

Predicting COVID-19 Cases Among Nurses Using Artificial Neural Network Approach

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We designed a forecasting model to determine which frontline health workers are most likely to be infected by COVID-19 among 220 nurses. We used multivariate regression analysis and different classification algorithms to assess the effect of several covariates, including exposure to COVID-19 patients, access to personal protective equipment, proper use of personal protective equipment, adherence to hand hygiene principles, stressfulness, and training on the risk of a nurse being infected. Access to personal protective equipment and training were associated with a 0.19- and 1.66-point lower score in being infected by COVID-19. Exposure to COVID-19 cases and being stressed of COVID-19 infection were associated with a 0.016- and 9.3-point higher probability of being infected by COVID-19. Furthermore, an artificial neural network with 75.8% (95% confidence interval, 72.1-78.9) validation accuracy and 76.6% (95% confidence interval, 73.1-78.6) overall accuracy could classify normal and infected nurses. The neural network can help managers and policymakers determine which frontline health workers are most likely to be infected by COVID-19.

KEY WORDS: COVID-19, Neural network, Personal protective equipment, Prediction

C COVID-19, caused by the SARS-CoV-2 virus, has led to continuing worldwide pandemic disease. It is mainly transmittable via tiny droplets generated by breathing, sneezing, coughing, or speaking and direct contact with an

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Data availability: The MATLAB codes of classifiers are available by reasonable request from the corresponding author.

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infected subject or indirect contact through contaminated surfaces.¹ The coronavirus pandemic has caused all units of some hospitals to be dedicated to infected patients and even surgical units to be closed.² Among people in different job groups, healthcare workers, including nurses, are on the front lines of exposure with COVID-19 and thus are highly at risk of becoming infected and even transmitting the virus to their families.³ Some estimates have demonstrated that healthcare workers are approximately 11 times more likely to develop COVID-19 disease; among them, those reporting inadequate access to personal protective equipment (PPE) were at a 23% higher risk. Such findings emphasize the importance of providing adequate PPE to the health workforce.⁴⁻⁶

In addition to having access to adequate supplies of PPE, staff needs to be appropriately trained in the effective use of such equipment. For example, prolonged use of a medical mask, gown, face shield, or respirators might increase the risk of COVID-19 infection; improper placement of face shields or medical masks on the face can be an important factor in spreading contamination.^{7,8} A study conducted by Yassi et al⁹ (2009) demonstrated limited supplies of PPE in hospitals, inadequate knowledge of health workers about how to use respirators, and lack of training programs related to infection control strategies. Another research in Washington State confirmed a lack of knowledge among health workers about infection control practices and PPE usage.¹⁰

Nurses who are in the closest contact with COVID-19 patients are at the highest risk of infection. A study conducted in China among 116 doctors and 304 nurses revealed that all the staff had access to appropriate PPE and were trained to use the equipment correctly.¹¹ Several pieces of literature affirmed that the effectiveness of PPE depends on the relative knowledge of staff, proper hand hygiene, close monitoring of health workers regarding compliance with health protocols, and provision of continuous feedback to staff in order to improve their work procedures.¹² Through applying these strategies, none of the study participants reported COVID-19 symptoms during the study period. Knowing the suitability of different PPE in various clinical conditions and proper use of them enables nurses to protect themselves against environmental hazards and avoid unnecessary costs due to improper use of PPE.¹³

In coronavirus disease, the role of nurses in controlling the adverse consequences of this crisis is so significant that

countries with enough nursing staff have lower mortality rates.¹⁴ Among the various resource constraints, the shortage of human health resources significantly pressures the health system. The absence of nurses from work because of being infected with COVID-19 results in an unbalanced workload, stress among existing nursing staff, dissatisfaction with working conditions, reduced efficiency, increased human error, and, ultimately, inferior quality of services provided to patients.¹⁵ Despite the importance of providing adequate PPE in healthcare settings and training staff about the proper use of such equipment, limited studies have examined the relationship between these two factors and nurses' absenteeism in the workplace due to COVID-19 infection.

Artificial intelligence (AI) and machine learning play a key role in healthcare systems. Machine learning can predict health risks by identifying patterns of risk markers and improving the efficacy of care while reducing cost. Artificial intelligence helped researchers during the COVID-19 pandemic in six different areas: (1) providing early warnings, (2) tracking and forecasting, (3) data analysis, (4) prognosis and diagnosis, (5) treatment and care, and (6) social control.¹⁶ Many healthcare systems have turned to AI models for early screening of COVID-19-infected patients by checking their symptoms and characteristics.^{17–19} In a study, researchers designed an AI-based diagnosis instrument of COVID-19 infection that worked by analyzing the cough sound of individuals.²⁰ Many studies have been designed based on AI and computed tomography images to diagnose the COVID-19 more accurately.²¹ In this study, we aimed to investigate the status of being infected by COVID-19 and resulting absenteeism from the workplace among nurses at different levels of access to PPE, exposure to COVID-19 cases, training, and emotional stress. For this aim, we used machine learning to identify the key features and behaviors that determine the status of being infected or not among nurses.

METHODS

Design

The present study aims to analyze the data set of nurses in Qazvin, Iran, to forecast which frontline health workers are at the most risk of COVID-19 infection.

Study Population

We conducted this descriptive-analytical study in 2020 among 220 nurses categorized in two equal groups: a group of nurses infected by the COVID-19 virus and had to leave their work for a while as sick leave and the other healthy group who did not take sick leave. The sample size was determined by Cochran's sample size method.²² According to the World Health Organization, a confirmed COVID-19 patient is a person whose COVID-19 laboratory test is positive, regardless of symptoms and clinical signs.

Ethics Statement/Confirmation of Patient Permission

The Qazvin University of Medical Sciences' Ethics Committee approved this study, and patient permission is not applicable.

Data Collection

We collected data through a self-designed questionnaire, including personal and demographic information, type of PPE used by personnel, the method and extent of PPE use among health workers, and type and amount of training about the proper use of PPE. They required information about several vacations and absences from work due to being infected by the coronavirus. We developed the questionnaire based on existing guidelines in PPE, how to use them properly, and how to apply health protocols and infection control strategies in clinical environments.

After preparing the initial version of the questionnaire, it was examined by several experts, including academic members in healthcare management, nursing, and medical equipment engineering, to ensure the face validity of the model and omit any duplicate or pointless issues. Finally, we checked a questionnaire to investigate the quantity and quality of PPE use among nurses and their training courses for its validity and reliability. Besides, a pilot study was conducted among 20 participants selected from a research population to analyze reliability. Also, Cronbach's α was calculated to demonstrate the internal consistency of the questionnaire.

Finally, we applied a content validity index to quantitatively assess the content validity ratio and select the most critical questions and their proper organization. Therefore, we asked some experts to score each item of the questionnaire in a 3-degree range (unnecessary, unnecessary but helpful, or necessary). Then, we calculated content validity ratio based on the formula $(N_e - N / 2) / (N / 2)$. N_e represents the number of individuals who scored the item as necessary, and N is the total number of individuals who scored the questionnaire items. In the study, if the average score of responses were over 1.5 and calculated content validity ratio were between 0 and 0.75, the item was accepted and remained in the final questionnaire.²³ We asked panel experts to rate each item on a 4-point scale regarding relevancy, simplicity, and transparency regarding content validity index. If the content validity index were higher than 0.79, we considered the question appropriate, and if it were less than 0.7, we removed it from the final questionnaire.²⁴

Data Set Preparation for Classification

The numerical and categorical data of nurses were extracted from the questionnaire provided in Supplemental Digital Content 1 (see Supplemental Digital Content 1, <http://links.lww.com/CIN/A163>). The categorical features were coded to numeric values provided in Table S1. The data set comprised 22 features from 220 nurses, including their personal and demographic information, type and extent of

PPE use in the workplace, training about the proper use of PPE, and emotional stress. Data set was balanced and contained an equal number of individuals in two groups. At the data preprocessing stage, we removed redundant data, such as the type of symptoms and number of absenteeism due to being infected. Also, we eliminated missing values from the data set and used imputed data to train and test the model. Data were standardized, and continuous features were normalized to their maximum values.

Statistical Analysis

We conducted the statistical analysis using Stata software, version 13.0 (TX: StataCorp LP) and descriptive statistical analysis of data using mean \pm standard deviation and frequency (relative frequency). We used analysis of variance for normally distributed variables to compare continuous variables by the level of categorical variables and the same analysis for categorical variables with chi-square. We applied a multivariate regression analysis to assess the effect of several covariates, including exposure to COVID-19 patients, access to PPE, proper use of PPE, adherence to hand hygiene principles, stressfulness, and training among patients on the response variable.

Classification Models

We compared multiple classification algorithms, including decision tree (DT),²⁵ support vector machine (SVM),²⁶ naïve Bayes (NB),²⁷ *k*-nearest neighbor (KNN)²⁸ neural network classifier (NNC), and logistic regression,²⁹ to find which model has the best performance for classification of normal and infected nurses based on the data set.

The Minimum Redundancy Maximum Relevance (MRMR) algorithm was implemented to assess the most influential features on the outcome (two groups of nurses). This algorithm selects a subset of features that have the minimum mutual information themselves and have the maximum mutual information by the target. Finally, we used 10-fold random cross-validation through the abovementioned different classifiers to assess the model's accuracy.³⁰ Hyperparameter optimization was done, and trained models by 70% of data set were validated and tested by 30% of data set.

The structure of NNC is shown in Figure 1. The first layer includes 22 neurons, each corresponding to a unique feature. The hidden layer was placed after the input layer and contains 20 layers. Finally, the output layer includes two neurons, each corresponding to a unique class (class 1: nurses not infected by coronavirus, class 2: nurses infected by coronavirus). The NNC model has 20 hidden layers, and “tanh” hyperbolic function was used as an activation function. The scaled conjugate gradient algorithm was used to optimize the parameters (weight of interactions of neurons and values of bias) of NNC and train the model.

The MATLAB built-in functions *fitcsvm*, *fitcnb*, *fitctree*, and *fitcknn* have been used to train SVM, NB, DT, and KNN models, respectively, and training of logistic regression classifier and NNC was carried out by the “classification learner app” and “neural network pattern recognition” in MATLAB 2019a.

The multidimensional hyperplane generated by the SVM model for the classification of nurses (infected and noninfected nurses) has been optimized by the Bayesian optimization method. The optimization process was carried out to determine the best kernel function among Gaussian, linear, and polynomial, and estimate some parameters including kernel scale, box constraints, and polynomial order.

In the NB classification model, we used normal kernel functions for all of the features. The parameters of kernels have been optimized by the Bayesian optimization method.

In the DT classification model, Bayesian optimization was used to estimate the best values for the minimum value of leaf size and the maximum number of splits and select the splitting criterion among Gini diversity index, deviance, and twofold. The optimization revealed that the Gini diversity index and deviance were the best splitting criterion, and the optimum minimum number of parents and leaf nodes was 12 and 6, respectively.

In the KNN classification model, Bayesian optimization was used to estimate the number of neighbors and select the best distance calculating method among “city block,” “Chebyshev,” “euclidean,” “hamming,” “cosine,” “correlation,” “Jaccard,” “Mahalanobis,” “Seuclidean,” and “Spearman” and, also, select distance weight and singularity exponent.

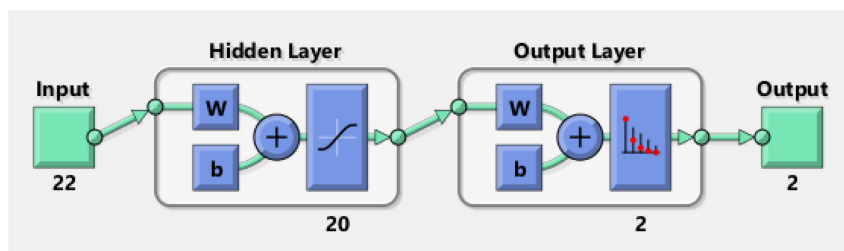


FIGURE 1. Structure of NNC for the prediction of which nurses are at risk of being infected by the coronavirus according to 22 features in the first layer.

RESULTS

In what follows, we present the results of descriptive analysis, regression method, and different classification algorithms.

Results of Descriptive Analysis

This study was conducted among 220 nurses categorized into two equal groups: a group of nurses infected by the COVID-19 virus and had to leave their work for a while as sick leave (group 1) and the healthy group who did not take sick leave (group 2). A comparison of some features between the two mentioned groups is provided in Table 1. As data depict in Table 1, there was no significant difference in sex, job title, shift type, and comorbidity between the groups. We found significant differences in exposure to COVID-19 cases and emotional stress between groups ($P < .05$).

Regarding the adherence to health guidelines, as provided in Table 2, our data indicated statistically significant differences regarding the number of PPE available to nurses per shift, access way to PPE, adherence to hand hygiene principles, and proper use of PPE between groups ($P < .05$). In the second group, a more significant number of nurses had access to more PPE during each shift. Furthermore, adherence to hand hygiene guidelines and proper use of PPE were pursued more strictly, and training courses were held more continuously in this group.

Results of Regression Analysis

In the multivariate analysis (Table 3), access to PPE and training were respectively associated with a 0.19- and 1.66-point lower score in being infected by COVID-19 ($\beta = -0.1973$;

95% confidence interval [CI], -0.0028 to -0.3974 ; $P < .05$) ($\beta = -1.667$; 95% CI, -1.315 to -0.4694 ; $P < .05$).

Table 3 depicts the marginal effects of predictive factors on being infected by COVID-19 among nurses. As data reveal, a unit change in having stress and exposure to COVID-19 cases will increase the probability of being infected by COVID-19 by 2.32 and 0.004 units, respectively.

As provided in Table 4, exposure to COVID-19 cases and having stress regarding being infected by COVID-19 were associated with a 0.016- and 9.3-point higher probability of being infected by COVID-19 ($\beta = 0.016$; 95% CI, 0.0007 - 0.0328 ; $P < .05$) ($\beta = 9.3$; 95% CI, -2.9107 to -0.0507 ; $P < .05$). Furthermore, a unit change in the proper use of PPE and training will respectively decrease the probability of being infected by 0.04 and 0.36 units, respectively.

Results of the Neural Network Model

Figure 2 shows the Pearson correlation heat map between features of the data set in both normal (left panel) and infected (right panel) groups.

Black pixels in heat map represent non-significant correlations ($P > .05$) between features. The warm and cold colors of heat map represent the positive and negative correlation, respectively, between data set features. Comparison of panels revealed that hand rub use in not infected nurses rather than infected nurses positively correlates with training.

The accuracy of different machine learning algorithms is provided in Table 5. As provided in Table 5, the NNC has the best performance, and its accuracy in the validation group is 75.8% (95% CI, 72.1-78.9). Also, NNC overall accuracy

Table 1. Nurses' Characteristics in Study Groups

Group Characteristic		Group 1		Group 2		P
		Frequency	%Frequency	Frequency	%Frequency	
Sex	Male	18	16.4	15	13.6	>.05
	Female	92	83.6	95	86.4	
Job title	Practical nurse	4	3.6	5	4.5	>.05
	Nurse	96	87.3	99	90	
	Supervisor	6	5.5	4	3.6	
	Educational supervisor	1	0.9	1	0.9	
	Clinical supervisor	2	1.8	1	0.9	
	Nursing manager	1	0.9	0	0	
Shift type	Circular	103	93.6	103	93.6	>.05
	Fixed	7	6.4	7	6.4	
Comorbidity	Yes	17	15.5	13	11.8	>.05
	No	93	84.5	97	88.2	
Exposure to COVID-19	In-hospital exposure	86	78.2	69	62.8	<.05
	Out-of-hospital exposure	11	10	17	15.4	
	Both types of exposure	13	11.8	24	21.8	
Having stress regarding COVID-19	Yes	74	67.3	58	52.7	<.05
	No	36	32.7	52	47.3	

Table 2. Access to PPE and Adherence to Hand Hygiene Principles in Study Groups

Group Characteristic		Group 1		Group 2		P
		Frequency	%Frequency	Frequency	%Frequency	
Access to PPE (number per shift)	0	4	3.6	5	4.5	<.05
	1	104	94.6	93	84.6	
	2	1	0.9	8	7.3	
	3	1	0.9	4	3.6	
Access way to PPE	Hospital provision	96	87.3	79	71.8	<.05
	Personal provision	1	0.9	4	3.6	
	Charity provision	3	2.7	5	4.5	
	All items	10	9.1	22	20	
Proper and timely use of PPE	Rarely	3	2.7	2	1.8	<.05
	Sometimes	1	0.9	0	0	
	Often	19	17.3	8	7.3	
	Always	87	79.1	100	90.9	
Adherence to hand hygiene principles	Rarely	1	0.9	1	0.9	<.05
	Sometimes	5	4.5	1	0.9	
	Often	8	7.3	9	8.2	
	Always	96	87.3	99	90	
Training about proper use of PPE	Rarely	4	3.6	5	4.6	<.05
	Sometimes	41	37.2	7	6.4	
	Often	11	10	30	27.3	
	Always	45	49.2	58	61.7	

regarding overall data set is 76.6% (95% CI, 73.1-78.6) (Figure S2). Also, the accuracy of other classification methods, including SVM, DT, logistic regression, KNN, and NB, was 71.8% (95% CI, 67.4-73.8), 71.3% (95% CI, 68.1-72.7), 70.7% (95% CI, 67.7-72.4), 70.1% (95% CI, 68.3-72.3), and 68.2% (95% CI, 65.9-70.2), respectively.

As shown in Supplemental Digital Content 2 (see Supplemental Digital Content 2, <http://links.lww.com/CIN/A164>), the MRMR algorithm identified the most influential features on the outcome.

As depicted in Figure S1, there is a drop in score between features. Tiny drops in the importance score indicate that the difference in feature importance is not significant. Moreover, the feature selection MRMR analysis revealed that the most influential predictors for classifying normal populations from infected ones are “training how to use mask properly,” “number of masks used per nurses,” “PPE availability,” “number of gloves used per shift,” “stress,” and “type of contact with

infected patients.” The mathematics of the MRMR algorithm is described in Radovic et al,³⁰ and it includes two stages. Stage 1 selects the feature set that jointly has the largest relevancy on the target class, and in stage 2, a small subset of the feature set is selected to conserve class-discriminative power. Then, the selected features by the MRMR algorithm are given to the neural network model as input to classify two groups of nurses. The neural network applies nonlinear functions and combines different features to design a nonlinear model with the best distinction power.

In contrast, the multivariate linear regression model expresses the outcome measure as a linear combination of predictors (features). Different mathematics of linear regression model and MRMR neural network model caused some differences between the results of these models. For instance, a subset of features including exposure to COVID-19, stressfulness, access to PPE, proper use of PPE, adherence to hand hygiene guidelines, and training are significant predictors by

Table 3. Multivariable Linear Regression of Potential Predictors on COVID-19 Infection

Characteristics	β	SD	Z	P > Z	95% CI
Exposure to COVID-19	0.016	0.0085	1.87	.01	(0.0007-0.0328)
Stressfulness	9.3	1.0107	0.92	.0358	(-2.9107 to -0.0507)
Access to PPE	-0.1973	0.1021	-1.93	.05	(-0.0028 to -0.3974)
Proper use of PPE	-0.1795	0.2174	-0.83	.409	(-0.6057 to 0.2465)
Adherence to hand hygiene guidelines	-0.4247	0.2508	-1.69	.090	(-1.9163 to 0.0668)
Training	-1.6672	0.5011	-1.33	.0183	(-1.3150 to -0.4694)

Table 4. The Marginal Effects of Predictive Factors on Being Infected by COVID-19

Characteristics	dy/dx	SD	Z	P>Z	95% CI
Exposure to COVID-19	0.0040	0.0021	1.87	.021	(0.0082-36.64)
Stressfulness	2.3208	0.000	0.92	.0382	(2.608-3.506)
Access to PPE	-0.0493	0.0225	-1.93	.053	(-0.0007 to 3.1583)
Proper use of PPE	-0.0448	0.0542	-0.83	.0408	(0.0614-0.3031)
Adherence to hand hygiene principles	-0.1053	0.0612	-1.72	.085	(-0.0146 to 0.7805)
Training	-0.363	0.0494	-0.74	.0461	(0.0604-0.3031)

the multivariate linear regression model. At the same time, the six top-scored features identified by the MRMR algorithm are training how to use masks properly, number of masks used per nurse, PPE availability, number of gloves used per shift, stress, and exposure to COVID-19 (contact). Both methods identify some of these predictors. The MRMR neural network model as a nonlinear method and multivariate linear regression model as a linear model can complement each other, and their results do not have any inconsistency.

The confusion matrix of training (left-top), test (left-down), and validation (right-top) and total (right-down) data sets are in different panels of Supplemental Digital Content 3 (Supplemental Digital Content 3, <http://links.lww.com/CIN/A165>).

As shown in Figure S2, the accuracy of the NNC in the distinct train, test, validation, and overall data sets is 78.3%, 69.7%, 75.8%, and 76.6%, respectively.

Model assessment reveals that the NNC can predict the risk of infection by COVID-19 in health workers based on their demographic and PPE-related information. The receiver operating characteristic curve of NNC for train, test, validation, and overall data sets was depicted in Supplemental Digital Content

4 (Supplemental Digital Content 4, <http://links.lww.com/CIN/A166>).

DISCUSSION

This study investigated the status of being infected by COVID-19 and resulting absenteeism from the workplace among nurses at different levels of access to PPE, exposure to COVID-19 cases, training, and emotional stress. This study is one of the few studies to empirically examine the influencing factors on the incidence of COVID-19 among hospital frontline workers. Our findings are consistent with what we expected, given that all the predictors, including training, PPE availability, stress management, and clear protocols to decrease exposure to COVID-19 cases, were critical in reducing the incidence of COVID-19 among nurses. In this regard, some studies mentioned more contributing factors, such as lack of infection control programs and safety practices, poor communication, lack of isolation wards, and insufficient knowledge of personnel on how to use PPE^{7,31-33} correctly. A study conducted by Alser et al³⁴ (2020) revealed that a significant number of the health workforce did not have proper access

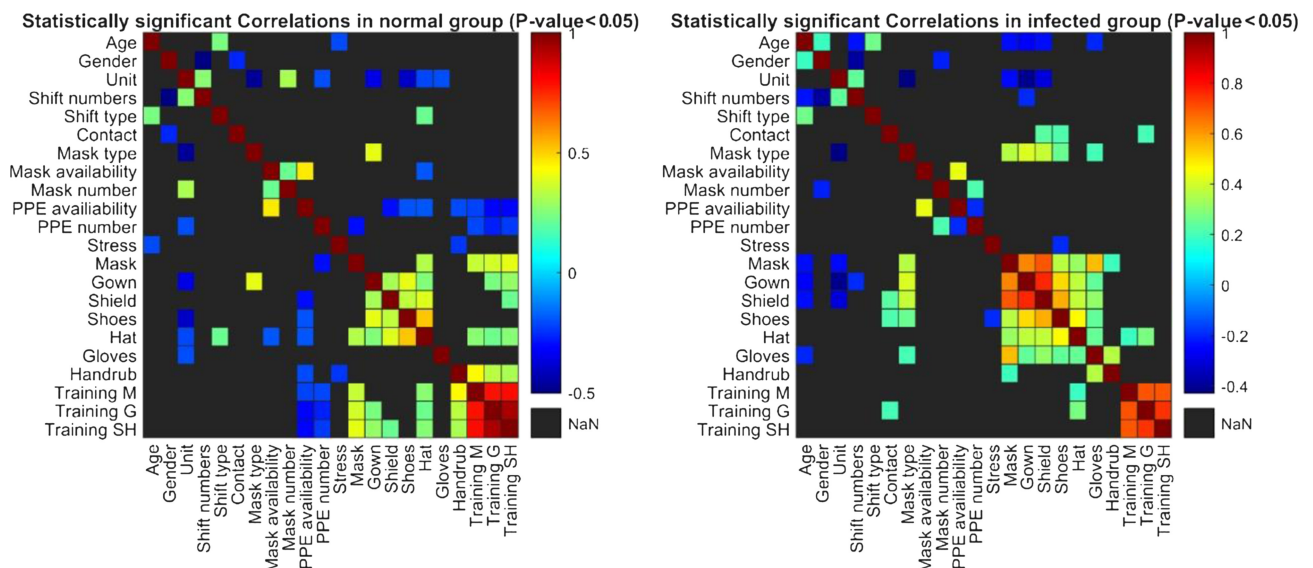


FIGURE 2. Correlation heat map between data features of both normal (left) and infected (right) nurses.

Table 5. The Validation Accuracy of Being Infected in Health Workers With COVID-19 Using 10-Fold Random Cross-validation

Type of Classifier	Accuracy
NNC	75.8% (95% CI, 72.1-78.9)
SVM classifier	71.8% (95% CI, 67.4-73.8)
DT classifier	71.3% (95% CI, 68.1-72.7)
Logistic regression classifier	70.7% (95% CI, 67.7-72.4)
KNN classifier	70.1% (95% CI, 68.3-72.3)
NB	68.2% (95% CI, 65.9-70.2)

to PPE, faced stress due to existing deficiencies, and felt unready to perform their work activities effectively. In line with these findings, similar evidence has emphasized the necessity of evaluating the supply chain as a priority of decision-making in resource allocation to ensure the availability of necessary PPE at the right time.³⁵ A study in Ghana revealed that physicians who had proper access to PPE were more prepared to work than their counterparts.⁷ Several reports have demonstrated that many health workers reported a lack of appropriate PPE. Many doctors and nurses were also forced into working without this essential equipment.³⁶

Literature affirms that preparedness activities should include training on health protocols and safety practices, timely diagnoses of infected personnel and isolating them from others, provision of adequate PPE, and close staff monitoring in compliance with safety guidelines.⁷ Among these factors, training has got particular importance due to its crucial role in increasing the knowledge and self-efficacy of the health workforce about COVID-19 prevention and management.^{37,38} However, even with adequate PPE, healthcare workers who care for patients with COVID-19 remain at an increased risk. This issue highlights the importance of ensuring PPE availability and other aspects of appropriate use, including the correct order to fit and remove PPE in clinical situations. About three-quarters of Pakistani doctors reported they did not receive the correct size of N95 respirator. It predisposes clinical staff to infection.³⁹

According to our results, most nurses were exposed to the COVID-19 virus in the hospital while providing healthcare services to patients. Similarly, the Kassem et al⁴⁰ study affirmed that most clinical staff with COVID-19 had encountered a suspected or confirmed COVID-19 patient in the past 2 weeks. These staff members mainly were those suffering from comorbid conditions such as diabetes and high blood pressure. Nurses are primarily at risk among frontline health workers due to direct contact with infected patients.⁴¹

The Minnesota Department of Health recommends that health workers with high-risk exposures stay in quarantine for 14 days and follow some safety protocols to keep themselves, patients, and co-workers safe.⁴² Although nurses have

to care for patients in an epidemic situation, many have concerns about being infected or transmitting the infection to others.⁴³ According to our results, nurses who experienced the feeling of fear and stress while providing healthcare services to COVID-19 patients were more likely to be infected. A study conducted among doctors in the United States and Pakistan revealed that most physicians were concerned about the possibility of transmitting the infection to their relatives and family members. Almost half of them were also afraid to work in such a pandemic situation.⁴⁴ Previous studies have similarly reported high rates of stress among nurses and doctors, which emphasizes the necessity of providing mental care to this particular population. A recent study by Xu and Zhang found that most nurses caring for COVID-19 patients had emotional reactions, including depression, anxiety, and fear.⁴⁵ In line with these findings, several supportive strategies targeting health professionals were proposed to provide mental health assistance during the COVID-19 pandemic.^{46,47}

Our study results also demonstrated that receiving training courses on the proper use of masks and gowns has a significant effect on the efficiency of using PPE and reducing the risk of infection. In this regard, Luong Thanh's systematic review demonstrated that training intervention led to more usage of PPE among the medical staff. Those who participated in motivational interviews received higher scores on the PPE safety checklist than others.⁴⁷ Similarly, several studies affirmed that staff participation in training programs was significantly related to reducing the risk of infection in the workplace.^{48,49}

Evidence-based prediction models can be used during the COVID-19 crisis to guide the hospital management system and healthcare administrators to make informed decisions about staff and patient care. Artificial intelligence-based fast prognostic/diagnostic instruments can increase the prognostic/diagnostic accuracy and guard healthcare frontline workers against more contact with COVID-19 patients. In a study by Iwendi et al., the authors presented a screening system based on the boosted Random Forest algorithm on the imbalanced data set of COVID-19 patients.¹⁷ Their data set contains the demographic, healthcare and travel data of COVID-19 patients worldwide, processed by different machine learning algorithms. In another study, a deep learning model predicted the fatality of a COVID-19 patient and answered whether a patient requires immediate care. In a study conducted by Sun et al., the authors provided a gradient boosted model for data-driven support of nursing home infection control.⁵⁰ Their model provides strategies for prioritizing resources to nursing homes at high risk of infection by predicting the risk of COVID-19 outbreak in nursing homes.

This study presented a NNC to analyze healthcare workers' obtained balance data set. The artificial neural network model of the present study can be used as a semi-autonomous

predictive system to assess which nurses are at most risk of infection by COVID-19. We evaluated this model using the metrics of accuracy and receiver operating characteristic curve, and it has an excellent performance in predicting nurses' risk of infection through analyzing their data.

CONCLUSION

It is essential to determine influencing factors and apply effective strategies to protect healthcare staff and reduce the burden of COVID-19 infection among frontline health workers. The neural network can help managers and policymakers determine which frontline health workers are most likely to be infected by COVID-19.

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