll on people and leads to much distortion in their lifestyle. Mental health has gone for a toss and overlooked. People in India do not have the privilege to expect support and deal with their mental health. To address this gap, we have attempted to use unconventional approaches like booming technologies. The proposed model is validated against other baseline techniques, including logistic regression, decision trees, random forest, bagging, boosting, and stacking ensemble learning. The proposed method outperforms other baseline techniques for attaining better accuracy. They are particularly suited to predicting psychological problems after recovering from the pandemic. For implementation purposes, choose features like age, gender, family history, seek_help, mental_health_consequence, phys_health_consequence, and a few other features. The proposed model is evaluated with the pandemic patients recovering dataset based on various performance matrices to calculate its effectiveness.

INTRODUCTION

The widespread outbreak of SARS-CoV-2 continues to challenge diagnosis and therapeutic methods. Temperature, congestion, breathlessness, joint stiffness, lightheadedness, gastrointestinal, and nasal congestion, loss of smell, and deliciousness are the usual significant signs of pandemic disease [1]. Additionally, there are still many psychological problems in surviving the SARS-CoV-2 pathogen. Major depressive disorder (MDD), post-traumatic stress disorder (PSTD), anxiety, OCD (obsessive-compulsive disorder), and drowsiness are the commonly recognized psychological problems [2]. After recovery, most PANDEMIC patients show neurological problems with perceptual processing, attentiveness, and focus. This seems to be a considerable problem in MDD. These can emerge even after minor contamination [3].

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Learning as much about the underlying reasons for the pandemic gives us a better understanding of the fundamental psychological illnesses. This information may also assist clinicians in improving patient care, and politicians emphasize non-pharmaceutical initiatives. Such demographic features will also be relevant in the formulation and assessment of targeted therapies on the quality of patient care [4].

Perceived discomfort is described as an uncomfortable feeling marked by indications of sadness, and it is recognized as a widespread psychiatric disorder in the nation [5]. As social development and associated difficulties are not widely acknowledged in the public sphere, and with the worldwide pandemic, these silent and persistent disorders may go unrecognized. Isolation to different locations, restriction of autonomy, anxiety, panic of limitation, financial losses, adaptability to the usual way of life, and developing uncertainty are the few identified common emotions during confinement [6]. The PANDEMIC epidemic has added extra pressure on the general public's emotional stability, making them more prone to psychiatric diseases. Based on the most recent investigations, significant discomfort and obstacles faced by PANDEMIC have contributed to the deterioration of cognitive well-being [7], an upsurge in aggressive inclinations [8], and amplification of also before the psychiatric illnesses [9], to mention a multitude. These lead to a significant impact on patient associations and societal factors [10], as well as a rise in incidents of gender-based consequences [11] and substance misuse [12].

The remaining work is categorized as follows: The second section delves into the related works of post-pandemic psychological disorder. In section 3, the proposed work methodology is elaborated. Section 4 experimental environments and examines the performance of the proposed method. This is followed by section 5 discussion about the theme of the proposed work, section 6 concluded remarks, and finally, section 7 suggests directions for future enhancement.

2. RELATED WORK

Continuous discomfort due to intensifying pre-existing neurological challenges can lead to catastrophic depression. People with these conditions who don't even receive adequate therapy have a significant prevalence of psychiatric illnesses [13]. Persistent pressure can progress to melancholy, and anxiety can lead to inappropriate pain perception and modification, increasing the chance of acute pain development. Significant nervousness or the existence of stress has been seen in over 50 percent of the total of chronic pain patients [14]. According to neurocognitive data analysis, persistent depression, inflammation, or other psychological issues interact with interconnected nervous system regions such as the brainstem, cortex, and artery nucleus [15].

Stress and tension impact anybody in a community to a significant proportion. Researchers recommend that those isolated or quarantined feel considerable nervousness, rage, bewilderment, and tension [16]. Mental illnesses throughout the PANDEMIC disease outbreak have found that infected people exhibit a variety of causes of psychological anguish, including distress, anxiety, tension, changes in mood, nervousness, sleeplessness, behavioral problems, PTSD, and frustration [17,18]. Nonetheless, it isn't easy to foresee the emotional and mental repercussions of PANDEMIC in the current environment. Investigations demonstrate that people's afraid of the Disease's uncertain cause contributes to its transmission. [19].

Several investigations have looked into determinants of psychological health outcomes of the shutdown, with or without a concentration on socio-demographic characteristics. Maternal age, femininity, surviving without a spouse, the

existence of physiological or mental disorders, uneducated, low earnings or joblessness, or work in the healthcare service were commonly found to be related to a significant probability of psychological abnormality [20, 21]. While the relationship between general socio-demographic characteristics and cognitive care issues during the disease outbreak has been adequately investigated in recent days, findings related to specific cognitively taxing stress factors or psychic cognitive therapy and one's effects in instigating symptoms of depression are somewhat inconclusive. Furthermore, adaptive cognitive methods were linked to poor psychological disorders [22, 23]. Another, nevertheless, attempted to find substantial neuroprotective impacts of concern coping and effective stress management methods for distress, nervousness, and stress during the PANDEMIC shutdown, highlighting the use of further research on the topic.

3. METHODOLOGY

The massive growth in COVID instances and its detrimental influence on mental stability constitute an experimental study investigating the frequency and factors of psychological distress. An inquiry of this nature will aid in identifying the minority communities that are in danger. Officials will be able to devise measures with a more consistent methodology. Furthermore, the analysis findings will allow for the promotion of protective and uncertain characteristics. Unpredictable the outbreak's duration and the likelihood of a new disease variant, another phase is chance, which needs individual and societal preparedness.

Following COVID, a diverse variety of psychiatric conditions have been recognized as constituting a vital community healthcare problem:

1. Anxious problems
2. PTSD
3. OCD
4. fears
5. Nervous disorder.

Inference and resolving all such acute emotional processes is critical. If they remain unaddressed, they can lead to various more hazardous long-term psychiatric diseases that endanger their existence. Distress, anxiousness, functional impairment, and high numbers of psychiatric illnesses are linked to interrelated and co-occurring adverse outcomes such as discrimination, stress, and unpleasant lifestyle choices and activities.

Female gender harassment, financial deprivation, poor wealth disparity, inadequate or subservient socio-economic status and rank, and unrelenting duty for services are all significant risk factors for common psychological that adversely affect females. Because of the rising frequency of domestic violence against women and the equally frequent occurrence of PTSD due to such abuse, the female workforce is the most influential group of individuals afflicted by this neurological condition. The psychological consequences of long-term, accumulated emotional trauma have still not been thoroughly studied. [24].

The RF (random forest) tree classifying method is utilized to identify whether or not the therapy is employed. It is a tree-based ensemble learning method. The RF constructs many decision trees, combines them, and has a more efficient and precise forecast. It combines the votes from several decision trees to obtain the total based on the training instance.

BAGGING and BOOTSTRAP are ensemble models that combine bootstrap and aggregation. Provide quantitative word embedding data, numerous bootstrapped comment threads are extracted, which are then used to create a prediction model for each set of observations. The most accurate forecast is then formed by aggregating the data sample classification tree using an averaging procedure.

4. IMPLEMENTATION ANALYSIS

The data set is taken from Kaggle, which is publically available data, and it contains various possible factors were included in the data set: age, gender, family history, seeking help, mental health consequences, Phys health consequences, and socio-economic status. Furthermore, if people seemed to have a pre-existing chronic health condition, knew someone who had been identified with coronavirus, or recognized anyone who died due to PANDEMIC. Personal history of schizophrenia, ethnicity, seeking help, mental health consequences, physical health consequences, and recognizing age that people diagnose variables. We also looked at how gender and family history can correlate with age at mental anguish intensity.

Demographics of a sample data reported experienced a severe psychological problem. In sample data, some reported no difficulty. A few reported some discomfort, some significant reported discomfort, and others reported intense suffering due to exacerbating an underlying psychological illness.

Table 1. Statistical analysis of demographic age, dependents, isolation

	ID	Dem_age	Dem_dependents	Dem_isolation_adults
count	112792	112792	109287	93460
mean	63026.55267	39.046705	0.863067	1.563525
std	37120.21992	14.186779	1.651936	2.79197
min	5	18	0	0
25%	29011.75	27	0	1
50%	65816.5	37	0	1
75%	95342.25	49	2	2
max	125306	110	110	110

Table 2: Statistical analysis of demographics, kids, self, and relatives.

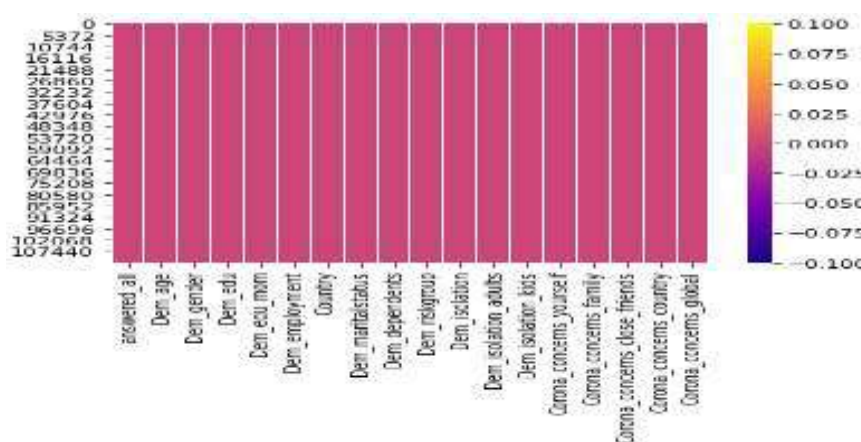|	Dem_isolation_kids	Corona_concerns_yourself	Corona_concerns_family
count	91909	99935	99531
mean	0.489114	4.0622	4.836704
std	1.311498	1.472877	1.20949
min	0	1	1
25%	0	3	4
50%	0	4	5
75%	1	5	6
max	110	6	6

Fig 1: The psychological demographic factors of post covid 19 patients
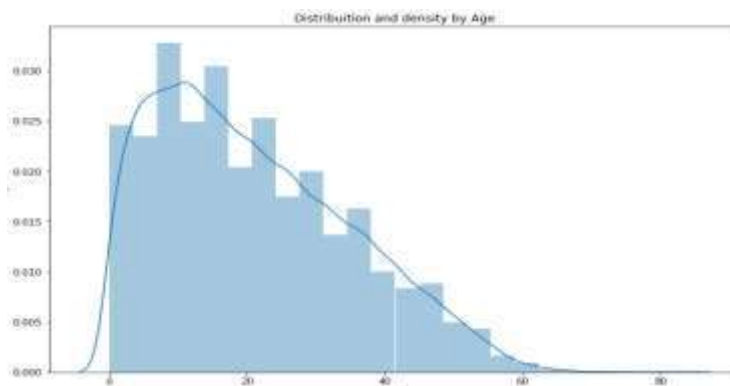
Fig 2: The post-COVID data set is divided based on patient age.

We utilized the AUC (Area Under the Receiver Operating Characteristic Curve) curve to analyze the method. The AUC method is the most commonly used methodology for assessing the prediction model. AUC indicates the quantity of computational complexity in AUC. Once the AUC is significant, the sample has a substantial prediction performance.

4.1 Logistic Regression: A logistic regression model is developed to analyze the effect of various indicators on the probability of generating post-PANDEMIC psychological disorder. The concept entailed functional characteristics such as age, gender, family history, seeking help, mental health consequences, Phys health consequences, and socio-economic status. PANDEMIC identifies factors after recovery, conversion to clinical severity, chronic conditions, and risk of complications.

Confusion matrix:

$$\begin{bmatrix} 13891 & 5525 \\ 6670 & 7752 \end{bmatrix}$$

Classification Accuracy: 64%
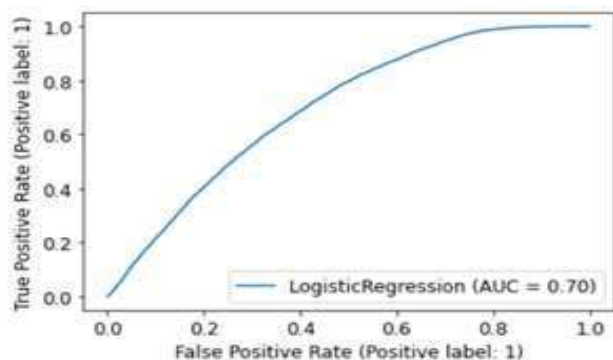
Fig 3: The AUC of logistic regression classification.

4.2 DT (Decision tree) algorithms are among the most popular machine learning algorithms, and building a tree determines which feature is more relevant. It divides a data source into homogeneous subgroups. Training examples with several features and various decision trees with varying depths can be built to train a system since it reflects every characteristic's significance. The decision tree algorithm highlighted the main predictors contributing to a better comprehension of changes in reported perceived stress.

Confusion matrix:

$$\begin{bmatrix} 13502 & 5914 \\ 5907 & 8515 \end{bmatrix}$$
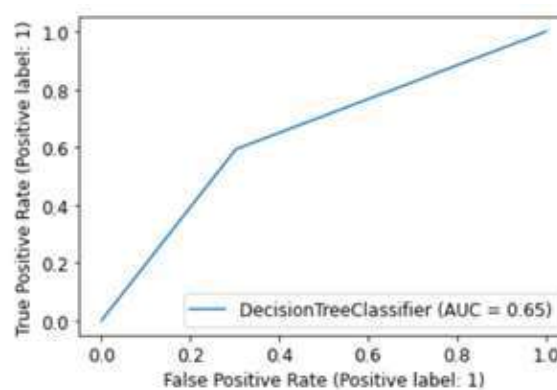
Classification Accuracy: 65%

Fig 4: The AUC of the DT classifier.

4.3 RF (Random forest): It is a training technique that consolidates multiple classification trees and anticipates them by aggregating the forecasting of the decision trees. The tree is constructed with a parent node which has the factor that contributes

substantially by splitting the sample classes. The tree is then divided into several nodes till a consequence is obtained.

Confusion matrix:

$$[[14306 \quad 5110]$$
$$[\ 5586 \quad 8836]]$$

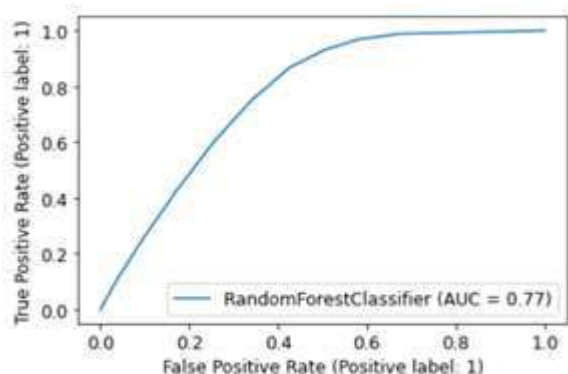Classification Accuracy: 68.3%

Fig 5: The AUC of the RF classifier

4.4. Bagging: Also known as maximum likelihood estimation, is a valuable and straightforward ensemble method [25]. Bagging generates training data with multiple copies of the complete training examples. It uses the probability method to learn various base classification techniques. Bagging reduces variance and is suitable for small datasets.

Confusion matrix:

$$[[14469 \quad 4947]$$
$$[\ 5881 \quad 8541]]$$
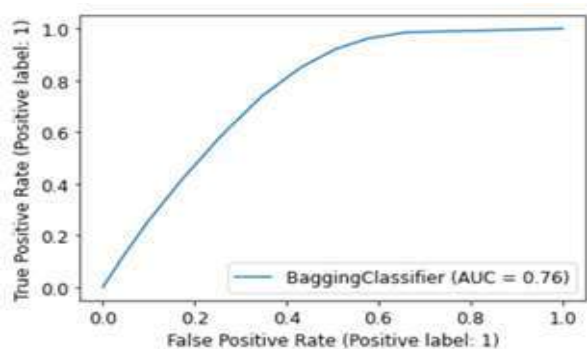
Classification Accuracy: 68%

Fig 6: The AUC of the Bagging classifier

4.5. Boosting: A recursive method integrates multiple ineffective classifiers, resulting in a moderate prediction error. Apart from bagging, in which the feature sets are leveraged duplicates, the

examples incorrectly classified by the preceding prediction model are used to boost the training examples for every prediction model. Boosting helps to reduce partiality in the method of training [26].

Confusion matrix:

$$[[13605 \quad 5811]$$
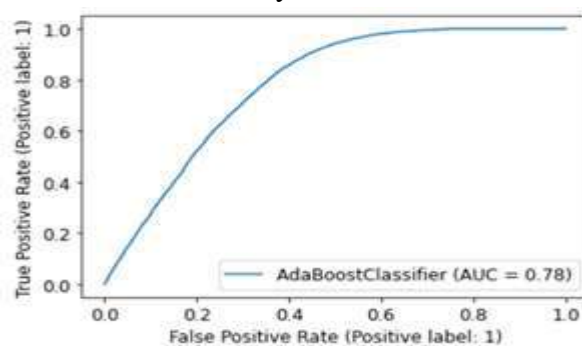$$[\ 4363 \ 10059]]$$

Classification Accuracy: 70%

Fig 7: The AUC of the Ada boosting classifier

4.6. Stacking: It attempts to improve classification precision by incorporating various relatively low learners and then consolidating them into a slightly elevated conceptual learning process [23]. The model enhances the detection performance of psychological disorders after recovery of covid 19 but is complicated to evaluate potentially. It builds a stacking classification system by integrating various independent learning processes forecasting.
[27].

Confusion matrix:

$$[[11322 \quad 8094]$$
$$[\ 2305 \ 12117]]$$

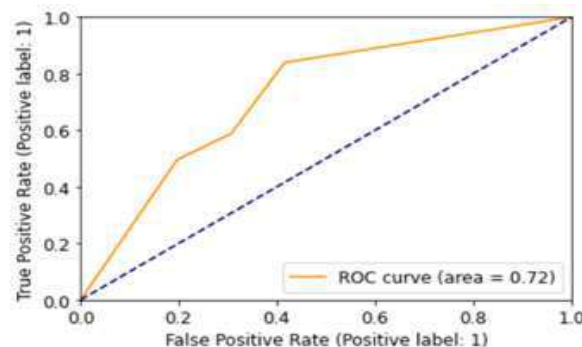Classification Accuracy: 69.2%

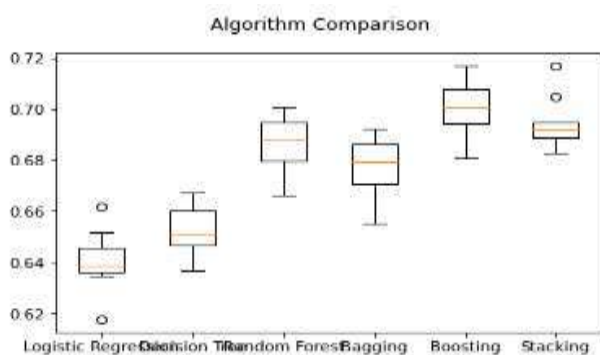**Fig 8: The AUC of stacking**

Fig 9: The comparison of ensemble classifiers

Logistic Regression: Mean Accuracy = 64.06% - SD Accuracy = 1.10%
Decision Tree: Mean Accuracy = 65.26% - SD Accuracy = 0.89%
Random Forest: Mean Accuracy = 68.64% - SD Accuracy = 1.10%
Bagging: Mean Accuracy = 67.71% - SD Accuracy = 1.15%
Boosting: Mean Accuracy = 70.02% - SD Accuracy = 1.03%
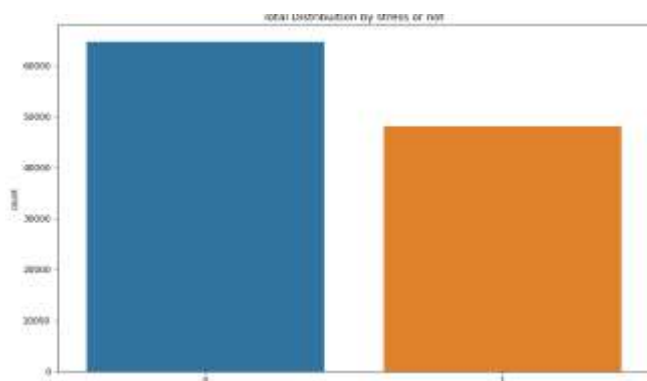Stacking: Mean Accuracy = 69.42% - SD Accuracy = 0.94%

Fig 10: The data of people who contain stress or not

5. DISCUSSION

The pandemic affects neurological problems and involves a variety of emotional issues. People's schizophrenia must be preserved, and effective treatments that can assist check and balancing vulnerable communities throughout an epidemic must be developed. There were reports of behavioral or psychological consequences, but additional evidence is required to examine the impact on mental well-being properly. Influencing factors for several prevalent psychological conditions are strongly associated with socioeconomic disparities, with the more significant the gap, the more the probability disparity. Efforts must be made to enhance the effects of ordinary life, making at conception and into early in life, younger adolescence, relatives forming and employment years, and even into adults. Activity at all phases of adulthood would enhance community psychological health and lower the likelihood of psychiatric illnesses connected with social stratification.

6. CONCLUSION

Our proposed method uses demographic factors such as age, gender, family history, seeking help, mental health consequences, Phys health consequences, and socio-economic status. Those are anticipated as individuals are more likely to be vulnerable to pandemic-related psychological impacts. These findings have emotional long-term health effects following the recovery of the epidemic and highlight the need for serious attention to the cognitive complexities of consciousness and self-quarantine and the establishment of efficient approaches to managing these epidemic repercussions. These worries are related to demographic, socioeconomic, and physiological aspects in diverse ways that should be recognized when devising methods to reduce the pandemic's emotional health consequences. The proposed ensemble model accurately classifies the patients' psychological illness of covid patients after their recovery.

7. FUTURE ENHANCEMENT

In the future, the intensifying incidence of post-COVID-19 patient anxiousness and the likelihood of sleeplessness and identifying potential risks among student populations by applying Fuzzy and CART algorithms for treatment adherence prediction. In the future, we will look into the interaction and mutual interdependence of potential risk indicators to optimize preventive strategies, interference in identifying the target, and performance.

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