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A NOVEL FEATURE SELECTION METHOD FOR PREDICTION OF FACTORS AFFECTING ANXIETY IN HEALTH CARE WORKERS DURING PANDEMIC

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Abstract

During the pandemic, hospital workers are more likely to report symptoms of sadness, anxiety, and stress. The objective of this study is to determine the elements that cause anxiety in pandemic among health care workers (HCWs). Survey comprising of latest and relevant articles stating the anxiety factors among HCWs of Saudi Arabia and rest of the remaining articles comprising of other countries stating anxiety factors of HCWs in their respective region were carefully analyzed and recorded. Moreover, a benchmark health care dataset is utilized and evaluated through proposed feature selection technique. Identified factors by proposed technique are than compared with the reported factors causing anxiety in health care workers of Saudi Arabia and other countries are analyzed. Chi-square, F_Chi and mRMR feature selection techniques are utilized to predict the factors affecting the anxiety of health care workers. The results enlisted the number of factors that contributed in accelerating anxiety among HCWs. Those factors were further applied for Classifiers like NC, KNN, AB and GB has low accuracy, precision and recall scores. However, classifiers namely MLP, NB, SGD and SVM has better overall accuracy scores. Among all, SVM Classifier stands out the most with Accuracy score of 91%, moreover 90% scores in Precision and recall.

INTRODUCTION

The viral corona virus outbreak started within suburbs of china has deteriorated the situation and led to public health emergency on international level on 11th of [1], [2] Health Organization (WHO) stats confirmed global cases of 233,503,524 of COVID-19 and among them deaths of 4,777,503 patients were confirmed only for the date of 1st Oct 2021 [3]. Health care workers (HCWs) around the world faces a major responsibility to work under dire pressure and hence most likely to get effected by the virus. China's Health commission reported more and 3,300 HCWs to be effected [4].

The massive work pressure has been adding to the psychological misbalance of HCWs. There are a lot of factors which affected the mental health of HCWs other than the fear of virus which included, health care area, location, dealing with emergencies, direct contact with virus infected patients, personal training required to handle virus and many other factors [5]. A Generalized Anxiety Disorder (GAD-7) score was reported in a study of around 582 HCWs of tertiary care teaching hospital in Saudi Arabia in which as shown in Fig. 1.

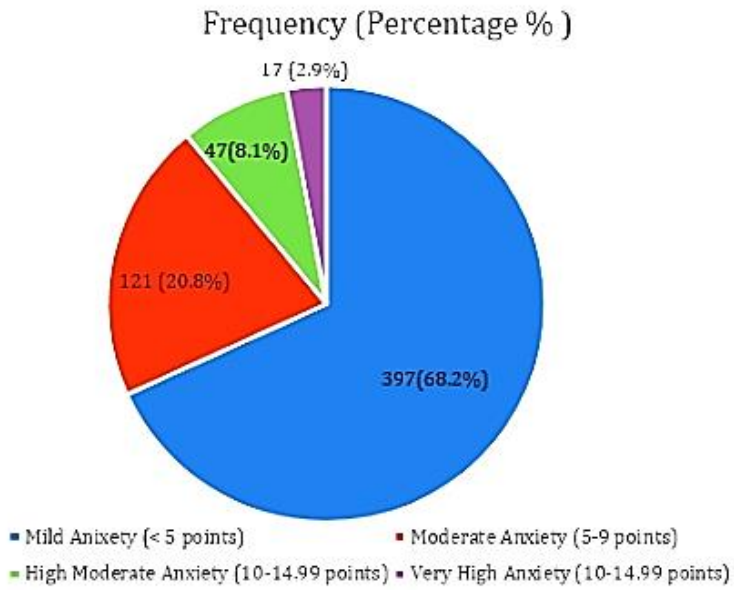

Figure 1. Generalized Anxiety Disorder Statistics of Health Care Workers in a Saudi Arabia tertiary care center during COVID-19

There has been numerous surveys and research been conducted in numerous regions of the world including Saudi Arabia and other gulf countries. There are different score based methods include Generalized Anxiety Disorder (GAD-7) [6], [7], Cross sectional study calculating Depression anxiety stress scale, HARS, BDI and ASDI scores [8], PHQ-9, GAD-7 and ISI [9]. There are ways where feature extraction/selection algorithm is employed which aids in selection of finding most affective features causing anxiety to HCWs. The proposed contribution of this paper is to:

1. Performed a Survey comprising of latest and relevant articles stating the anxiety factors among HCWs of Saudi Arabia and rest of the remaining articles comprising of other countries stating anxiety factors of HCWs in their respective region were carefully analyzed and recorded.

2. Developed a novel hybrid feature selection technique that effectively identifies the most optimal features contributing to anxiety among healthcare workers (HCWs) in Saudi Arabia during pandemic, using a publicly available benchmark dataset.

3. The optimal features are extracted using the developed hybrid feature selection method, resulting in improved model performance.

4. Compared the factors influencing anxiety disorders among HCWs in Saudi Arabia with those in other countries, as reported in the literature.

5. Evaluated the performance of the proposed feature selection technique using different classifiers and presented a comparative analysis.

2. Literature Review

This section is divided into two different domains of literature. Subsection 2.1 represent all their related work of machine leaning and feature selection-based algorithms. Subsection 2.2 represent the survey analysis in a tabular format extracted from all the latest papers about factors that effected the anxiety among HCWs during COVID-19 in Saudi Arabia as shown in Table 1 and factors the effected in anxiety among HCWs during COVID-19 in a rest of the world as shown in Tab. 2.

2.1 Algorithmic Technique Based Literature

In this subsection related research work based on feature extraction and machine learning based algorithms to find out the factors that are based as a reason of anxiety among health care workers during COVID-19 outbreak. An author named Mohid D. Gupta prepared a Machine Learning model based on Extra tree classifier and feature ranking which included the Heart rate variability (HRV) and questionnaire data of HCWs classified as front line, second line and non-COVID working domain. The findings concluded second line HCWs to have more Burn out rate i-e 20.5% than front line i-e 14.9% burn out rate [10]. However, the factors that were kept in the study for calculating the factors affecting anxiety weren't enough. Isabella Giulia Franzoi et al. conducted a cross-sectional study with 56 mental health physicians (MHPs) 57 not working with COVID-19 patients and 54 health physicians (HPs) working with COVID-19 patients. The study used Multivariate logistic regression and results were stated as MHPs are more likely to get state anxiety as compared to non-COVID department HPs [11]. These measures are extremely confusing and can be subjected to human errors while evaluating factors. Faisal Mashel Albagmi et al. in his research article used Support Vector Machines (SVM) for calculating prediction accuracy of factors affecting anxiety among general public dusing COVID-19. GAD-7 scale was used to scale the raw data from 3017 general participants from Saudi Arabia. SVM computed 100% accuracy [12]. However, the target audience was general public of Saudi Arabia therefore their research was not targeted. Another Chinese author Xaiofeng Wang et al. proposed a novel prediction model which is neural network based and optimization algorithm which had an ability to select the most ranked feature that has affected the most in contributing towards the anxiety of Chinese medical workers. Their prediction model generated the accuracy of 92%[13]. However, they claimed that their dataset has a lot of irrelevant and redundant features.

2.2 Survey Based Literature

In this subsection Literature survey has been presented on a tabular format gathered via closely analyzing the latest and most relevant literature. The literature includes stating the most relevant factors that contributed to the anxiety level of HCWs from different hospitals and health units in Saudi Arabia is discussed in Tab. 1. Tab. 2, present the Anxiety leading factors among HCWs in a country like Italy, Uk, Spain, Australia, USA, Malaysia, Finland, Palestine, and Iran.

Surveying the anxiety factors affecting HCWs in Saudi Arabia as shown in Fig. 2 and Survey has also been carried out about anxiety affecting factors of HCWs in rest of the benchmark countries as shown in Fig. 3. Both of the factors were compared and examined to extract the most uniquely common occurring factors that affected HCWs in all regions. The most uniquely common factors extracted via proposed methodology are

- Joint Family living led to more spread of a virus (Uniquely Common factors between Saudi Arabia and Italy)
- Sleeping Disorder (Uniquely Common factors between Saudi Arabia and Iran)

- No sentimental Aid from society (Uniquely Common factors between Saudi Arabia and Finland)

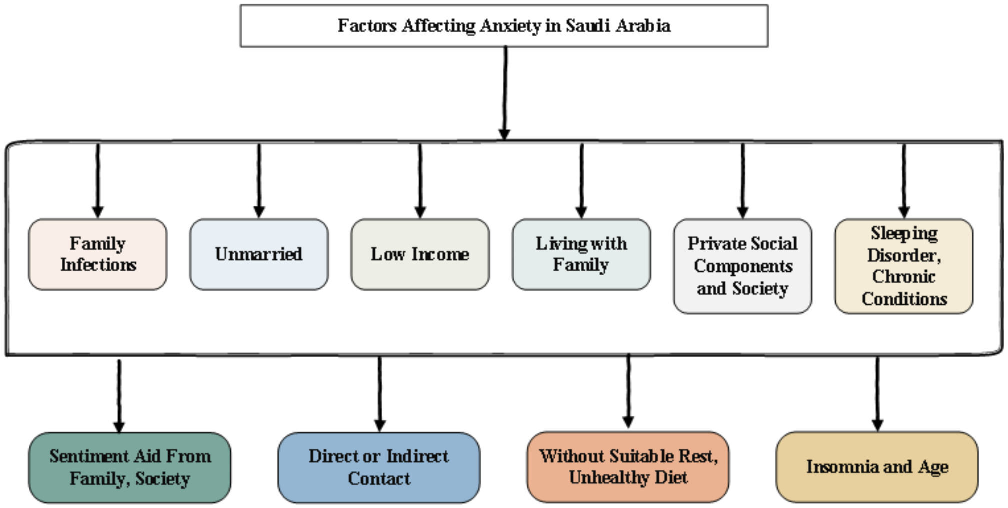

Figure 2: Factors effecting Anxiety in Saudi Arabia.

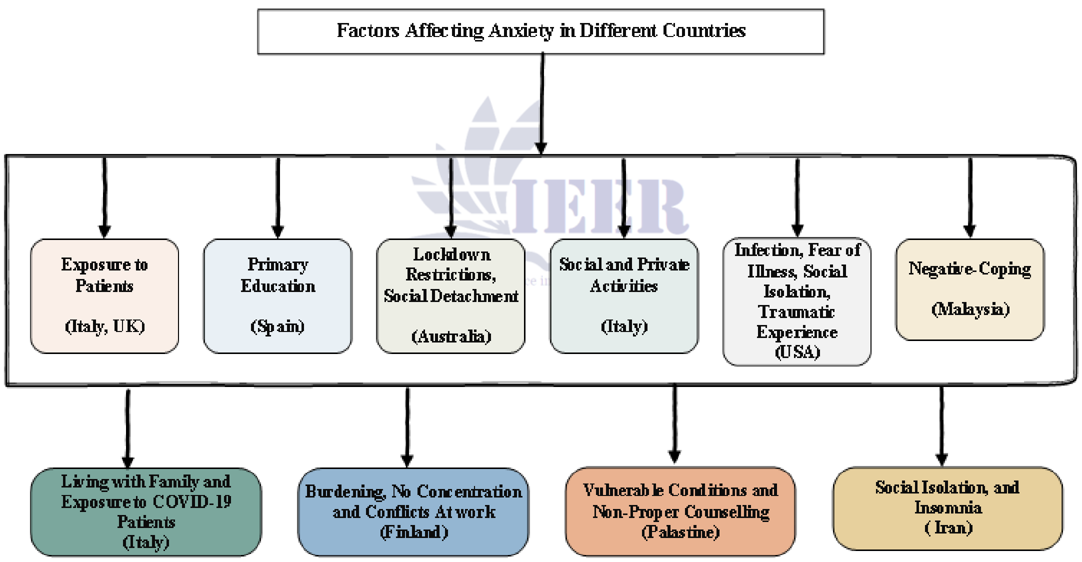

Figure 3: Factors effecting Anxiety in Different Countries

Table 1. Survey of Anxiety occurring factors among HCWs in Saudi Arabia.

Paper	Data Size	Population	Anxiety %	Reason for Anxiety
[14]	582 HCWs	Doctors, Nurses	41.1 %	Risk of transmission of infection to family
[15]	4920 HCWs	Nursing, Radiology Staff	68.5 %	Unmarried, living with person already having respiratory disease
[16]	2081 individuals participated	Nurses, Doctors	26.6 %	Low income and education level during COVID -19 lockdown causing anxiety and depression

[17]	720 participants	Nurses, Physicians, Pharmacists & Nutritionist	Minimal to mild anxiety (50.41% to 28.47%)	Working from isolated rooms, living with family causing insomnia and anxiety
[18]	737 HCWs	Doctors, Dentists, Pharmacist, Nutritionist and Nurses	99.9 %	Several elements are associated with mild to an excessive degree of fear and anxiety; these consist of private, social components and society
[19]	426 HCWs	Physicians and Nurses	58.9 %	HCWs who required sentimental aid from own family, society and medical institution showed worse mental disturbances in comparison with their correspondents who had been supplied emotional aid
[20]	804 participants	Doctor and Nurses	19.1 %	Female gender, Saudi nationality, younger age and direct contact with COVID-19 patients were the key risk factors for such issues
[21]	1678 HCWs	Consultants, physicians, nurses and clinical pharmacists	25.92 %	Clinical and paramedical body of workers without suitable rest, not having a healthy diet along with zero physical workout causing anxiety
[22]	53 HCWs	Nurses	37 % mild, 28.3% have moderate and 34% possess severe	Sleeplessness and age of nursing studies causing stress and anxiety
[23]	Not specified	Respiratory Therapists	24%–56%	Job-related stress, fear of errors, and challenging patient interactions
[24]	Not specified	HCWs in Various Wards	Not specified	Work environment and personal health concerns causing anxiety
[25]	Not specified	Doctors, Nurses, Support Staff	Significant increase	Inadequate psychosocial support and increased working hours during COVID-19

Table 2. Survey of Anxiety occurring factors among HCWs from different countries.

Paper	Region and Data Size	Population	Anxiety %	Reason for Anxiety
[26]	Italy, UK & 5275 HCWs	Doctors	20.1 %	Exposure to the COVID-19 patients causing traumatic effects on healthcare workers
[27]	Spain & 1422 HCWs	Doctors, Nurses	58.6 %	Working in hospital and having a *direct* contact with patients causing fear and anxiety
[28]	Australia & 7846 participants	Nurses, Doctors	59.8 %	Lockdown restrictions, social detachment and press broadcasting, have contributed to the excessive occurrence of mental health signs and symptoms in frontline healthcare employees
[29]	Italy & 265 HCWs	Physicians, Nurses, healthcare assistants	13.6 %	Both social and private activities causing mental disturbances
[30]	USA & 350 HCWs	Nurses and physicians	72 %	Exposure to the patients, moral injuries and unprecedented nature of epidemic causing stress
[31]	Malaysia & 200 HCWs	Doctors, Nurses, Assistant Medical Officers	36.5 %	Negative-coping techniques has determined to be notably correlated with anxiety and despair
[32]	Italy & 214 Italian HCWs	Nurses, physicians, physiotherapists, healthcare assistants, clinical psychologists	9.8 %	Healthcare workers not showing flexibility in their emotional response causing symptoms
[33]	Finland &1024 Participants	Psychologist, occupational therapists, dieticians and chemists	30% had mild, 10% moderate, 5% severe anxiety	Burdening, no concentration and conflict at work because of the fear of contracting the disease
[34]	Palestine & 1231 HCWs	Nurses and Doctors	69 %	Vulnerable conditions and non-proper counselling causing stress and anxiety
[35]	Global, 341,014 HCWs	Physicians, Nurses, Older Staff	38%	High workload, fear of infection, concern for family safety, and lack of support during the COVID-19 pandemic.
[36]	Global, 29 studies	Healthcare Workers	47%	Insomnia, anxiety, depression, PTSD, and stress due to psychological challenges faced during the COVID-19 pandemic.

[37]	USA, 1,100 HCWs	Various Roles	86%	Anxiety stemming from stress, exhaustion, burnout, and loneliness during the pandemic.
[38]	USA, 26,174 Public Health Workers	Public Health Professionals	53%	Symptoms of mental health conditions, including anxiety, due to pandemic-related challenges.
[39]	Jordan, Sample Size: 198	Healthcare professionals	Not explicit	Workload, long hours, protective gear discomfort, burnout
[40]	Saudi Arabia; 78 healthcare workers	Healthcare professionals in critical care, emergency, neurology, cardiology, pulmonology, and mental health departments	12.8% severe; 52.6% moderate; 28.2% mild	Exposure to patients' suffering and pain, leading to secondary traumatic stress. Factors include working in high-morbidity specialties, long working hours, and insufficient sleep.
[41]	Not specified; Data size not specified	Health care workers with post-COVID condition (PCC)	Data not specified	Mental health impairment associated with PCC. Factors include psychological and social elements impacting health care workers.
[42]	China; Data size not specified	Healthcare workers during the late 2022 Omicron COVID-19 outbreak	Data not specified	Factors influencing burnout include high workload, inadequate rest, and the psychological impact of the COVID-19 pandemic.
[43]	United Kingdom; Data size not specified	Diverse healthcare workers	Data not specified	Factors associated with long COVID among healthcare workers. The study examines prevalence and influencing factors.
[44]	Serbia; Data size not specified	Healthcare workers during the COVID-19 pandemic	Data not specified	Factors associated with burnout include high workload, emotional strain from patient care, and challenges related to the COVID-19 pandemic.
[45]	South Africa; Data size not specified	Healthcare workers during the COVID-19 pandemic	Data not specified	Factors associated with depressive and anxiety symptoms include increased social and occupational stressors in working environments and communities due to COVID-19.
[46]	Not specified; Data size not specified	Healthcare workers during the COVID-19 pandemic	Data not specified	Factors associated with mental health issues include excessive workload, risk of infection, and

				emotional distress due to the COVID-19 pandemic.
[47]	Not specified; Data size not specified	Healthcare workers during the COVID-19 pandemic	62.2%	Factors associated with anxiety disorders include elevated stress levels among healthcare workers during the pandemic.
[48]	Latvia; Data size not specified	Healthcare workers during the COVID-19 pandemic	Data not specified	Low self-esteem at the beginning of the pandemic increased the risk of depression by 87% and the risk of anxiety by 76%. Working in general practice (GP) practices is associated with double the risk of depression and anxiety compared to working in hospitals and specialized emergency medical services (SEMS). Direct contact with COVID-19 patients increased the odds of depression by 31%.
[49]	Global; Data size not specified	Healthcare workers during the COVID-19 pandemic	Data not specified	The study describes the impact of the COVID-19 pandemic on risk factors for suicide among healthcare workers and identifies evidence-based strategies and interventions to mitigate these risks. Factors include increased workload, emotional stress, and exposure to patient suffering.
[50]	Not specified; Data size not specified	Healthcare frontliners during the COVID-19 pandemic	Data not specified	The study investigates the prevalence of depression among healthcare frontliners during the COVID-19 crisis and identifies causative factors contributing to mental health challenges. Factors include increased workload, exposure to COVID-19 patients, and psychological stressors associated with the pandemic.

3. Proposed Novel Hybrid-Feature Selection Based Model

This Section presents a novel hybrid-feature selection technique, Chi-Square [51] with Minimum Redundancy Maximum Relevance (mRMr) [52]. The whole methodology is shown in Fig. 4. After the features has been a comparative study plan has been established to run the maximum state of the art classifiers over the selected feature set and compare the accuracies, precision and recall from extracted from classifiers. The latest classifiers that were used in a proposed methodology are Gradient Boosting (GB) [53], Nave Bayes (NB) [54], Multi-Layer Perceptron (MLP) [55], K-Nearest

Neighbor (KNN) [56] , Nearest Centroid (NC) [58], Support Vector Machines (SVM) [59] and AdaBoost [60].

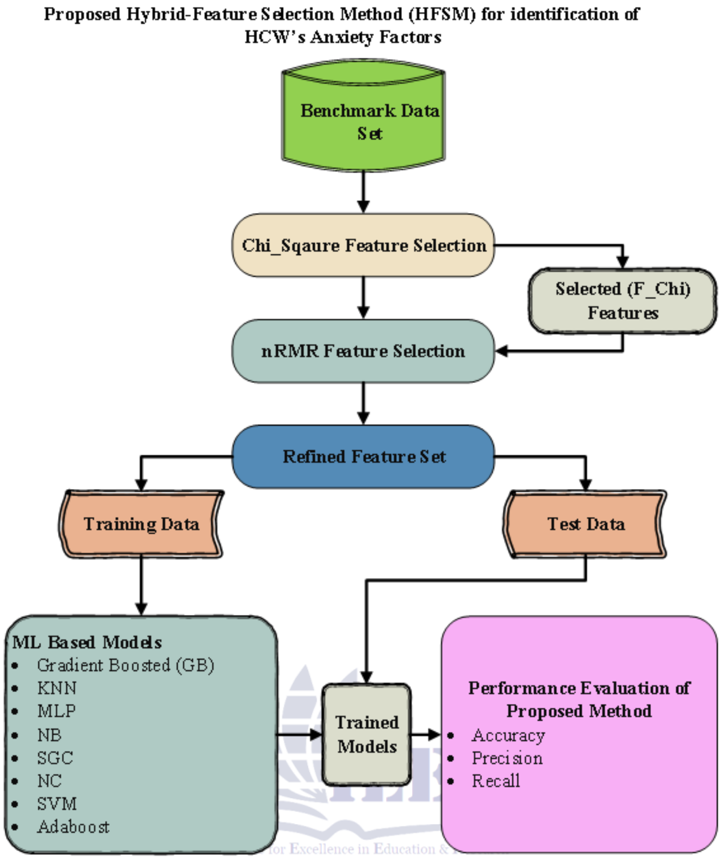

Figure 4: Proposed Hybrid Feature Selection Methodology regarding identification of HCW's anxiety factors.

3.1 Database Description

A benchmark dataset of health care worker is utilized for predicting factors affecting anxiety of health care workers. This dataset was collected by a Pakistani researcher from HCWs in Saudi Arabia. As shown in Table 3 dataset contains various healthcare workers including doctors, nursing staff, medical lab technologists and others etc. The target class we used in this dataset is known as PI1 (psychological implications). This dataset consists of 41 attributes and 427 instances.

Table 3: Dataset Description

Tables	Columns	Designation
Socio Demographic Characteristics	Age	Less than, Equal to, Greater than 30
	Gender	Male, Female
	Profession	Doctor, Medical Lab Technologist, Nursing, Others
	Development Name	The development name to which the building belongs, if any.
	Marital Status	Single, Married
	Experience (Years)	Less than 1 year, 1-5 years, 6-10 years, Greater than 10 years

	Siblings	1, 2, 3, 4+
	Sources of information about COVID-19	Consultation with Doctors, Hospital Staff, Conversation at workplace, with family and friends, Hospital posters, Cut outs, Newspaper and television shows
Knowledge Questionnaire items	K1	Do you have coronavirus background know how?
	K2	Do you have coronavirus background know how?
	K3	Does coronavirus have a positive-sense RNA structure?
	K4	Does contaminated food transmit coronavirus?
	K5	Will COVID-19 positive persons who are asymptomatic can infect others?
	K6	Is it necessary to wait for the COVID-19 incubation period to end before taking a sample for the test?
	K7	Person suspected of a COVID-19 isolation would only be a solution?
	K8	Children are less affected because they lack COVID-19 receptors?
	K9	Is it possible for Corona viruses to spread between different species?
	K10	COVID-19 has no effective treatment at the moment, however early identification of the symptoms and timely care can be effective for a patient
Practice Item Questionnaire	A1	Do you believe COVID-19 is entirely controllable?
	A2	Do you believe Pakistan will triumph over COVID-19?
	A3	Do you comply that enforcing the lock-down is important to protect others from deadly COVID-19?
	A4	Do you believe you have enough personal protective equipment (PPE) to deal with this outbreak?
	A5	Have you ever received any hand-washing instruction?
	P1	Can you count the number of times you handshake with people in a day since pandemic was on rise?
	P2	How often do you wash your hands in a day?
	P3	When you interact with a COVID-19 patient, how many times do you do so?
	P4	Do you ever teach others in your social circle about COVID-19 prevention?
	P5	Do you follow all of the processes for donning and doffing PPEs?
	P6	Do you observe the antiquates of coughing and sneezing?
Psychological Implications Questionnaire Items	PI1	Do you feel sadness and anxiety while the course of your work during the rise of Pandemic?
	PI2	Do you have any reservations about meeting up with your family after duty?
	PI3	Is it true that society members keep their boundaries closed from you as they fear from your hospital job, as they might catch virus from you?

	PI4	Do you get depressed while you're dealing with a COVID-19 patient?
	PI5	Do you ever feel overburdened while on duty?
	PI6	Have you ever abused or yelled at a patient or their attendant?
	PI7	Do you believe you are not giving your patients enough time that they might require under your care?
	PI8	Do you witness your seniors being less supportive towards you?
	PI9	Do you think you should resign from your current position in light of your current circumstances?
	PI10	Do you need any psychological assistance?
	PI11	Is your melancholy or anxiety caused by a lack of PPEs?
	PI12	Do you have any counselling sessions scheduled during this outbreak?

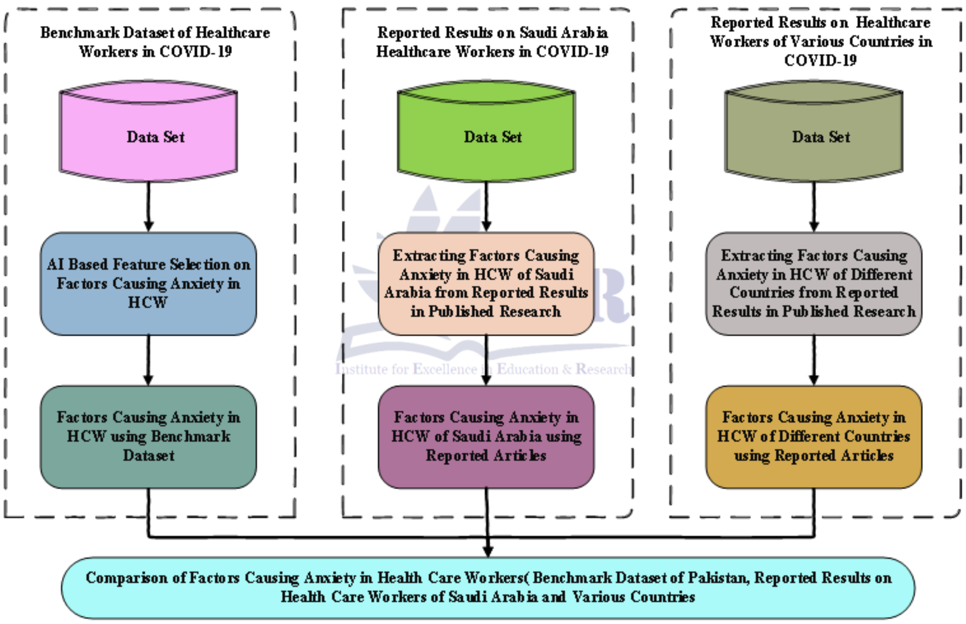

Figure 5: Dataset description

3.2 Feature Selection Technique

The steps involved in the feature selection process, including how Chi-square and mRMR work together

- **Chi-square**
- **mRMR**

The Chi-square and mRMR feature selection technique is a method for selecting the most relevant features from a large set of features. This technique is applied to the extended data features listed in table 3 to identify the most important features, which are then used to create the final feature set as mentioned in table 4. By selecting only the most relevant features, the model can improve its accuracy and reduce over fitting.

Table 4: Level Wise Feature Selection through Feature Selection Technique on Benchmark dataset of HCW.

Proposed Approach Feature Selection	Level	Selected Features
Chi-Square	1	"Work Experience", "Sources of information about COVID19","PI9","PI8","PI7","PI6","PI5","P14","P13", "P12","PI12" ,"PI11","PI10","P6"
Minimum Redundancy Maximum Relevance (mRMr)	2	"PI4","PI6","PI2","PI5","PI11","PI9","PI7","PI8" "PI10

3.3 Machine Learning Technique

- ***Gradient Boosting (GB):*** GB is powerful algorithm that forms a tree like structure, the preceding node error is minimized in the generational ones

$$L(f) = \sum_{i=1}^{n}(y_i - \mathrm{f}(x_i))^2 \qquad (1)$$

L is a loss function that minimizes the loss function to improve predictions.

- **Naive Bayes (NB):** NB is a classifier is based on probabilistic calculations works on features conditionally independent with given class labels.

$$P(\ C_K \mid X) \ = \frac{P(X \mid C_K)P(C_K)}{P(X)} \qquad (2)$$

3.3 Multi-Layer Perceptron (MLP): MLP has multiple layers of neurons that carries out deep learning as intermediate neurons are fully connected to each other.

$$\hat{y} = f(W_2 f + (W_1 x + \ b_1\ ) + \ b_2) \qquad (3)$$

Where W_1 and W_2 are weight adjusting factors using gradient descent

- ***K-Nearest Neighbor (KNN):*** KNN is a state-of-the-art classifier that classifies data based on the k samples of nearest neighbor in the feature space.

$$y = mode\ \{y_i\}\ i \in \ N_k\ (x) \qquad (4)$$

The equation above assigns a class y to a sample x based on the most frequent class label $mode\ \{y_i\}$among its k-nearest neighbors $N_k\ (x)$

- ***Nearest Centroid (NC):*** A centroid is calculated using mean of all the data point and a class is assigned whole sample is closest to the centroid in the feature space.

$$\hat{y} = \arg\ min_K\ |\mu_K - x| \qquad (6)$$

Above equation assigns a sample x to the class k whose centroid μ_K is nearest in terms of distance.

- ***Support Vector Machines (SVM):*** SVM finds the optimal hyperplane that help maximaises the margin between distinct classes.

$$Min_w \frac{1}{2} = ||w||^2 \qquad (7)$$

where w represents the weights of the hyperplane, and $||w||^2$ ensures a maximized margin between classes.

- ***AdaBoost:*** An ensemble method that combines multiple weak learners, adjusting the weights of misclassified samples to improve accuracy in subsequent iterations.

$$\mathrm{L}\ = \sum_{i=1}^{n} \exp(-\ y_i\ f(x_i)) \qquad (8)$$

Whereas L: The total loss across all samples, y_i is the true label of the i-th sample (+1 or -1), $f(x_i)$ The prediction for the i-th sample, calculated as a weighted sum of weak classifiers, lastly $\exp(-\ y_i\ f(x_i))$**:** Penalizes misclassified samples exponentially more, making their weights higher in the next iteration.

Algorithm 1: Features Extraction/Selection and Classifier Accuracy

Input:

- Dataset HCW

Output:

- Selected feature set FS_mRMR

- Performance metrics: Accuracy, Precision, and Recall

Steps:

1. Load the dataset HCW.

HCW ⟵ Input dataset

2. Apply Chi-Square feature selection to HCW.

F_χ² ⟵ ChiSquareSelection(HCW) // F_χ²: Set of features selected by Chi-Square

3. Input F_χ² into the mRMR (Minimum Redundancy Maximum Relevance) feature selection algorithm.

FS_mRMR ⟵ mRMRSelection(F_χ²) // FS_mRMR: Final selected feature set

4. Train a classifier using FS_mRMR and evaluate its performance.

- Split dataset HCW into training and testing subsets:

HCW_train, HCW_test ⟵ Split(HCW)

- Train a classifier using the training subset and selected features:

Model ⟵ TrainClassifier (HCW_train, FS_mRMR)

- Evaluate the classifier on the testing subset:

PerformanceMetrics ⟵ Evaluate(Model, HCW_test)

5. Compute the following performance metrics:

-Accuracy = (TP + TN) / (TP + TN + FP + FN)

- Precision = TP / (TP + FP)

- Recall= TP / (TP + FN)

6. Output the final selected feature set FS_mRMR and the performance metrics: Accuracy, Precision, and Recall.

Algorithm 1 defines the methodological basic steps performed to reach to the results. Fig.4 presents the methodological approach of conducting a survey. Comparative analysis of Saudi Arabian HCWs anxiety factors were extracted, through exploiting a latest literature. Moreover, comparative analysis of similar factors of HCWs from the rest of the countries like Italy, UK, Spain, Australia, USA, Malaysia, Finland, Palestine, and Iran has been extracted. The proposed methodology as shown in Fig. 4 is also a revolutionary contribution that was performed over a benchmark dataset as mentioned in Fig. 5 and later, they were quantified through classification algorithm.

4. Results and Discussion

4.1 Implementation Details

Data set was according to 80/20 train/test split and we used of holdout to ensure robust evaluation. Python 3.8 was used for the analysis, together with Scikit-learn for machine learning and Matplotlib for data visualization. A computer running Ubuntu 20.04, with an Intel Core i7 processor and 16GB of RAM, was used for the experiments.

4.2 Performance Metrics

The performance of each classifier was measured using Accuracy, Precision, and Recall metrics, defined as:

Accuracy: (TP + TN) / (TP + TN + FP + FN) (9)

Precision: TP / (TP + FP) (10)

Recall: TP / (TP + FN) (11)

The results obtained using a first method is shown in Table 4 i.e., running a feature Selection Algorithm over a benchmark data set containing anxiety occurring factors of HCWs working in Saudi Arabia. The most contributing factors proposed algorithm extracted were:

- PI2 i.e., HCWs felt hesitation while meeting with their family members after duty.
- PI4 i.e., HCWs while performing their duties felt depressed while during handling any COVID-19 patient.
- PI5 i.e., H CWs while performing their duties felt over-burdened.
- PI6 i.e., HCWs while performing their duties abused and shouted over their patients or attendants.
- PI7 i.e., HCWs while performing their duties felt that they are not giving enough time to the patient which are essential for them.
- PI8 i.e., HCWs in their work environment felt that their seniors have negative biases towards them
- PI9 i.e., HCWs while performing their duties felt that they should be resigning from their current job
- PI10 i.e., HCWs in their work environment felt that they require some psychological support
- PI11 i.e., HCWs in their work environment felt that the deficiency of PPEs is the reason for their depression or anxiety

The proposed paper has adopted two different approaches to record results of leading factors that affected HCWs while Pandemic was on rise. Those two approaches were:

- Application of Feature extraction-based algorithm to the bench mark dataset and later used eight different classifiers to find the accuracy of the proposed technique
- Surveying Latest literature where many authors have already enlisted the leading facts that affected HCWs from Countries like Saudi Arabia and similar factors of HCWs in countries like Italy, UK, Spain, Australia, USA, Malaysia, Finland, Palestine, and Iran.

5.3 Results Analysis

A publicly accessible benchmark dataset of 427 cases and 41 features—which indicate factors influencing anxiety among healthcare workers (HCWs) during the COVID-19 pandemic—was used to assess the suggested technique. The dataset contained behavioral, psychological, and demographic characteristics. The most pertinent features were extracted using the Chi-square and Minimum Redundancy Maximum Relevance (mRMR) approaches. Different machine learning classifiers were then trained and assessed using these features.

Recent applications of machine learning and deep learning across various domains emphasize the importance of robust evaluation using accuracy, recall, F1-score, and AUC-ROC [60-84]. These studies collectively demonstrate the reliability and generalizability of ML/DL models when assessed with comprehensive performance metrics.

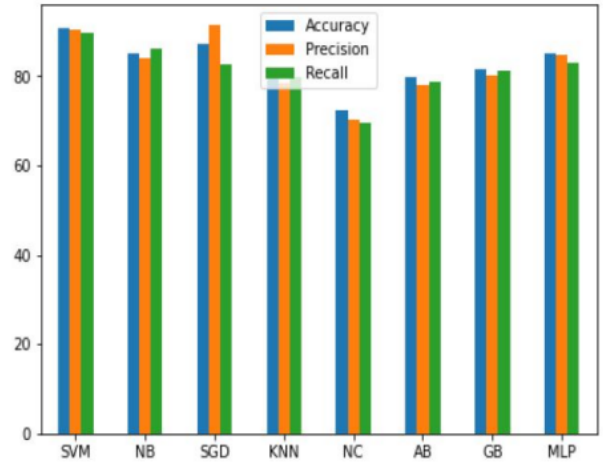

Figure 6: Frequency Bar chart representing overall accuracy, precision and recall of different classifiers

Table 5: Performance Spectrum of Comparative analysis of Accuracy Measures produced by different classifiers

High Performance | Moderate Performance | Low Performance

Classifier	Accuracy (%)	Precision (%)	Recall (%)
Support Vector Machine (SVM)	91	90	90
Multi-Layer Perceptron (MLP)	88	87	86
Naïve Bayes (NB)	87	86	85
Gradient Boosting (GB)	82	80	81
K-Nearest Neighbor (KNN)	78	77	76
AdaBoost	75	73	74
Standard Geographical Classification (SGC)	73	71	72
Nearest Centroid (NC)	71	70	68

In comparison, classifiers such as Gradient Boosting and Nearest Centroid showed relatively lower performance, with accuracy scores below 80%. Detailed performance results for each classifier are depicted in Table 5 and Figure 7. Among the chosen classifiers are Naïve Bayes (NB), Multi-Layer Perceptron (MLP), K-Nearest Neighbor (KNN), Gradient Boosting (GB); SVM outperforms for the classification. Additionally, the confusion matrix of the SVM classifier is presented in Figure 8, highlighting its ability to classify anxiety factors with minimal errors. The comparative results showcase the efficacy of the proposed hybrid feature selection method.

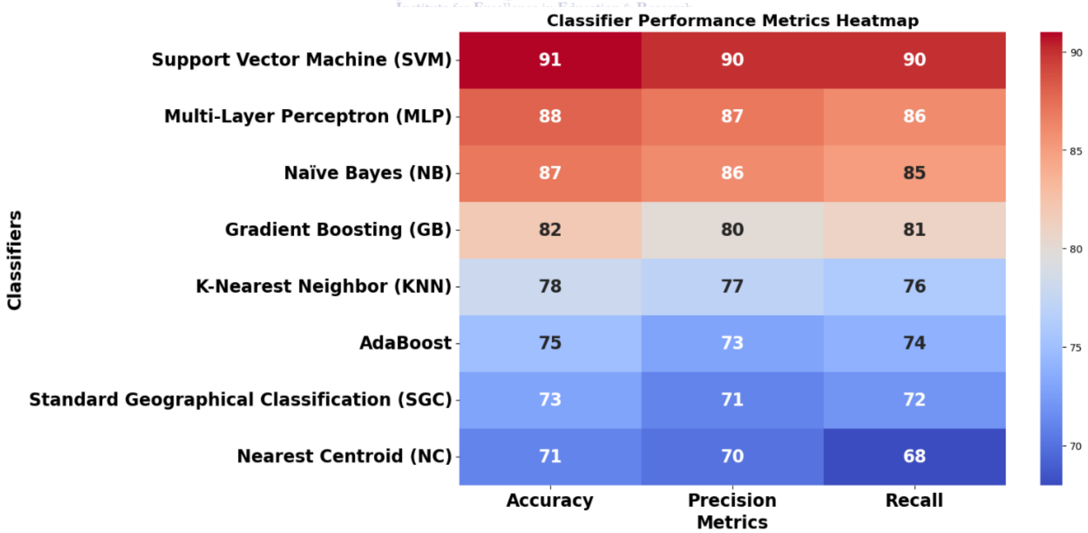

Figure 7: Individual Spectrum of Accuracy, Precision and Recall obtained from different classifiers

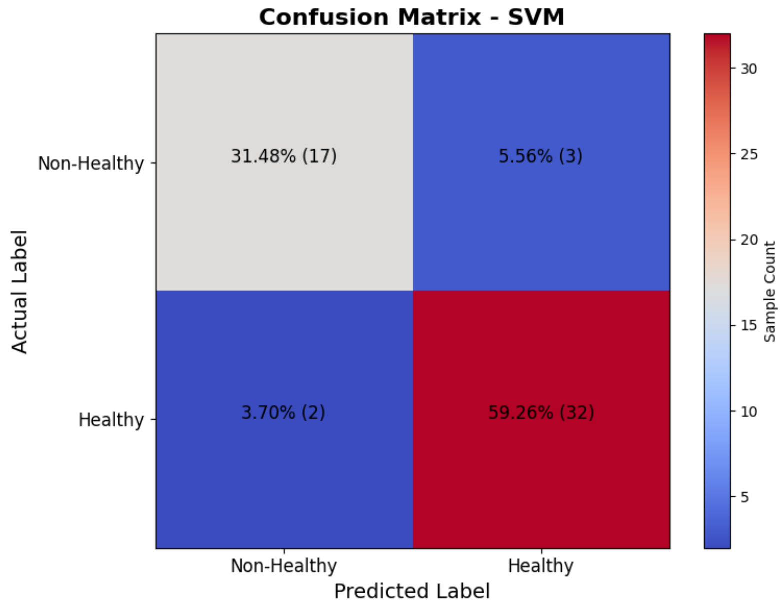

Figure 8: Confusion Matrix of SVM displaying TP, TN, FP and FN

6. Conclusion

It has been concluded as this paper aimed to find the leading factors that affected in anxiety among HCWs in Saudi Arabia during COVID-19 outbreak. Therefore, a hybrid feature selection-based Algorithm is applied over a bench mark data set containing anxiety occurring factors of HCWs working in Saudi Arabia. Feature Selection algorithm extracted the most contributing factors among that data that contributed in anxiety among HCWs in

Saudi Arabia. Later the proposed technique was evaluated using accuracy on eight different classifiers. Another method of surveying was conducted to exploit the latest literature and find out the most contributing and then the most common factors that affected HCWs among Saudi Arabia and rest of the target Countries.

7. Future Work

The novel feature selection approach produced great results. However, some relevance should have been formulated for algorithmic and survey-based anxiety finding factors. Therefore, for the future work, more resources would be devised to gather up both the findings of algorithm-based factors and survey-based factors. So, in this way contribution to intelligent findings and solution-based recommender systems can be formulated. This would help in making society prepared for health-related challenges that might occur in future.

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